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FINAL PROJECT REPORT

ENHANCING RARE DESERT PLANT MAPPING FOR CONSERVATION AMID RENEWABLE ENERGY PLANNING

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Project data, scripts, and model results are available by contacting the report authors.

PREFACE

The California Energy Commission Energy Research and Development Division supports public interest energy research and development that will help improve the quality of life in California by bringing environmentally safe, affordable, and reliable energy services and products to the marketplace.

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Enhancing Rare Desert Plant Mapping for Conservation Amid Renewable Energy Planning is the final report for Mapping Habitat Distributions of Desert Rare Plants from Optimized Data (grant number 500-10-017) conducted by University of California, Davis Department of Evolution and Ecology. The information from this project contributes to Energy Research and Development Division's Energy-Related Environmental Research program.

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ABSTRACT

California's deserts are home to a number of rare plants, and little is known about where they might conflict with renewable energy development. It is important to effectively use the limited data about these plants to expedite planning and permitting. This project developed and applied geographic analytical approaches to support conservation assessment for rare plant species in areas slated for renewable energy development in the California deserts.

New species distribution models were generated for nine rare plants of potential conservation significance to the Desert Renewable Energy Conservation Plan. These representative rare plants have life histories, distributions, and ecology likely to be impacted by utility-scale solar energy development. Models for seven of the species were validated with four years of field checking, which yielded new occurrences for six of the seven target species.

The models were based on the best available data during four consecutive years of field validation, including assigning geographic coordinates (georeferencing) to herbaria specimens by the California Consortia of Herbaria. They successfully demonstrated the information that was gained using geographic and statistical modeling, limitations for these models, and important considerations for their interpretation. Significant findings include that the majority of new plant occurrences were located close to existing populations, suggesting that using field surveys is essential rather than over-relying on predictive models and that the conservation value of habitat near known occupied areas can be high. Models for many species were superimposed to identify hot spots of high rare species richness. Study results provided vital information about rare plant distributions in the Desert Renewable Energy Conservation Plan area and interpreted the species distribution models for both desert rare plant species conservation and renewable energy development planning.

Keywords: rare species, rare plants, species distribution modeling, Mojave Desert, Sonoran Desert, Desert Renewable Energy Conservation Plan, solar energy, land use change, Maxent, *Asclepias nyctaginifolia*, *Castela emoryi*, *Cymopterus deserticola*, *Eriophyllum mohavense*, *Grusonia parishii*, *Linanthus maculatus*, *Mentzelia tridentata*, *Mimulus mohavensis*, *Penstemon albomarginatus*

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EXECUTIVE SUMMARY

Introduction

The California deserts have some of the highest solar energy resources in the nation. Applications for new utility-scale solar energy generating plants to tap these resources have increased dramatically in recent years. The deserts are also fragile ecosystems that are easily damaged and slow to recover. They provide habitat for many rare plant species that have not been well studied because of the remoteness of much of the region. A significant challenge in analyzing the biological resource impacts of solar development in the Mojave and Colorado Desert Region is the lack of detailed information about where sensitive plants and animals occur. This knowledge is fundamental to assessing the impacts of utility-scale solar energy development within regional and local contexts. This vital information can help balance the needs for biological conservation and renewable energy in landscape-scale planning, such as the Desert Renewable Energy Conservation Plan.

The cumulative impacts on rare desert plant populations that will result from proposed renewable energy project development within the California deserts represent imminent threats to the long-term viability of self-sustaining rare plant populations. Complicating the assessment of project impacts and development of suitable mitigation and restoration measures is that little is known about the botanical resources of the Mojave and Sonoran Deserts relative to other ecoregions in California.

When assessing project impacts on desert rare plants, these questions must be answered:

1) What is the extent and abundance of rare plant populations within the region?
2) Do rare plants growing on the proposed sites of utility-scale energy installations also occur in other locations?
3) If so, how should these undiscovered locations be identified?

Without a complete understanding of the distribution of rare plant species associated with project proposals, an assessment of the cumulative impact to rare desert plant populations from renewable energy projects and identifying suitable habitat for mitigation would lack a scientific foundation. Statistical species distribution models have previously been used to identify potential new localities of rare species and model potential shifts in their habitats with global climate change; however, the usefulness of these models in applied conservation settings requires additional, and region-specific, study. In addition, rare species present particular challenges to statistical modeling methods because, by nature, they have few known locations or occurrences on which to base models.

Project Purpose

This project helps address the lack of detailed information by developing models that predict habitat suitability for a group of rare desert plant species representative of those affected by renewable energy development within the Mojave and Colorado Desert regions. These models were based on the best available data and several years of field validation. Points where these species had been observed but lacking accurate data about their locations were to be improved to contribute to the database of best available data. The project also determined the usefulness of such models in identifying habitat areas beyond those places where modeled species are currently known to exist.

Project Process and Results

The Consortium of California Herbaria refined the geographic coordinates (georeferencing) for 11,700 records of special-status plants from the Mojave and Colorado deserts as part of this project. Latitude and longitude data from these records obtained during the project were used to improve the models for desert rare plant species.

Enhanced species distribution models were developed for a group of special-status and sensitive plant species within the Mojave and Sonoran Desert regions that improved the modeler's ability to predict species distributions. The project successfully advanced the methods to generally predict rare plant locations by: 1) acquiring improved data from survey and herbarium records not previously available; 2) comparing the effects on predictive accuracy of two types of distribution models and of the level of detail of spatial environmental data; 3) including expert opinions of suitable habitat in the models, evaluating their effects on accuracy; and 4) validating preliminary models with field surveys.

Model predictions were greatly improved by addition of species occurrence points and the increased locational accuracy of herbarium records. For the majority of species, geographic distance to a known occurrence was a good predictor of site-suitability, highlighting the conservation value of habitat near known occupied areas. A composite model of a group of rare desert plant distribution models identified several areas of elevated rare species richness that show promise for additional botanical survey and appear to have high conservation value.

Project Benefits

This project advanced the best available science for several rare plants within the Desert Renewable Energy Conservation Plan area and provided comprehensive information on the distribution of suitable habitat of seven rare plant species of conservation concern that are or are likely to be impacted by utility-scale solar energy development. The models helped locate 66 previously unknown occurrences of these rare plants.

Nine rare species distribution models were provided to the Desert Renewable Energy Conservation Plan team in 2013 to use for developing the plan. Methods were also provided directly to plan consultants for improving rare species modeling approaches and field validation locality data for seven rare plant species.

The georeferenced data file for 11,700 herbarium specimens of special-status plants collected in the Mojave and Colorado deserts has been shared with the California Natural Diversity Database, along with the field survey data, making a substantial contribution to the available scientific knowledge about these species that can be used in future planning and assessment for renewable energy.

Overall, this project provides a method and an assessment of the accuracy and potential usefulness of habitat suitability models for rare plant conservation and mitigation planning to help minimize the impact of renewable energy development in the California deserts.

CHAPTER 1: Introduction

1.1 Use of Species Distribution Models to Guide Landscape-Scale Planning for Solar Energy and Resource Conservation

Balancing social objectives for clean, reliable energy with conservation of native plants and animals requires understanding of the ecology and distribution of focal species, their ecological communities, and ecosystems (Scott et al. 1993, Scott et al. 2002). In the rapidly changing landscape of the California Deserts and the North American Desert Southwest, the pace of development presents challenges for regional habitat conservation planning.

Species distribution models (SDMs) are a set of predictive spatial tools that have attracted interest from planners for their ability to aid conservation planning and assessment (see reviews by Peterson 2001, Franklin 2010, Guisan et al. 2013). These methods have the potential to help characterize locations of suitable habitat for species of conservation interest across entire landscapes based on limited data that may be available from smaller survey areas. Species distribution modeling, also referred to as niche modeling, refers to a set of methods that generally utilize mathematical models in a GIS framework to identify associations between environmental variables and species localities. The most common goal of these methods is to identify locations on a given landscape that are environmentally suitable for a species to occur based on previously collected data, and where those locations may be in the future under changed environmental conditions. In the past five years, over 2,000 scholarly articles have been published on the topic of distribution modeling[1], illustrating both the widespread interest in applying these models and the challenges in assessing a method that is in a state of flux as researchers refine existing approaches and develop new techniques (e.g. Franklin 2010). The results of this report were motivated by a need to distill and apply key findings from the field of distribution modeling in the conservation setting of the Desert Renewable Energy Conservation Plan (DRECP).

Driven in part by the National Environmental Policy Act (NEPA) hierarchy of goals to avoid, minimize, restore, or offset anthropogenic impacts to listed species, California is in the midst of an intensive assessment and planning process for renewable energy development in the deserts conducted by multiple state agencies, consulting groups, and non-governmental agencies. The DRECP ~~is~~ was intended to be a Natural Community Conservation Plan (NCCP) under California's NCCP Act of 2003. It may also serve as a Habitat Conservation Plan~~s~~ (HCP) under Section 10 of the U.S. Endangered Species Act. As with conservation lessons learned from other large scale NCCPs/HCPs, the lessons learned from California as it institutes regional renewable energy development across the desert region will be applicable to continued resource management around renewable energy both in California and beyond (Franklin et al. 2011).

[1] Search of Thomson Web of Science on 8/23/14 for exact phrase "species distribution" or "niche" combined with "model", "modeling" or "models" published since 2009.

1.2 Project Scope

The use of SDMs to guide conservation efforts has a long history, but as models have become more widely used and refined, there has been recent interest in making concrete policy decisions and drawing conservation boundaries based on the results of models (Guisan and Zimmermann 2000, Elith and Burgman 2003, Loiselle et al. 2003). Rare species are often the focus of conservation-oriented application of SDMs, yet they pose several challenges to the statistical methods commonly deployed. First, by definition, rare species have few occurrences and/or restricted geographic ranges (Rabinowitz 1981). Many rare species are habitat specialists, meaning that they may be most strongly influenced by unique soil or geological conditions than by broad environmental factors such as rainfall and temperature typically used in SDM construction. Furthermore, there is a general assumption that a species' distribution reflects its environmental tolerances; however, plant species that are rare may have restricted distributions because they are unable to disperse to suitable areas, are limited by lack of pollinators or soil mutualists, or may have declined due to anthropogenic influences (Williams et al. 2009). Both geographic range size and ecological specialization can influence the performance and interpretation of SDMs (McPherson et al. 2004, Segurado and Araujo 2004, Elith et al. 2006).

The goal of this project was to develop models for a focal set of rare plant species potentially impacted by solar energy development, to assess models in the field, and to make recommendations for the interpretation and application of rare plant species distribution models in an applied conservation framework (e.g., landscape-scale renewable energy planning). A specific objective was the validation of model predictions with field-collected data, a robust model assessment method that is rarely deployed (Franklin et al. 2011, Peterson et al. 2011). An additional project goal was to assess approaches for managing some of the challenges of rare species distribution modeling and interpretation by evaluating the effects of distributional patterns, spatial clustering, and data scarcity on model predictions and scores. In order to accomplish these tasks and to improve the data available for rare species distributions in the California desert region, the accuracy of species occurrence data was improved by assigning specific, researched geographic coordinates to historical accounts on species locations (i.e., georeferencing).

The project study area is the planning area for the DRECP (Figure 1). The modeling boundary was constructed based on a preliminary DRECP boundary, which was kept for modeling due to the initial development and construction of remote sensed variables for the original boundary. The total area covered by DRECP is over 35,000 square miles.

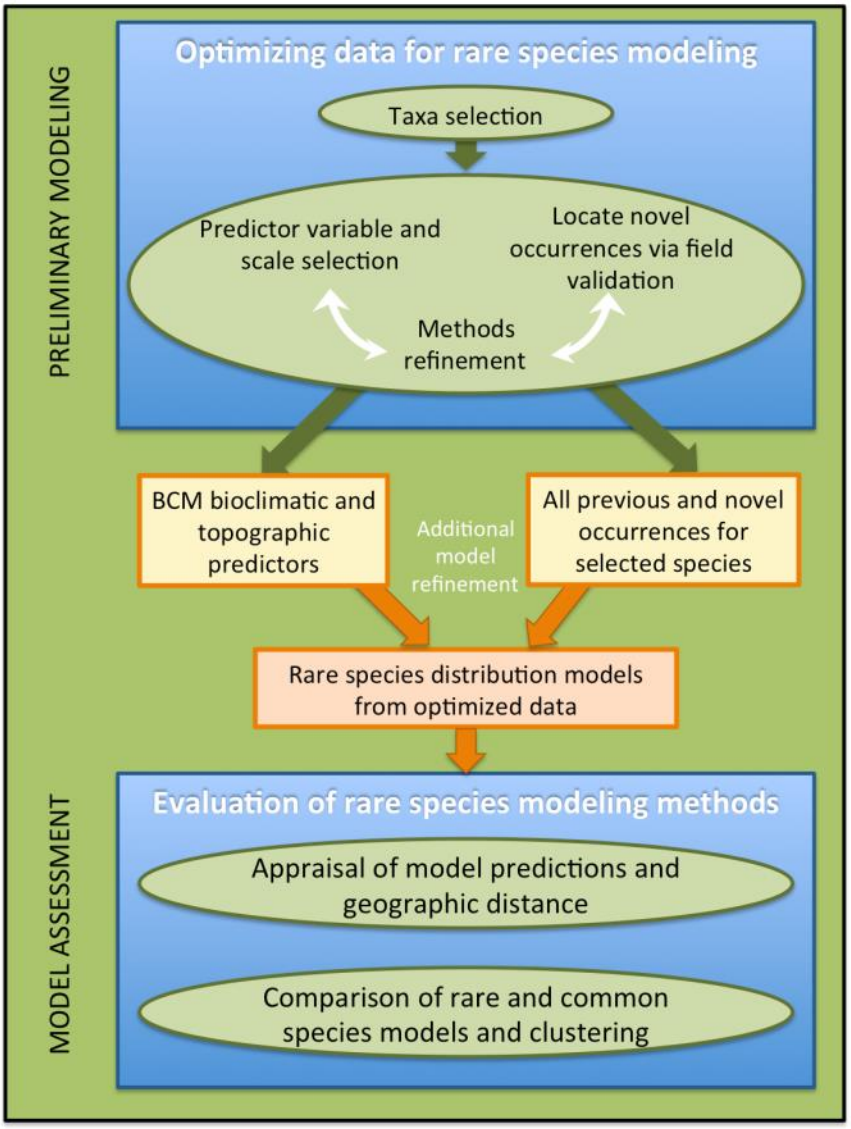
Figure 1: Map of Project Area and DRECP Planning Area

1.3 Objectives and Organization of Report

The project consisted of three main elements: (1) georeferencing of species occurrence data for the California desert region, (2) the iterative development and field validation of models based on optimized data and (3) the evaluation of rare species modeling methods and model assessment metrics (Figure 2). Chapter 2 presents methods and results of georeferencing of desert plant occurrences conducted by the California Consortium of Herbaria (CCH) through a subcontract. This and the relatively fine-scale environmental data acquired for modeling represent what the researchers term "optimized" data, meaning the data that has been refined for predicting rare species distributions. Chapter 3 presents methods for the selection of target species and preliminary modeling methods, including use of the dataset provided by the CCH. Chapter 4 presents the final modeling methods, including methods used for field validation, and assessment of models with respect to geographic distance. Finally, Chapter 4 compares methods for correcting model assessment scores to handle spatial clustering and autocorrelation, which are common issues in the evaluation of rare species model predictions. Chapter 5 shows how species distribution models can be used to identify hot spots of rare

species richness. A journal article on new occurrences of the rare shrub *Castela emoryi*, crucifixion thorn, resulted in part from this research (Bell and Herskovits 2013).

Figure 2: Flow Chart of Project Tasks and Workflow



Chapters 2 and 3 detail the preliminary modeling and iterative model refinement phases. Chapter 4 details the model assessments. BCM = Basin Characterization Model.

CHAPTER 2:
Georeferencing Plant Specimens

2.1 Introduction

Botanists have collected plant specimens for decades and preserved them in herbaria. A herbarium specimen includes plant material plus a record of attributes, such as the location of its collection, name of the collector, and date. One of the many important uses of herbarium data is that they provide location data for collections of rare plant species. These data can be used as occurrence records for species distribution modeling, among other things.

Often the location information recorded and preserved with herbarium specimens is in text form and not directly useable in GIS analysis or SDMs. Lack of data on the distribution of rare plants has limited the opportunities for SDMs. This portion of the project determined latitude and longitude data from the information on ~12,000 herbarium specimens of special status plants collected in the Mojave and Colorado deserts (Imperial, Inyo, eastern Kern, northern Los Angeles, eastern Riverside, San Bernardino, and eastern San Diego counties, Figure 3). This new, improved data will be valuable for renewable energy and conservation planning.

2.2 Data Products

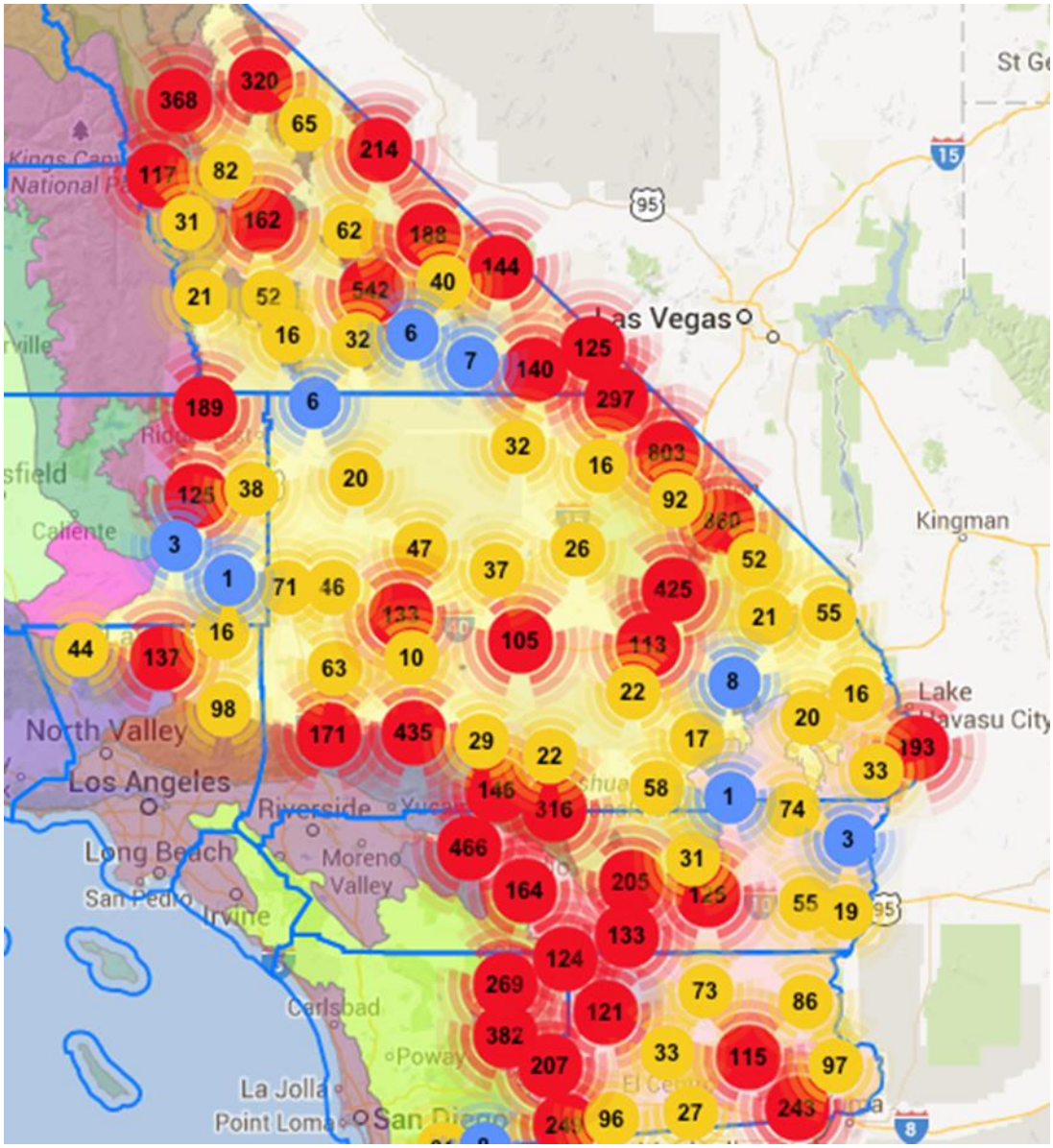
All specimens included in the work had been previously databased, and the records were obtained through the Consortium of California Herbaria (CCH), a group of 26 herbaria in California and beyond. Most records were georeferenced using an interface that was custom-built by information technology staff at the University and Jepson Herbaria (UC/JEPS). Archived specimens and botanical field notebooks housed at UC/JEPS made it possible to validate or elaborate on ambiguous locality information during georeferencing. Coordinate data were stored in the CCH buffer file (for display) as well as returned to the home institution for upload into institutionally managed databases.

The final data set contains 11,700 records with latitude and longitude coordinates. The majority of coordinates in this data set have error values estimating the precision of the mapped coordinates, a key piece of information for utilizing them in modeling and planning. Records representing 484 species names were georeferenced. As of June 28, 2013, there were 1,006,052 records that were georeferenced; thus the number added by this project (to the total CCH) was approximately 1%. For each georeferenced occurrence, an error radius was assigned from the centroid and based on the perceived accuracy of the locality. For example, three miles south from the junction of two specified roads will have a smaller error than a record that previously had the location only denoted as "Bakersfield." Most of the errors ranged from 1 m to 30,000 m.

All data were checked to verify that the county of origin reported for each collection matched the mapped coordinates for the specimen. Erroneous records were corrected or omitted. The data are displayed via the CCH interface (http://ucjeps.berkeley.edu/consortium/) and were returned to the home institutions for inclusion in local databases. The California Natural

Diversity Database (CNDDB), which is the state's central repository for sensitive plant and animal data, has also been sent an electronic copy of the data.

Figure 3: Localities of Herbarium Specimens Georeferenced by this Project



Georeferenced CCH data as presented via the online interface through Google Maps. The color of the symbol and the number inside indicate the number of specimens within an area (blue 1-10, yellow 11-100, red >100). Clusters display a rough approximation of an area occupied by a group of georeferenced localities. The numbers represent the number of records at the location. The online version of this map has a scaling zoom function.

CHAPTER 3:
Optimization of Data for Rare Species Distribution Models and Results of Field Surveys

3.1 Introduction

SDMs, also referred to as ecological niche models or habitat suitability models, use environmental data and species occurrences to construct models that predict a species' geographic range (Peterson 2001, Anciaes and Peterson 2006, Phillips et al. 2006, Elith and Leathwick 2009). The technique is commonly used to identify potential localities for rare species (Engler et al. 2004, Parolo et al. 2008, Csergoe et al. 2009, Thorn et al. 2009) and to predict where a species may move in response to climate change (Kueppers et al. 2005, Loarie et al. 2008, Wiens et al. 2009). These models can also be useful conservation tools for objectively identifying potentially suitable habitat for rare species within large planning areas. With the ready availability of GIS data on environmental conditions and software for model implementation, SDMs are easily generated. However, the accuracy of such models is highly dependent on the quality of the environmental layers and species occurrence records, as well as on the statistical approaches used to identify environmental conditions associated with the occurrences of particular species (see review Elith and Leathwick 2009). Because selection of appropriate environmental layers and quality control of species occurrence data represent the foundation for building accurate models, the initial phase of model development included identification of key environmental layers and acquisition of improved data on species occurrences.

3.2 Methods

3.2.1 Study Species Selection

Target species were carefully chosen to meet several different criteria, including sufficient data for modeling, relevance to planning for the balance between renewable energy and biological conservation, and feasibility of locating in the field. The CNDDB was initially queried for species that had at least 15 occurrences and were listed by the state of California, the federal Endangered Species Act, the California Native Plant Society (CNPS), or considered imperiled by the NatureServe heritage network. This minimum number of known occurrences (preferably supplemented with additional data) is necessary for reasonable accuracy of habitat suitability models (Wisz et al. 2008). Several different factors of species geographic and spatial distributions were also considered in target species selection including geographic extent. A wide geographic extent and taxonomic spectrum was included to increase the applicability of findings to other locations and species throughout the desert region. A range of life histories, with perennial succulents, woody shrubs, and herbaceous annuals were also included. In addition, species were selected based on their affinity for site conditions that are most likely to be impacted by utility scale solar energy development. For example, species were selected that occur at low to moderate elevations (0-3500'), in non-forested sites, and with a significant proportion of occurrences outside of already designated conservation areas. Finally, species that are known to occur within areas suitable for energy installations were also included (*Asclepias*

nyctaginafolia and *Grusonia parishii*), and/or species that have been previously identified in permitting reviews (*Penstemon albomarginatus*).

In the taxon selection process, maps of candidate rare species were overlaid and examined for groups of species that occur in similar "hot spot" habitats. By modeling habitat that is occupied by multiple rare species, the efficiency of field survey efforts and the applicability of findings to the conservation to additional species were increased. This enhanced the conservation applicability of this work, since identification of such habitat may be of value to conservation and mitigation efforts.

For simplicity, taxa are referred to as "species" throughout this report, despite the presence of some taxa on the initial list that are in need of taxonomic study and may represent conservation or taxonomic units below the species level (e.g., subspecies). The following steps were used to develop the initial target species list:

1) Started with 372 California Rare Plant Rank (CRPR[2]) species that occur within the DRECP planning area.
2) Limited list to taxa with 15 or greater CNDDB Element Occurrences[3] (EOs) (will later consider species with fewer EOs for demography or as special cases)
3) Limited to taxa that occur at elevations feasible for solar development, resulting in 61 species (-70-3500')
4) Mapped distributions of these 61 species and considered their distributions as they would affect modeling:
    a. Are occurrences clumped in a narrow way that suggests strong sampling bias or extreme propagule limitation?
    b. Are occurrences so widely distributed that it would be unrealistic to sample their modeled range?
    c. Are occurrences in preferred study areas:
        i. Near other rare species that could be included (for efficiency, budget)
        ii. In areas of pending permitting or pending construction (Ivanpah, I-10, Western Mojave, Owens Valley)
        iii. Clustered with other rare species in a way that suggests potential to identify and prioritize rare species hot spots.
5) Excluded CA Rare and CRPR 4 species

[2] https://www.cnps.org/cnps/rareplants/ranking.php

[3] Plant taxa, animal taxa, and natural communities in the CNDDB are referred to as "elements." An "element occurrence" (EO) is a location record for a site which contains an individual, population, nest site, den, or stand of a special status element.

6) Considered if species most commonly occur in forested habitat. Species were not excluded based on this alone, but left it as a criterion for consideration.

7) Considered notes in CNPS data layer on rare desert species; excluded species with "less than 5 known occurrences."

8) Prioritized species that occurred in high rare plant areas, general areas around Ivanpah, Barstow, Coachella Valley and some areas to the East and South of the Salton Sea. Rationale is that species should be selected that occur in general areas so that the project(s) is logistically feasible.

9) Excluded species that occurred only or predominantly in protected lands.

10) Excluded species that occur only in the Owens Valley. This area has received a lot of attention and is probably less at risk for solar development than other areas (although wind development remains an option).

11) Excluded CRPR 3 species.

12) Lower emphasis on species with CRPR of two.

13) Prioritized inclusion of annuals since there are few to pick from that are high profile.

14) Consulted botanical and ecological experts, including: Jim Andre, Naomi Fraga, Steve Schoenig, Shannon Still, Kelly Amsberry, Amber Swanson, Bruce Baldwin, Bruce Pavlik, Danny Reinke, and Christina Lund.

These criteria were used to develop an initial list of 65 candidate rare species (Table) for species distribution modeling. Then the researchers refined the selection to produce a final list of rare species that were the focus of modeling and field validation based on model outcomes.

Table 1: Initial Candidate Species List Used in Preliminary Model Development

Scientific name	Common name	Listed[1]	CRPR[2]
Abronia villosa var. *aurita*	Chaparral sand-verbena		1B.1
Acanthoscyphus parishii var. *goodmaniana*	Cushenbury oxytheca	FE	1B.1
Allium nevadense	Nevada onion		2.3
Androstephium breviflorum	Small-flowered androstephium		2.2
Arabis dispar	Pinyon rock-cress		2.3
Arabis shockleyi	Shockley's rock-cress		2.2
Arctomecon merriamii	White bear poppy		2.2
Asclepias nyctaginifolia	Mojave milkweed		2.1
Astragalus albens	Cushenbury milk-vetch	FE	1B.1

Scientific name	Common name	Listed[1]	CRPR[2]
Astragalus cimae var. *cimae*	Cima milk-vetch		1B.2
Astragalus insularis var. *harwoodii*	Harwood's milk-vetch		2.2
Astragalus jaegerianus	Lane Mountain milk-vetch	FE	1B.1
Astragalus magdalenae var. *peirsonii*	Coachella Valley milk-vetch	FE	1B.2
Astragalus tricarinatus	Triple-ribbed milk-vetch	FE	1B.2
Astrolepis cochisensis ssp. *cochisensis*	Scaly cloak fern		2.3
Calliandra eriophylla	Pink fairy-duster		2.3
Calochortus excavatus	Inyo County star-tulip		1B.1
Calochortus palmeri var. *palmeri*	Palmer's mariposa-lily		1B.2
Calochortus plummerae	Plummer's mariposa-lily		1B.2
Calochortus striatus	Alkali mariposa-lily		1B.2
Canbya candida	White pygmy-poppy		4.2
Carnegiea gigantea	Saguaro		2.2
Castela emoryi	Emory's crucifixion-thorn		2.3
Castilleja lasiorhyncha	San Bernardino Mountains owl's-clover		1B.2
Colubrina californica	Las Animas colubrina		2.3
Chloropyron tecopense	Tecopa bird’s beak		1B.2
Coryphantha alversonii	Alverson's foxtail cactus		4.3
Coryphantha chlorantha	Desert pincushion		2.1
Cymopterus deserticola	Desert cymopterus		1B.2
Cymopterus gilmanii	Gilman's cymopterus		2.3
Ditaxis claryana	Glandular ditaxis		2.2
Ditaxis serrata var. *californica*	California ditaxis		3.2
Enneapogon desvauxii	Nine-awned pappus grass		2.2
Erigeron parishii	Parish's daisy	FT	1B.1
Eriogonum ovalifolium var. *vineum*	Cushenbury buckwheat	FE	1B.1
Eriogonum umbellatum var. *juniporinum*	Juniper sulphur-flowered buckwheat		2.3
Eriophyllum mohavense	Barstow woolly sunflower		1B.2
Eschscholzia minutiflora ssp. *twisselmannii*	Red Rock poppy		1B.2
Grusonia parishii	Parish's club-cholla		2.2
Linanthus maculatus	Little San Bernardino Mtns. linanthus		1B.2

Scientific name	Common name	Listed[1]	CRPR[2]
Loeflingia squarrosa var. *artemisiarum*	Sagebrush loeflingia		2.2
Lotus argyraeus var. *multicaulis*	Scrub lotus		1B.3
Mentzelia polita	Polished blazing star		1B.2
Mentzelia tridentata	Creamy blazing star		1B.3
Mimulus mohavensis	Mojave monkeyflower		1B.2
Mirabilis coccinea	Red four o'clock		2.3
Monardella robisonii	Robison's monardella		1B.3
Opuntia basilaris var. *brachyclada*	Short-joint beavertail		1B.2
Penstemon albomarginatus	White-margined beardtongue		1B.1
Penstemon stephensii	Stephens' beardtongue		1B.3
Penstemon utahensis	Utah beardtongue		2.3
Petalonyx thurberi ssp. *gilmanii*	Death Valley sandpaper-plant		1B.3
Phacelia coerulea	Sky-blue phacelia		2.3
Phacelia nashiana	Charlotte's phacelia		1B.2
Pilostyles thurberi	Thurber's pilostyles		4.3
Plagiobothrys parishii	Parish's Popcorn Flower		1B.1
Prunus eremophila	Mojave Desert plum		1B.2
Psorothamnus fremontii var. *attenuates*	Narrow-leaved psorothamnus		2.3
Saltugilia latimeri	Latimer's woodland-gilia		1B.2
Salvia greatae	Orocopia sage		1B.3
Senna covesii	Coves' cassia		2.2
Sidalcea covillei	Owens Valley checkerbloom	CE	1B.1
Sphaeralcea rusbyi var. *eremicola*	Rusby's desert-mallow		1B.2
Xylorhiza cognate	Mecca-aster		1B.2
Xylorhiza orcuttii	Orcutt's woody-aster		1B.2

[1] Listed refers to federal and state listing status: federally endangered (FE), federally threatened (FT), or California endangered (CE). [2]California Rare Plant Ranks (CRPR) are designated by the California Native Plant Society, and reflect status in 2010.

Geographic restriction of the study area and consultation with experts were particularly helpful steps in narrowing down the species list. Geographic restriction increased the efficiency and the scope of work able to be accomplished on each taxon because it limited the appropriate search area for field validation efforts. The goal was also to find species that would be appropriate candidates both for this report and the concurrent demographic study being conducted by

Moore, Pavlik, McIntyre and others (grant # PIR-10-047). Consultation with experts yielded information on the feasibility of locating and identifying species in the field, as well as their vulnerability to solar energy development.

The initial target species list was increasingly narrowed over the field season based on the field findings in the initial 2011 field season, preliminary models, and ongoing consultation with experts. The final target species list consisted of nine rare native vascular species, seven of which were selected for field validation (Table). Five of the selected species were considered by the Independent Science Advisers as candidates for covered species listing or as other "species of planning interest" under DRECP (Spencer et al. 2010), and four were included in the Draft Covered Species List issued by the Renewable Energy Action Team (REAT) on June 17, 2013. Scientific names are used when referring to these species throughout this report.

Table 2: Plant Species for Which Final Models Were Produced

Scientific name	Species code	Common name	DRECP status[1]	Field validation	Federal	CRPR[2]
Asclepias nyctaginifolia	ASC	Mojave milkweed		●		2.1
Castela emoryi	CAS	Emory's crucifixion-thorn		●		2.2
Cymopterus deserticola	CYM	Desert cymopterus	DCSL		BLM	1B.2
Eriophyllum mohavense	ERI	Barstow woolly sunflower	DCSL	●	BLM	1B.2
Grusonia parishii	GRU	Parish's club-cholla		●		2.2
Linanthus maculatus	LIN	Little San Bernardino Mtns. linanthus	DCSL			1B.2
Mentzelia tridentata	MEN	Creamy blazing star		●		1B.3
Mimulus mohavensis	MIM	Mojave monkeyflower	DCSL	●	BLM	1B.2
Penstemon albomarginatus	PEN	White-margined beardtongue	ISP	●		1B.1

[1]DRECP status indicates consideration for DRECP covered species listing by either the Independent Science Panel (ISP) in 2012 or the Draft Covered Species List (DCSL) released by the REAT in 2013.
[2]California Rare Plant Ranks (CRPR) are designated by the California Native Plant Society.

3.2.2 Occurrence Data Acquisition

Data were used from the following sources to parameterize habitat suitability models for each of the selected target species: 1) CNDDB element occurrences, 2) novel records of "data mined" occurrences, which are described below, 3) expert opinion, and 4) absences from field validation of preliminary models.

Element occurrence data for targeted rare plant species from the CNDDB were used to populate preliminary models for each target taxon. These records were updated regularly throughout the project and later included records from the California Consortium of Herbaria (CCH). The later records were updated in 2012 and included newly georeferenced specimens from the CCH, which prioritized our study species (Chapter 2). To obtain the most complete occurrence dataset available for each taxon, the authors also worked to "data mine" files located at regulatory agency field offices, online, and in private and public herbaria for specimen records related to academic research. In addition, Mojave Desert vegetation and rare plant occurrence data resulting from the National Park Service (NPS) Mojave Network botanical database were examined and additional occurrences were added to model inputs as appropriate. Additional occurrence records uncovered through this research were reported to the California Department of Fish and Wildlife Biogeographic Data Branch for review and entry into the CNDDB.

3.2.3 Data for Modeling – Environmental Datasets

3.2.3.1 Climate Layers

Two climatic data sets were used: 1) the Worldclim dataset of 1 km 19 Bioclim layers (Hijmans et al. 2005; http://www.worldclim.org) rescaled to ~270 m, and 2) a data set based on the 270 m climate surfaces of the California Basin Climate Characterization Model (Flint and Flint 2012b; http://climate.calcommons.org/dataset/10), which were used to generate a corresponding set of Bioclim variables. We calculated an independent set of Bioclim values from the Basin Characterization Model in order to compare different climate data sets using standard variables. The variables used in these datasets are listed in Table 3 along with a brief description of each variable. Preliminary models based on the two scales of climate data were compared to assess the utility of downscaled data in this context.

3.2.3.2 Remotely Sensed and Topographic Layers

Three remotely sensed predictors were used that represent and/or are correlated with key abiotic and biotic components of plant habitat. Albedo is a measurement of surface reflectivity that can capture variation in substrates. The normalized difference vegetation index (NDVI) is correlated with the amount of photosynthetically active vegetation. Mean NDVI corresponds with differences in average primary productivity across the region. The ratio of spring (February-April) to late summer (July-September) NDVI is a simple index that captures temporal variability in the amount of photosynthetically active vegetation across the year. Both mean and variability in NDVI are commonly used in distribution modeling as a proxy for variation in vegetation characteristics. These predictors were constructed based on remotely sensed variables available from data available via NASA's MODIS portal (http://modis.gsfc.nasa.gov/data/). Each variable was calculated based on data from 2000-2010 at the 270 m resolution (Table 3).

Table 3: Environmental Variables Used for Species Distribution Modeling

Variable type	Variable	Description
Topographic	Slope complexity	Standard deviation of slope within a 2 km area
Topographic	Elevation	SRTM 90m Digital Elevation Database
Topographic	Slope	Interpolated from 90m (Digital Elevation Map) DEM
Topographic	Aspect	Interpolated from 90m DEM
Topographic	Northness	Measured as cosine of Aspect, ranging from 1 (north) to -1 (south).
Biological	Productivity	2000-2010 Normalized Difference Vegetation Index (NDVI) from NASA MODIS remotely sensed imagery (monthly average across year).
Biological	Vegetation seasonality	Ratio of Fall:Spring NDVI
Bioclimatic	Mean annual temperature	BIO1
Bioclimatic	Mean diurnal temperature range	BIO2, mean of monthly max temperature minus min temperature
Bioclimatic	Isothermality	BIO3 = BIO2/BIO7*100
Bioclimatic	Temperature seasonality	BIO4, temperature Seasonality (Coef. of Var of monthly mean temperatures, x100)
Bioclimatic	Maximum temperature	BIO5, maximum temperature of warmest month (°C, x10)
Bioclimatic	Minimum temperature	BIO6, minimum temperature of the coldest month (°C, x10)
Bioclimatic	Temperature annual range	BIO 7, defined as BIO5 minus BIO6
Bioclimatic	Wet quarter temperature	BIO8, mean temperature of wettest quarter (mm)
Bioclimatic	Dry quarter temperature	BIO9, mean temperature of driest quarter (mm)
Bioclimatic	Warm quarter temperature	BIO10, mean temperature of warmest quarter (mm)
Bioclimatic	Cold quarter temperature	BIO11, mean temperature of coldest quarter (mm)
Bioclimatic	Annual precipitation	BIO12, annual precipitation (mm)
Bioclimatic	Wettest month precipitation	BIO13, mean precipitation of the wettest month (mm)
Bioclimatic	Driest month precipitation	BIO14, mean precipitation of the driest month (mm)

Variable type	Variable	Description
Bioclimatic	Precipitation seasonality	BIO15, Coefficient of variation of monthly precipitation
Bioclimatic	Wettest quarter precipitation	BIO16, mean precipitation of the wettest quarter (mm)
Bioclimatic	Driest quarter precipitation	BIO17, mean precipitation of the driest quarter (mm)
Bioclimatic	Warmest quarter precipitation	BIO18, mean precipitation of warmest quarter (mm)
Bioclimatic	Coldest quarter precipitation	BIO19, mean precipitation of coldest quarter (mm)
Substrate	Surface reflectivity	2000-2005 monthly average albedo from NASA MODIS Remote Sensed Imagery
Soil	pH	Soil pH (pH scale) from 0-50 cm soil depth, derived from SSURGO database. The map unit area weighted average of the soil component, horizon depth weighted average.

Two independent sets of bioclimatic data were used: 1) the standard 1 km Worldclim bioclim dataset, and 2) a bioclim dataset calculated from the 270 m resolution Basin Characterization Model.

A 270-m DEM was used to generate topographic variables for final modeling including elevation, slope, and aspect. In addition, an index of topographic heterogeneity was estimated using the standard deviation of slope of raster cells in a ~1-km^2 (4x4 grid cell) area. Plants are sensitive to soil conditions, but few soil variables other than pH are readily available at large scales for modeling plant occurrences. Therefore, average pH of soil polygons was extracted from the Soil Survey Geographic (SSURGO) database (http://soils.usda.gov/survey/geography/ssurgo/) to a 270-m resolution raster as a continuous metric of variation in substrate.

3.2.4 Preliminary Modeling Methods

A central objective was to generate models that would best predict new occurrences of the rare target species to guide field surveys. To meet this objective, model predictions were honed such that they were most likely to identify unsurveyed locations where the species is most likely to be found. This is in contrast to the broader area in which the species should be considered a possible member of the plant community for management purposes.

A three-stage approach was used to build, assess, and finalize distribution models for the focal species. First, preliminary models were built for each species using a limited set of predictor variables and standard Maxent modeling methods. Maxent is a program for modeling species' distributions from presence-only data by minimizing the relative entropy between the probability density of the presence data and the probability density of the landscape characteristics (Elith et al. 2011). It is commonly used by ecologists in academic and industry

settings. Second, field surveys were conducted based on preliminary model predictions. Third, final models were built based on all predictor variables and occurrences, including field data, and applied methods to assess both potential biases and model fit. In a final round of modeling two approaches were compared for selecting predictor variables (Chapter 4).

Species distribution models were developed using Maxent v. 3.3.3. Maxent models were implemented and evaluated using the R packages DISMO (Hijmans et al. 2013) and SDMTools (VanDerWal et al. 2014). Default Maxent methods were applied to generate an informal series of models for each taxon of interest based on all variables, subsets of potentially meaningful variables, and the subsets determined via jackknife evaluations of the contribution of each predictor to full models.

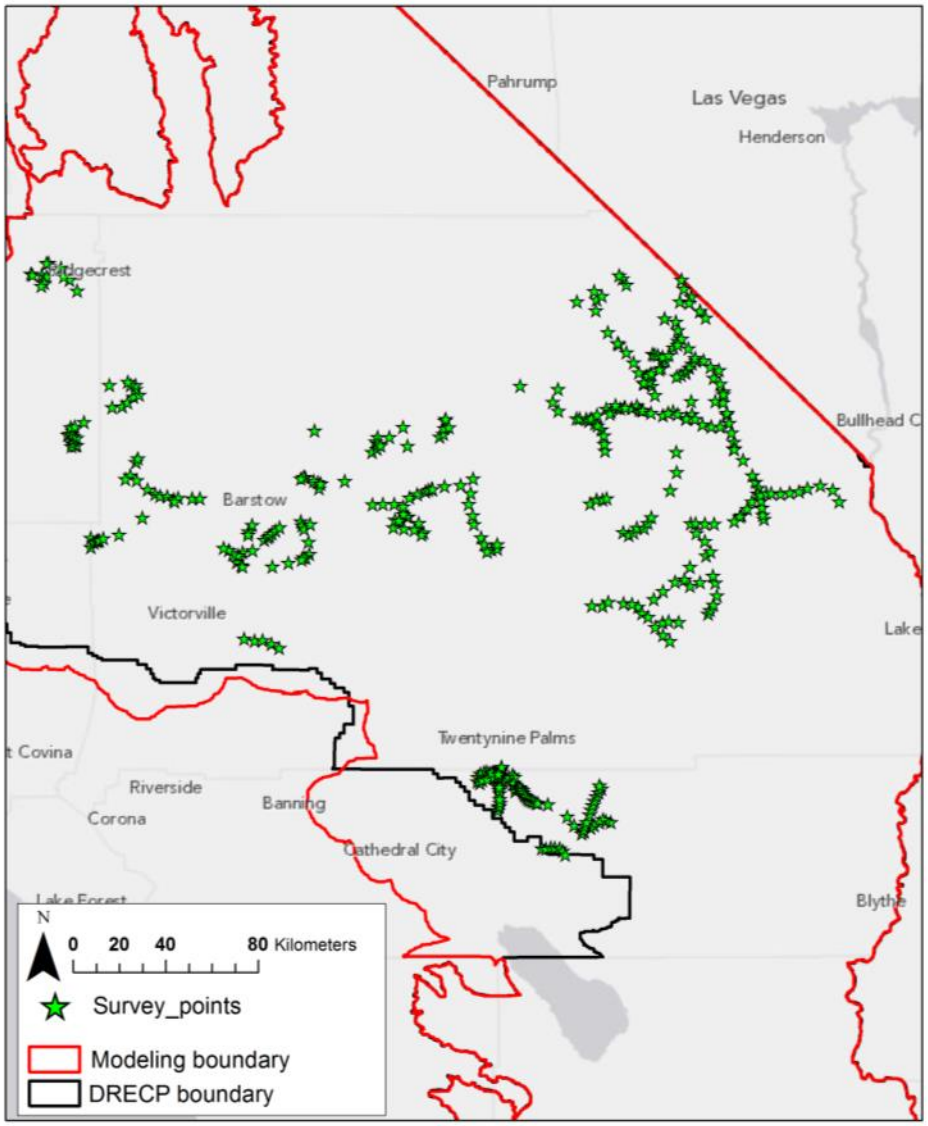
3.2.5 Use of Preliminary Models

Preliminary models were used to broadly guide field survey efforts to encompass suitable and suitable habitat from a range of model predictions, and to design field survey routes described below. Models built on all variables, only bioclimatic variables, and only topographic and soil variables were constructed for each species (Table 3). These models were evaluated based on bootstrapped AUC scores with 25% of the data withheld for testing, with all preliminary models indicating reasonable model fit (AUC > 0.8). Models were visually compared to identify areas of high and low suitability unique to particular models and common across multiple models. Field survey routes described below attempted to incorporate both of these types of predictions.

3.2.6 Field survey methods

Seasonally from 2011 to 2014, field surveys for seven focal species were conducted based on the preliminary models to evaluate the efficacy of such models in identifying previously unrecorded occurrences (Table 2). Note that models for *C. deserticola* and *L. maculatus* were requested by the California Energy Commission after field surveys began and that these species were not included in the ground truthing effort. For each target species, several (10-15) transects were identified through known and predicted distributions that varied in the probability of predicted occupancy. Transects were surveyed during peak flowering time in each year for each species. Some transects were dropped due to lack of accessibility, including private or military ownership. Because of spatial and environmental overlap across target species, suitable habitat for all target species was scouted on each survey, effectively increasing the per-species sampling effort. Along each transect, data points were taken periodically (~ 3 km) on the presence or absence of suitable habitat for all species able to be identified at the time of the survey, based on the habitat conditions at existing known occurrences. Where habitat was deemed within the range of suitability for a target species, a 1-km diameter circle was surveyed on foot. When species were positively found, the precise location was recorded for submittal to CNDDB. Absences were also recorded with a subset of habitat characteristics. Field survey routes were planned to encompass areas where all models predicted suitable habitat, as well as unique areas of prediction from particular models.

Figure 4: Overview of Field Survey Points for Assessing the Results of Species Distribution Models for Seven Focal Rare Plant Species



3.3 Results of Field Surveys

A total of 418 sites were surveyed for focal species, resulting in 66 new occurrences of rare species (Table , Figures 5-10). New occurrences ranged from 34 for *Grusonia parishii* to 2 for *Mimulus mohavensis* and *Penstemon albomarginatus*. Maps providing an overview of newly documented localities in relation to previously documented localities are presented in Figures 5 to 10.

Table 4: Number of New Localities (66) Found as a Result of Field Surveys

SPECIES	New Localities
Asclepias nyctaginifolia (Mojave milkweed)	4
Castela emoryi (Crucifixion thorn)	0
Eriophyllum mohavense (Barstow woolly sunflower)	11
Grusonia parishii (Parish's club cholla)	34
Mentzelia tridentata (Creamy blazing star)	13
Mimulus mohavensis (Mojave monkeyflower)	2
Penstemon albomarginatus (white-margined beardtongue)	2

The large number of new occurrences for the cactus *Grusonia parishii* established its regional range boundaries in California, and provided additional evidence that it occurs in two disjunct populations centered in the vicinity of Joshua Tree National Park and the Mojave National Preserve, with intervening areas lacking populations (Figure 3.7).

For *Mimulus mohavensis*, *Asclepias nyctaginifolia* and *Mentzelia tridentata*, surveys resulted in new locations within the known distribution of the species. The large number (13) of new localities for *Mentzelia tridentata* suggest that within its narrow range it may be more widespread than previously documented. In addition to occurrences within the known range of *Eriophyllum mohavense*, a new locality was found approximately 20 km away from previously documented occurrences, extending the known range of this taxon.

Although new localities were not documented for *Castela emoryi*, valuable information was obtained as a result of surveys. The survey of *Castela emoryi* was conducted by team members Tasya Herskovits and Duncan Bell (Rancho Santa Ana Botanical Garden), across the range of this widespread, yet rare species, and resulted in a journal paper documenting a biologically novel occurrence of significant importance for *Castela emoryi* in Rice Valley, comprised of over 2500 individuals (Bell and Herskovits 2013). While *Castela emoryi* was known to occur at this location previously, the large extent of the population was unknown. This occurrence is only the second population of *C. emoryi* in the state known to have greater than 1000 individuals and is adjacent to the Rice Solar Energy Project under construction at the time of the survey but currently on hold.

Based on the results of field surveys and incorporation of new localities, models were generated for use in DRECP planning for all focal species, plus *Cymopterus deserticola*. These models were uploaded to the Conservation Biology Institute's Data Basin site (databasin.org) for analysis and mapping for dissemination with regulators and stakeholders. Continuous and binary (based on the Maximum Sensitivity plus Specificity, MSS, threshold) depictions of model results are presented in Appendix A. Details on model assessment are provided in Chapter 4 of this report.

3.4 Discussion: Qualitative Use of Models in Field Surveys

The model-guided field surveys resulted in 66 new occurrences of the focal rare species. Preliminary models were useful as hierarchical planning tools to identify potentially suitable areas to include in field surveys and guided the selection of field survey transects spanning a range of model suitability predictions.

Due to the large scale of the modeling and survey efforts, expert biological knowledge was used to identify areas likely to support target species regardless of model prediction. This guidance was particularly important in geographic areas with fine-scale substrates and topographic features that are not possible to capture with the scale of environmental data used in model development. The intersection of model predictions and expert opinion was qualitatively useful in identifying new occurrences, particularly when combined with analysis of aerial photographs.

For example, preliminary models consistently identified a valley to the north of known occurrences of *Penstemon albomarginatus* as potential habitat (Figure 3.3). Areas of open sand, an aspect of critical habitat for *P. albomarginatus*, were readily observed in aerial photos of the area, suggesting that it was important to include in evaluation of model performance for this sand-dependent species. Field surveys of this area resulted in the only new occurrence documented for *P. albmomarginatus*, and defined the northern edge of its geographic range. Because of the lack of replication of new occurrences, statistical evaluation of models for this species, based on field survey results was not possible.

In some cases, the preliminary models identified broad areas that were climatically similar but differed in soil or substrate characteristics associated with known occurrences, giving the impression that models were of limited usefulness in identifying new occurrences. Plant distributions are controlled by these broad factors, but are more constrained by local topography, fine-scale soil attributes, and dispersal limitation. Inclusion of variables that inform these patterns and processes at a finer scale than possible via GIS would be necessary to yield excellent models of their distributions. For these reasons, field surveys based on model predictions and expert biological opinion failed to document many new occurrences for *Ascepias nycataginifolia*, *Mimulus mohavensis*, or *Castela emoryi*. This was partly due to the 270-m scale of modeling, which was focused on broad scale climatic and habitat characteristics used in conservation planning efforts, as opposed to very fine scale modeling (10s of meters) that has identified plant occurrences in other studies (e.g., Wright et al. 2006).

Figure 5: Previously Known and New Locality Records for *Eriophyllum mohavense*, Barstow Woolly Sunflower

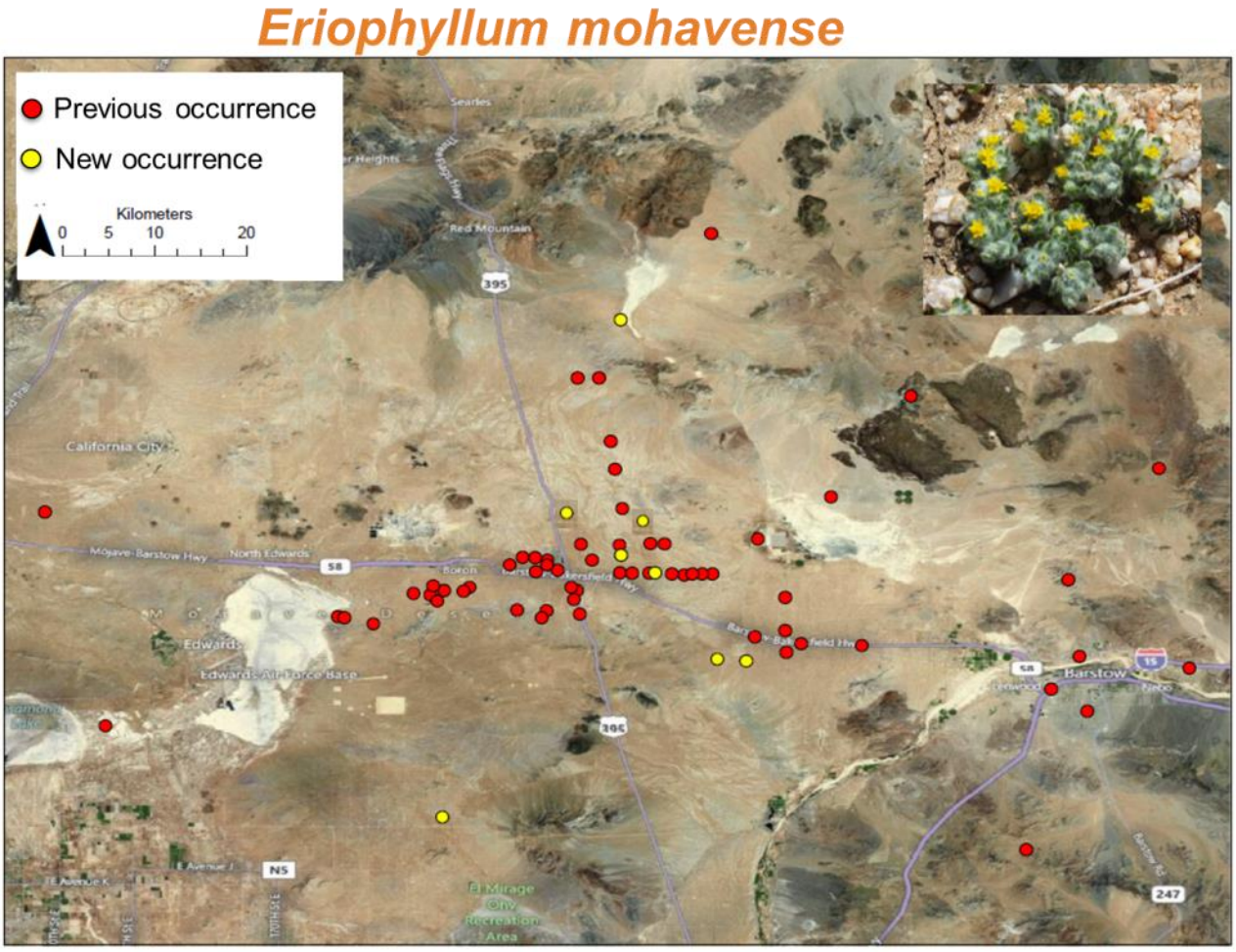


Figure 6: Previously Known and New Locality Records for *Penstemon albomarginatus*, White-Margined Beardtongue

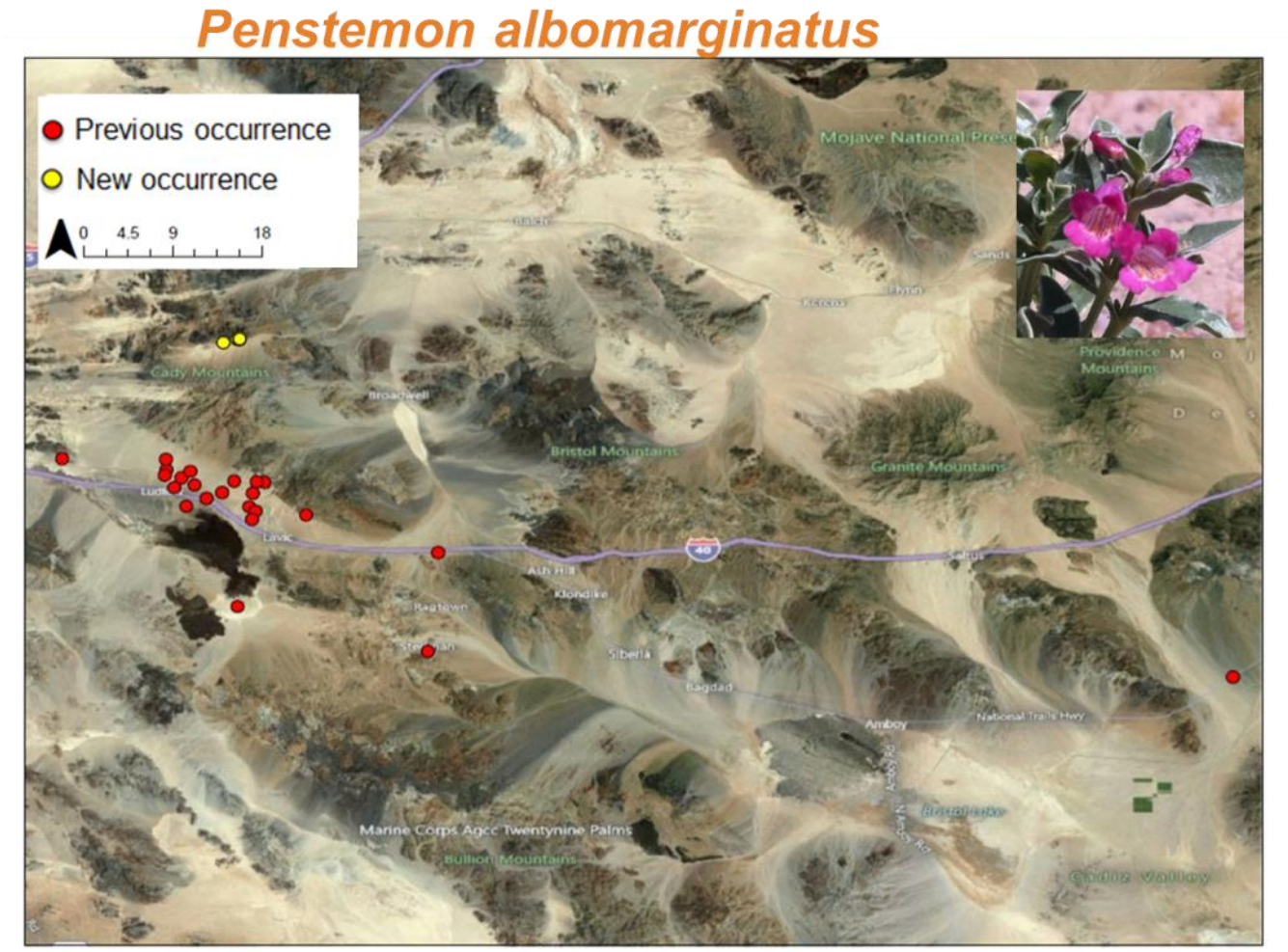


Figure 7: Previously Known and New Locality Records Discovered during Field Surveys for *Asclepias nyctaginifolia* and in Consultation with a Botanical Expert

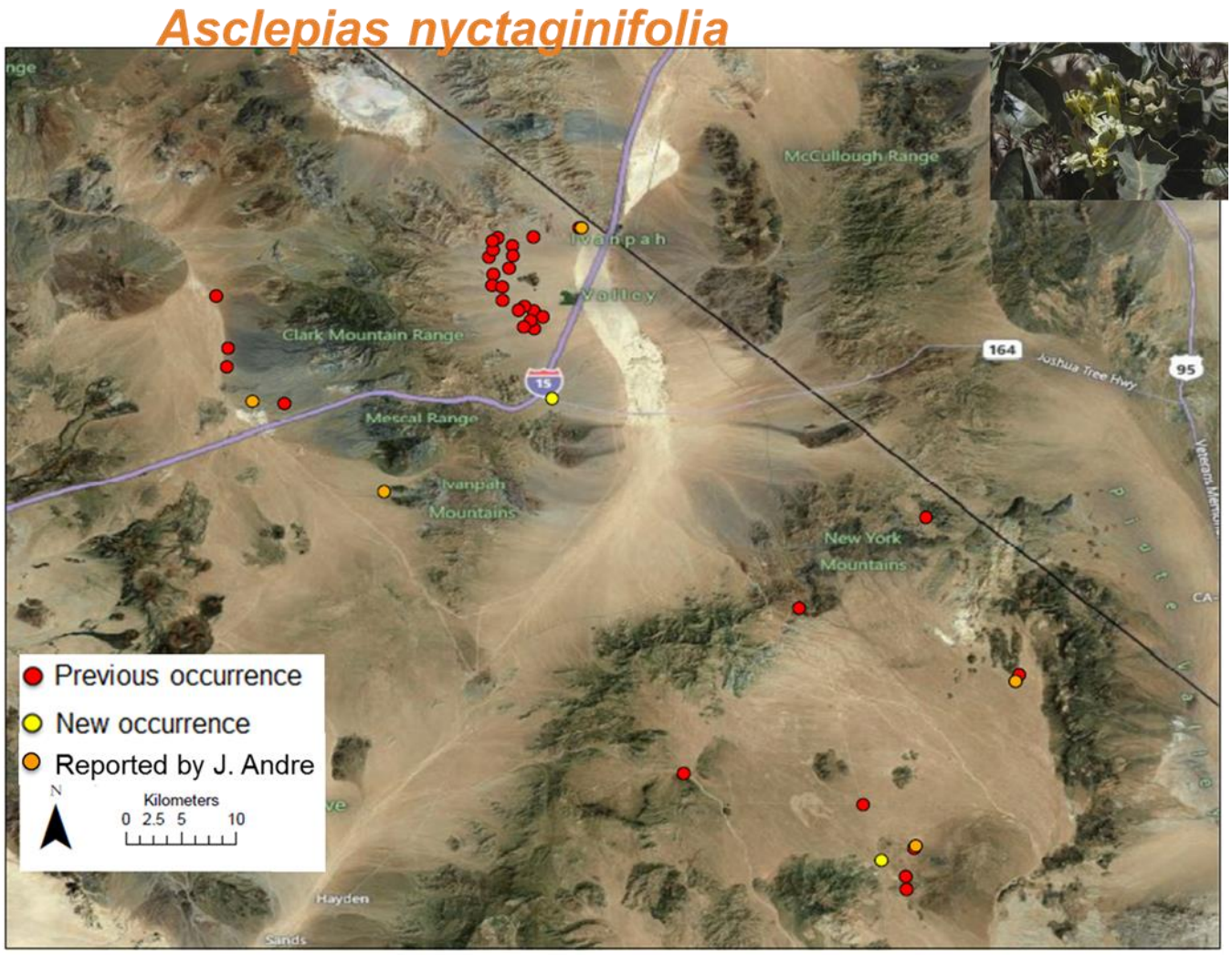


Figure 8: Previously Known and New Locality Records Discovered during Field Surveys for *Mimulus mohavensis*

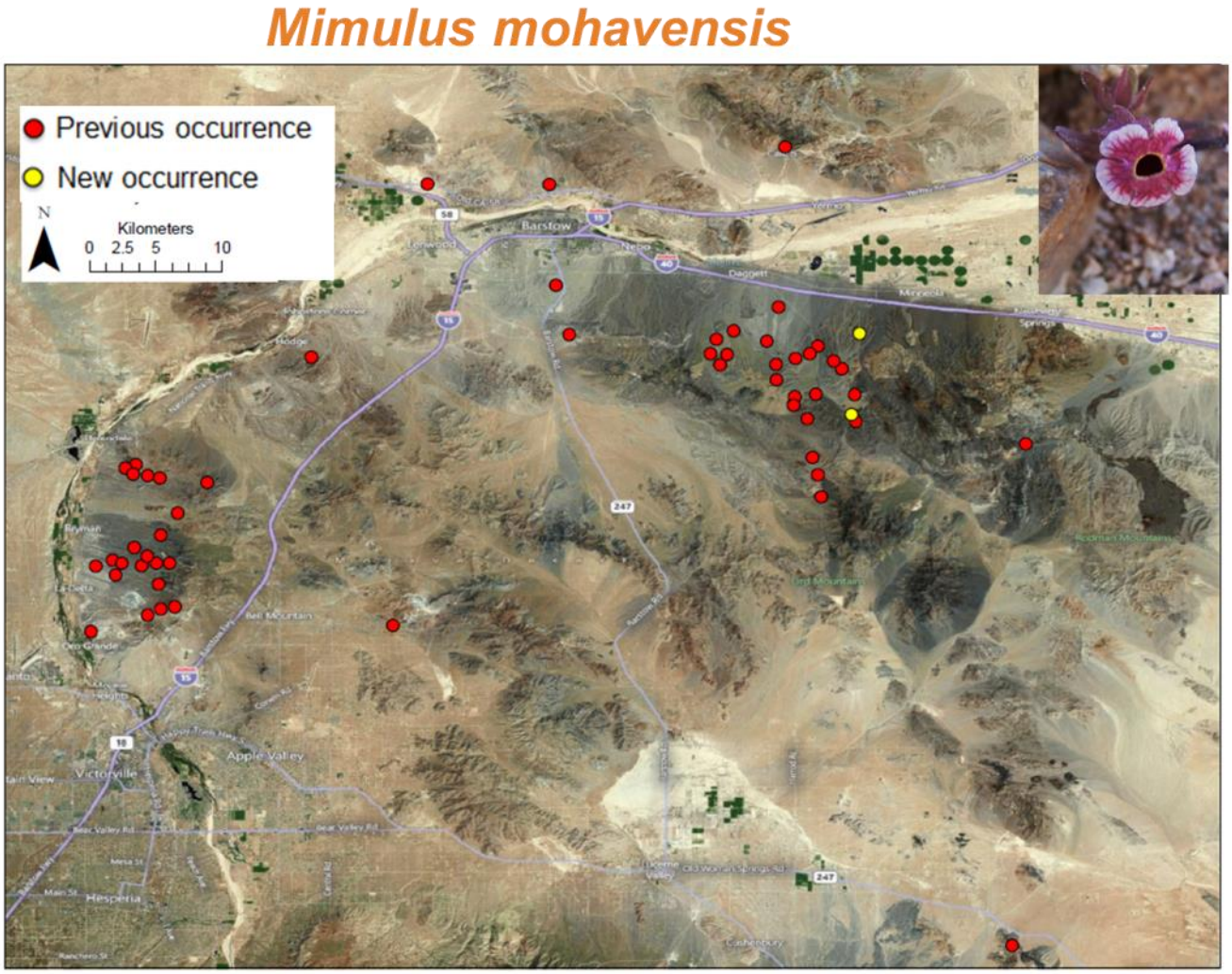


Figure 9: Previously Known and New Locality Records Discovered during Field Surveys for *Mentzelia tridentata.*

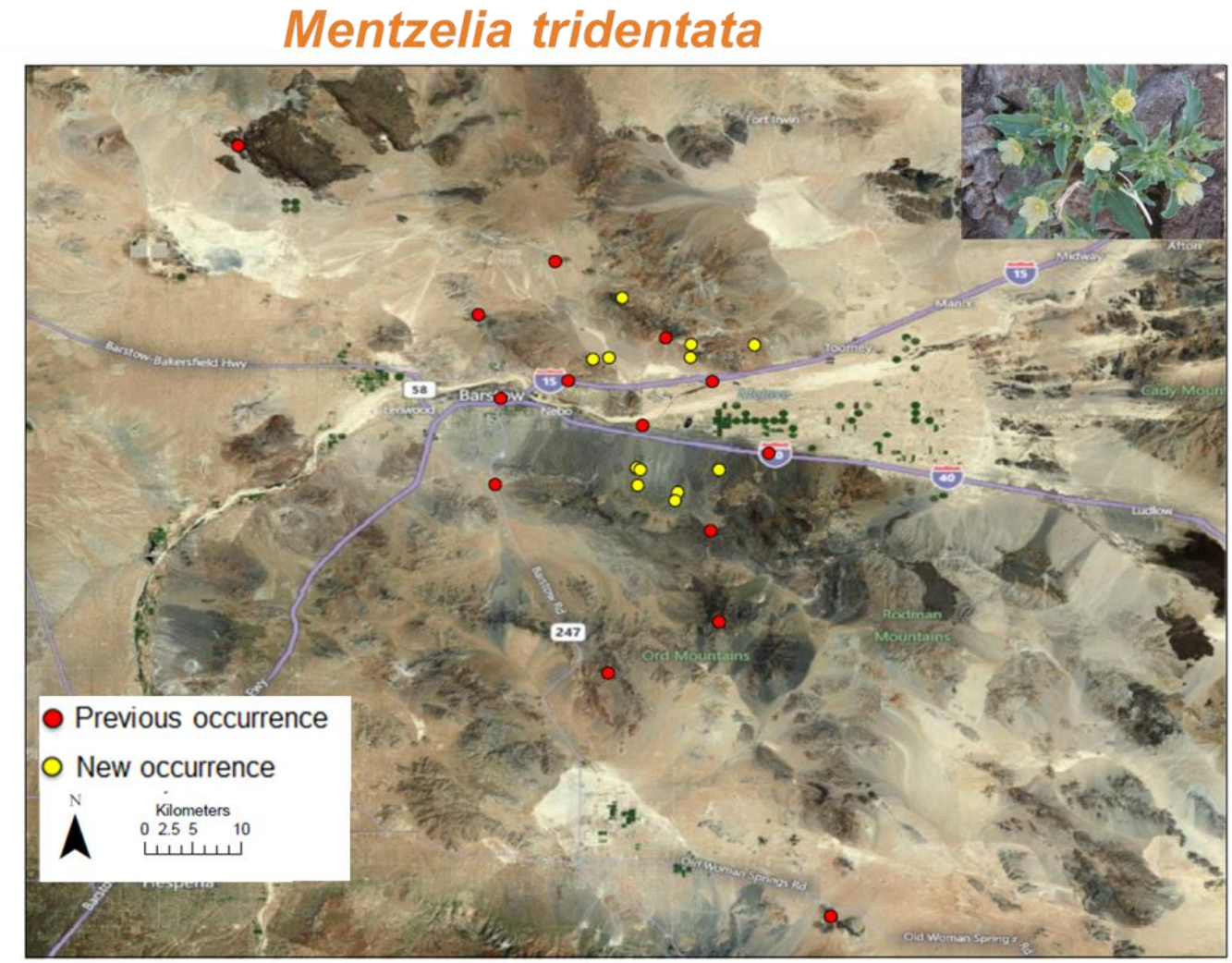
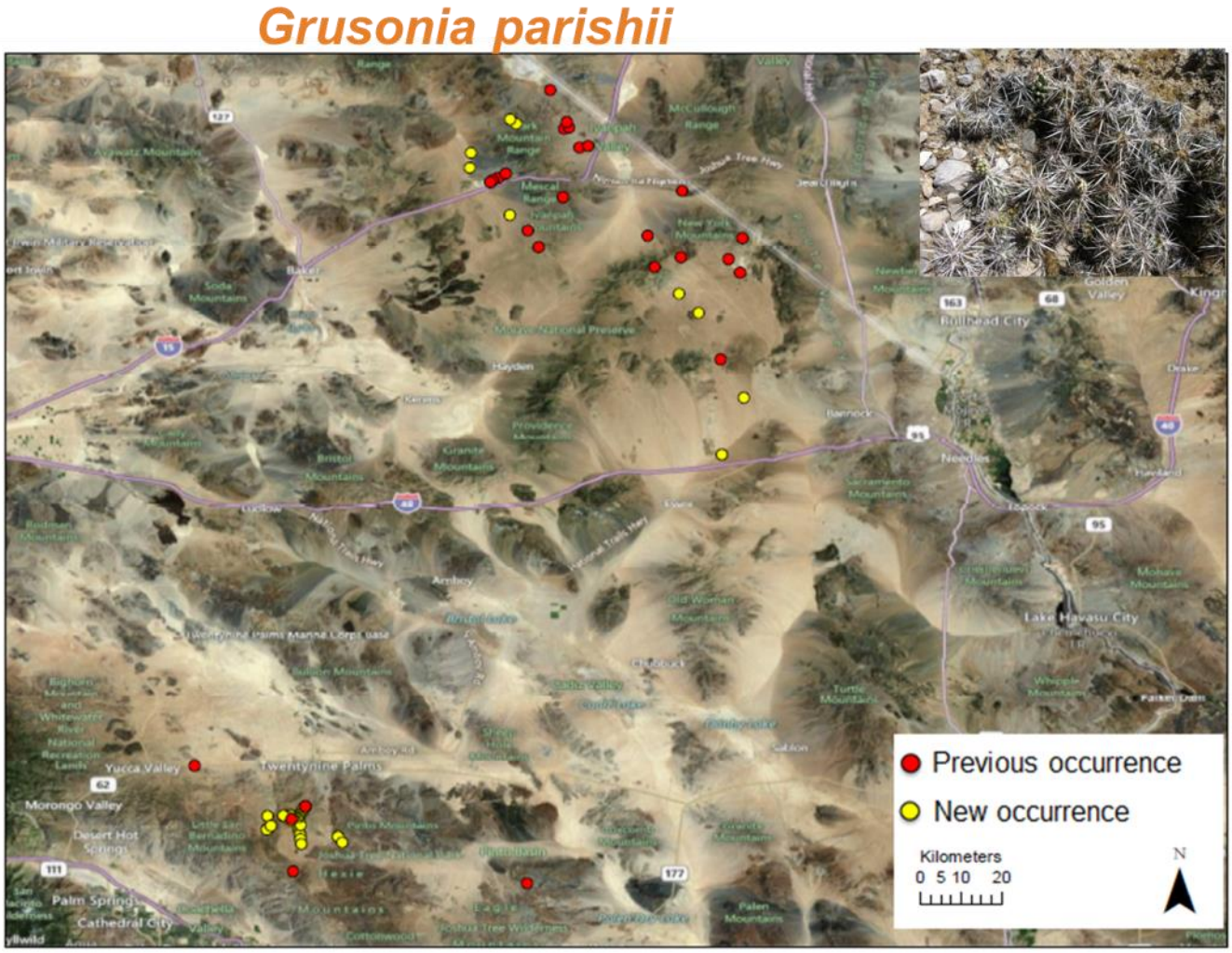


Figure 10: Previously Known and New Locality Records Discovered during Field Surveys for *Grusonia parishii*



CHAPTER 4:
Assessment of Model Predictions with Respect to Field Surveys and Distance from Known Populations

4.1 Introduction

Rare plants present unique challenges to the application of species distribution models (Williams et al. 2009, Hijmans 2012, Guisan et al. 2013). In addition to having few occurrences, which may limit the predictive power of models, rare species' distributions are often geographically restricted and clustered. This characteristic counterintuitively can both make it easier to build a model that accurately captures the distribution of a rare plant, but reduces statistical confidence in the model itself. For example, a plant that is entirely restricted to the floor of Death Valley could be perfectly predicted across the California desert by a single variable - elevation. In fact, any characteristic that distinguishes Death Valley from other desert areas could be used to predict the distribution of this plant, whether or not that factor is biologically meaningful. This confounding relationship between a species and environmental variables is a form of spatial autocorrelation that is a central problem in species distribution modeling (Crase et al. 2012). In contrast, a species that is distributed in numerous areas across the desert may be more difficult to predict because the model must identify a set of unique environmental characteristics that are in common among geographically distant areas where a species grows. Thus, it has been found that model accuracy may be inflated for rare species relative to common species, suggesting that models for rare species should be interpreted cautiously despite having high statistical scores (Elith et al. 2006, Jiménez-Valverde et al. 2008).

One approach that evaluates the predictive capacity of models built for species with tightly clustered distributions is to compare 1) a model built using solely geographic proximity to known occurrences with 2) a model built on environmental predictors (Hijmans 2012). If a model based on environmental predictors does not perform better than a model based on geographic proximity, then the environmental model may only be reflecting geography and not underlying environmental factors that limit a species distribution. This approach may be of great utility to evaluation of SDMs for rare species. If the environmentally predicted model performance is similar to the performance of the model built solely on geographic proximity, then its predictions should be interpreted with greater caution (Hijmans 2012). As an illustration of how important geographic proximity can be, Rodríguez-Rey et al. (2013) found that SDMs of invasive species, which appeared to identify environmental conditions that predicted their invasion over time, actually performed no better than models based on geographic proximity from the initial introduction points. This suggests that SDM results may not always identify environmental characteristics of suitable habitat, but may instead be identifying any environmental condition in close proximity to known occurrences.

Here, for a set of rare desert plant species of conservation concern, the performance of SDMs built via two approaches were compared to assess the effects of geographic proximity (also referred to as spatial autocorrelation) in occurrence data on model performance. For each of

seven rare plant species in the California desert region, SDMs were built based on two methods for including environmental variables: A) a generic distribution modeling approach commonly used in applied conservation settings in which a standard set of bioclimatic (Bioclim) factors are utilized (Hijmans et al. 2005), and B) a "tailored approach." In the tailored approach, statistics were used to identify a more-predictive subset of predictive variables (methods below) and used this subset of variables for subsequent model construction. These two approaches were compared for species-specific models based on only geographic distance in order to address the issue of how informative distribution models are for rare plant species. The following questions were addressed:

1) How do 'standard Bioclim' and 'tailored' distribution models compare in their ability to predict novel rare plant occurrences?
2) Are models generated via either method better at predicting novel occurrences than geographic distance alone?
3) Given tradeoffs in model effort and limitation to model conclusions in cases with restricted distributions, how is modeling recommended to be used in applied conservation?

4.2 Methods

4.2.1 Final Model Development

In a final round of model development, the preliminary models, outlined in Chapter 3, were improved in several ways: 1) comparison of model score statistics to evaluate geographic bias, 2) revision of occurrence data to include database updates, 3) thinning of clustered occurrence points, and 4) comparison of three sets of predictor variables based on refinement of variable selection.

Maxent methods applied in preliminary modeling were again used. Models resulting from a standard and a tailored variable selection approaches were compared. Using the standard approach, models were built using the 19 standard Bioclim variables (referred to as Bioclim_BCM) calculated from a downscaled PRISM-based data set (Flint and Flint 2012a). Under the tailored approach, a subset of the modeling variables were selected such that the least correlated and most informative of the Bioclim_BCM variables and the non-climatic variables were incorporated, as described below. Models were evaluated based on the standard and widely used AUC statistic, and compared with a null calibrated AUC statistic (Hijmans 2012), which compares the difference in AUC between a null model based solely on the geographic distance from testing and training points, to a model developed using predictor variables other than geographic distance. The standard AUC statistic is the subject of much debate in distribution modeling (see Peterson et al. 2008) but is used here as it the most widely used statistic to evaluate distribution models at the time this study was implemented, and because it is the statistic generally used in applications of distribution modeling in applied conservation. Use of reduced subsets of predictors via variable selection was employed to diminish over-fitting associated with using a large number of highly correlated variables, a well-known issue in distribution modeling.

4.2.2 Predictor Variable Data and Variable Selection

For each species, models built on the following sets of predictors were compared: 1) *Bioclim predictors* -- 19 bioclimatic variables derived from a 270-m downscaled PRISM based dataset (Flint et al. 2012), 2) *Tailored subset of predictors* -- a best subset of all bioclimatic and non-bioclimatic variables. All climate based variables used in models were derived from 270 m downscaled PRISM data utilized in the Basin Characterization Model (BCM; Flint and Flint 2012). The BCM uses PRISM data downscaled by interpolation from native 4-km products to 270 m. Output products from the BCM include the water balance metrics described below, and a suite of others not used in our study (Flint and Flint 2012).

The following predictor selection protocol was conducted for the Bioclim subset predictors for the occurrence points of each focal plant species. First, all pairwise correlations between the 19 Bioclim_BCM variables were generated. Where a variable was correlated with one or more other variables with a correlation coefficient greater than 0.7, a single predictor variable was selected by a combination of statistical evaluation and likely biological relevance of the variables. Second, a jackknife Maxent model was used to assess model gain due to each predictor, its contribution to model fit in isolation from other predictors. Predictors that had low values in model gain were dropped. When results were tied, the variable that had the most obvious biological value to the focal species was selected. This methodology resulted in selection of between 10 and 16 variables per species out of a total of 24 (Table 5). The most commonly used variables across models were: albedo, vegetation seasonality, northness, slope, and slope complexity.

Table 5: Environmental Variables Used in Final Modeling

	ASC	CAS	CYM	ERI	GRU	LIN	MEN	MIM	PEN
Albedo	●	●	●	●	●	●	●	●	●
Average NDVI		●	●	●		●	●	●	●
BIO1									
BIO2						●	●		●
BIO3		●	●					●	
BIO4		●		●	●	●	●	●	
BIO5									
BIO6		●	●		●		●		●
BIO7	●	●		●				●	
BIO8		●				●			
BIO9	●	●	●	●		●	●	●	
BIO10									●
BIO11							●	●	
BIO12						●			●
BIO13		●							
BIO14		●	●		●		●	●	●
BIO15	●	●	●	●	●	●	●		
BIO16			●						
BIO17				●			●		
BIO18		●	●			●	●	●	
BIO19					●		●		
Elevation			●	●					
Vegetation seasonality	●	●	●	●	●	●	●	●	●
Northness	●	●	●	●	●	●	●	●	●
Slope complexity	●	●	●	●	●	●	●	●	●
Slope	●	●	●	●	●	●	●	●	●
pH	●	●	●	●	●	●	●		●

For each variable ● denotes use as a predictor in the Bioclim subset and best subset models. Species are represented by the first three letters of their genus see Table 3.2 for full plant names and Table 3.3 for Bioclim factor names.

4.2.3 Finalization of Occurrence Points

Occurrences for final model construction included updated data from the CNDDB, CCH (Chapter 2), and our field surveys from 2011-2013 (Chapter 3). From the full set of possible occurrence data, records with suspect occurrences were eliminated, and occurrences separated by less than 3 km were subsampled. Suspect occurrences were identified as those with low spatial accuracy (e.g., locality information referred only to the vicinity of a large town or geographic region) or those both remote from the core range of a taxon and lacking a voucher specimen, photograph or other documentation. Subsampling of records in close proximity was conducted to improve spatial independence within the occurrence data. We identified all points within 3 km of other occurrences- groups of these were referred to as "clustered points." We then selected the maximum number of possible records that were separated by 3 km. Where multiple solutions were possible, a random selection of points from groups of clustered points that were within 3 km of one another was made.

4.2.4 Model Evaluation

For species with adequate new occurrences based on field surveys (at least five new occurrences, *E. mohavense*, *M. tridentata* and *G. parishii*), models were evaluated based on their ability to discriminate between new occurrences and sites where the target species was not found. These sites likely represent a combination of true absences and failure to detect the species (due to small population size or dormancy). For species without adequate field survey data (surveys that resulted in less than five occurrences, *M. mohavensis*) the data were divided into 2/3 training and 1/3 testing and repeated 100 times to obtain a bootstrapped average cAUC score. The model with the highest cAUC value was selected as the best model. In cases where the population sampling was adjusted to reduce the number of points within 3 km (*E. mohavense* and *M. mohavensis*), a random selection of points was incorporated into the bootstrap procedure to sample across variation due to different sets of occurrence points.

The best performing set of predictor variables was used where occurrence points were reduced to avoid occurrences within 3 km, then predictions were made for 100 models built on resampled sets of occurrence points. For all models a threshold based on Maximum Sensitivity plus Specificity (MSS) is presented. This metric represents a combination of two types of information: 1) how good a model is at detecting occurrences (sensitivity) and 2) how well it discriminates occurrences from other areas (specificity). It is important to note that Maxent model output is naturally continuous, and that multiple thresholds may be applied to the same prediction, with very different results.

4.2.5 Geographic distance and spatial bias methods

The standard and tailored models were evaluated based on three metrics: AUC, cAUC (a metric of AUC for a species distribution model relative to a geographic null mode), and a geographically corrected AUC (termed pwdAUC for 'pairwise distance corrected'). Detailed methodology for these metrics can be found in Hijmans (2012). cAUC is calculated as:

$$\text{cAUC} = \text{AUC}_{\text{model}} - \text{AUC}_{\text{geographic null}} + 0.5$$

This formula calculates an alternative AUC score based on the difference between the score of a model built on environmental data and the score of a model built on geographic distance alone (geographic null). A model performing no better than random has AUC scores equal to 0.5. If the geographic null model performs very well relative to the model built on environmental data than the geographic corrected model score, AUCc, will be close to 0.5. A cAUC value of 0.5 indicates that an environmentally-based SDM and a geographic null model for the same occurrence data perform equally well (or poorly). In contrast, a cAUC value close to 1 indicates than an SDM is performing much better than a geographic null in predicting species occurrences (Hijmans 2012).

Model scores were averaged by species for each model type and then compared via ANOVA within three model score types: 1) pairwise distance adjusted AUC for all bioclim variables versus the best subset, 2) cAUC for all biolim variables versus the best subset, and 3), crossvalidated AUC (AUCcv) for all biolim variables, the best subset ("tailored approach"), and the geographic distance only model. For each species and model score type, additional ANOVAs were used to compare the performance of each model type. In each case (species averages and within species), Tukey's HSD test was used to determine pairwise differences between models.

In addition to comparing model scores based on SDMs with those from geographic distance models, for species with field survey testing data, geographic distance from known points was regressed with model scores. This was done in order to test whether distance from a known point was significantly correlated with model predictions.

4.3 Results

4.3.1 Final Models

In addition to quantitative analysis, final models were visually inspected (Appendix A) and compared to those produced by other experts (Frank Davis, Dudek, and Conservation Biology Institute) in informal workshops organized by California Energy Commission staff. Comparisons were not made quantitatively, but in general this group agreed on areas that were indicated as being of highly suitable or of very low suitability. Model scores based on a standard metric of cross-validated AUC suggested models with good fits (Table 6) with many models having AUC values exceeding 0.9. In contrast, pwdAUC scores, which constrained model testing to distances consistent with distances between known localities suggested that models had limited ability to discriminate between known occurrences and background habitat as values were low (0.52 to 0.74). These results suggest that there is a lack of power to predict distribution at the scales and with methods typically used in applied conservation, and that, as others have pointed out, model evaluation based on standard metrics of AUC may lead to inflated confidence in model predictions (e.g., Jimenez-Valverde et al. 2008).

Table 6: Suitable Habitat Thresholds

Species	Max sensitivity + specificity threshold	AUC-cross validation	pwdAUC
Grusonia parishii	0.35	0.956	0.721
Castela emeroyi	0.51	0.887	0.631
Mentzelia tridentata	0.22	0.936	0.638
Penstemon albomarginatus	0.43	0.865	0.741
Asclepias nyctaginifolia	0.58	0.941	0.523
Cymopterus deserticola	0.44	0.94	0.67
Mimulus mohavensis	0.4	0.93	0.72
Eriophyllum mohavensis	0.24	0.855	0.651

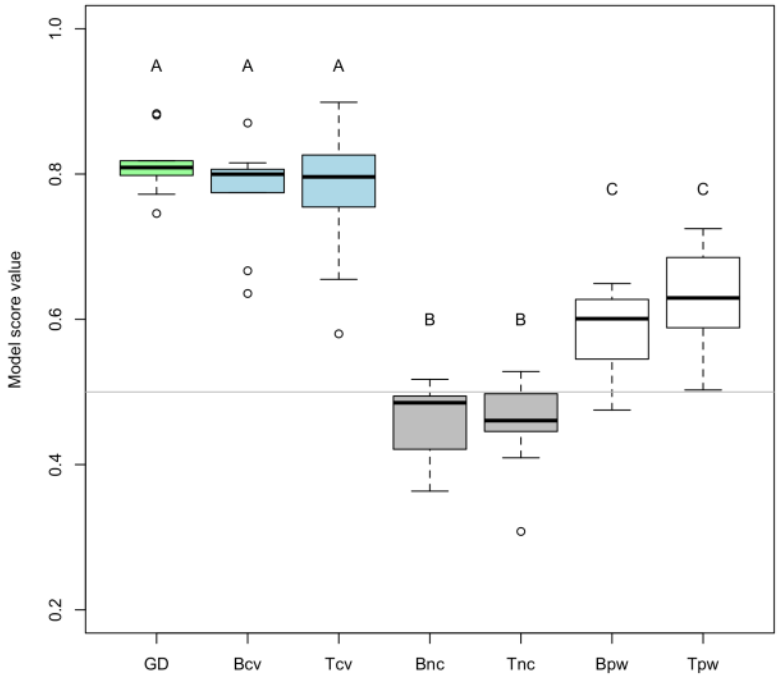
Suitable Habitat Thresholds (MSS), AUC and pwdAUC (adjusted for geographic distance between training and testing points), for best models for focal species.

4.3.2 Comparison of Model Scores

There were no significant differences between species average model scores for any of the three groups (Figure 12). When all species were considered, ascertaining the best subset of variables did not provide a significant improvement in model scores compared to use of all Bioclim variables. Furthermore, neither the all Bioclim variables together nor the best subset were able to consistently outperform the geographic distance only model. However, there was substantial, though inconsistent, variation in the performance of the different model types within species (Figure 12).

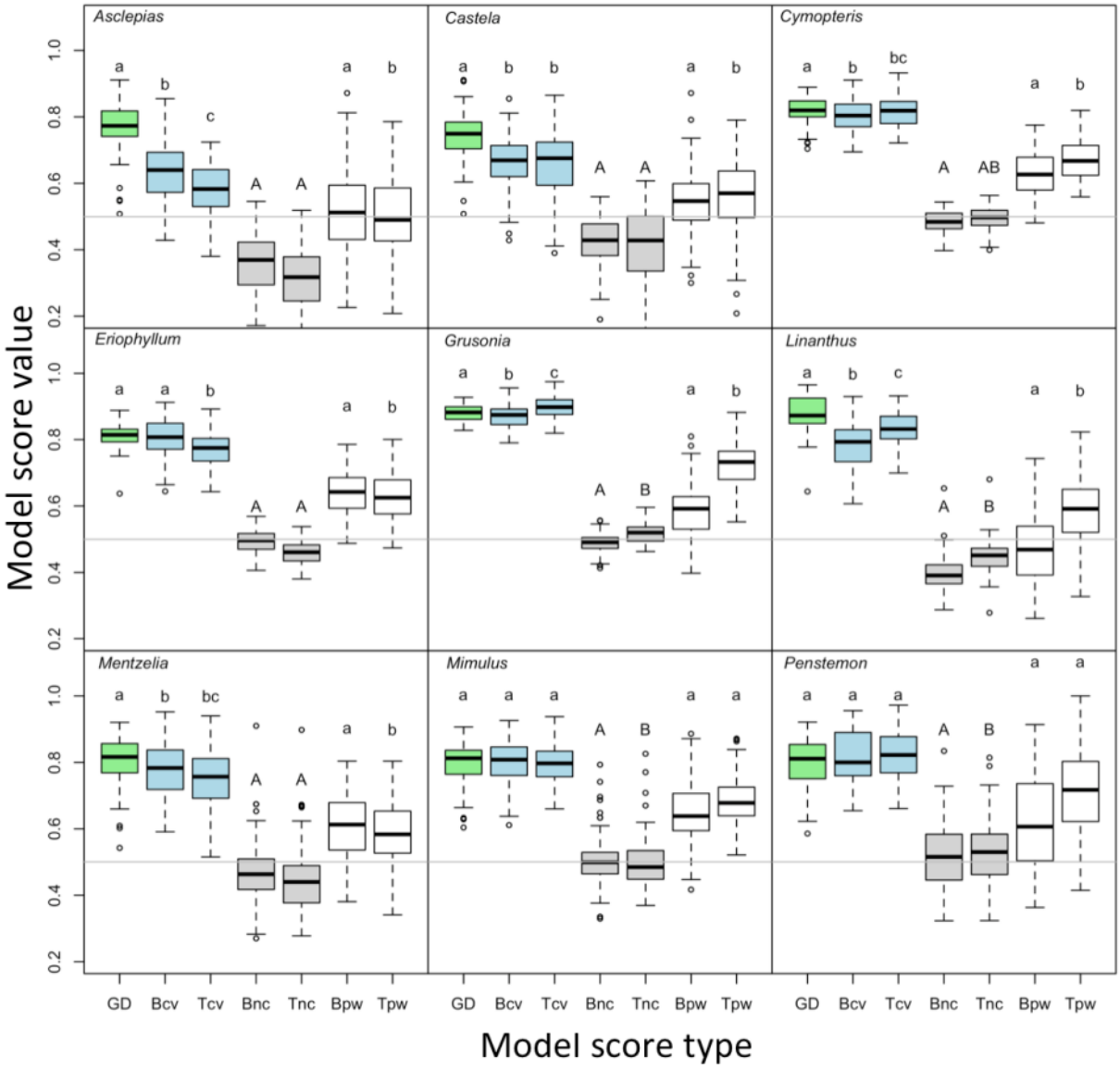
Only in a minority of cases, 3/9, did subsetting the environmental variables consistently improve model scores: *Cymopterus deserticola*, *Grusonia parishii*, and *Linanthus matculatus* (Figures 13 and 14). For each of these species, subsetting the available environment data improved model scores for all three metrics AUCcv, cAUC and AUCpw, suggesting that the process of hand-picking environmental variables reduced the noise on environmental predictors in the subsequent distributions models. In the majority of cases there was no quantitative improvement in model scores after careful environmental variable selection. For 5/9 models geographic distance performed better than both the model based on all Bioclim variables and the handpicked subset, and for 8/9 models geographic distance alone performed better than at least one of these models (Figure 14).

Figure 11: Across All Focal Species, Summary of Results of Different Model Score Metrics and Predictor Selection Approaches for Nine Rare Plant Species



Three separate ANOVAs were used to make statistical comparisons between sets of model scores: 1) geographic distance model (GD), AUCcv from Bioclim (Bcv) and tailored (Tcv) models, 2) “null-calibrated” cAUC from Bioclim (Bnc) and tailored (Tnc) models, and 3) pairwise AUC from Bioclim (Bpw) and tailored (Tpw) models. Different letters above each box plot within each test represent differences significant to the $p<0.05$ level. Tukey’s HSD was used to distinguish differences between geographic distance and AUCcv scores.

Figure 12: Summary of Results of Different Model Score Metrics and Predictor Selection Approaches for Nine Rare Plant Species



For each species, three separate ANOVAs were used to test for statistical differences within three sets of model scores: 1) geographic distance model (GD), AUCcv from Bioclim (Bcv) and tailored (Tcv) models, 2) "null-calibrated" cAUC from Bioclim (Bnc) and tailored (Tnc) models, and 3) pairwise AUC from Bioclim (Bpw) and tailored (Tpw) models. Different letters above each boxplot within each test represent differences significant to the $p<0.05$ level. Tukey's HSD was used to distinguish differences between geographic distance and AUCcv scores.

4.3.3 Field Presence Model Score and Geographic Distance

For all three species (*Eriophyllum mohavense*, *Grusonia parishii*, and *Mentzelia tridentata*), model score was significantly correlated with the minimum distance between newly discovered

occurrences and previously known occurrences (Figure 14). This provides additional evidence that distance from known populations is a strong predictor of new occurrences. Furthermore, it suggests that models as constructed are not identifying suitable habitat in distant locations from known populations, as new occurrences that fell below the habitat threshold used in this study were those that occurred at the greatest distance from known populations.

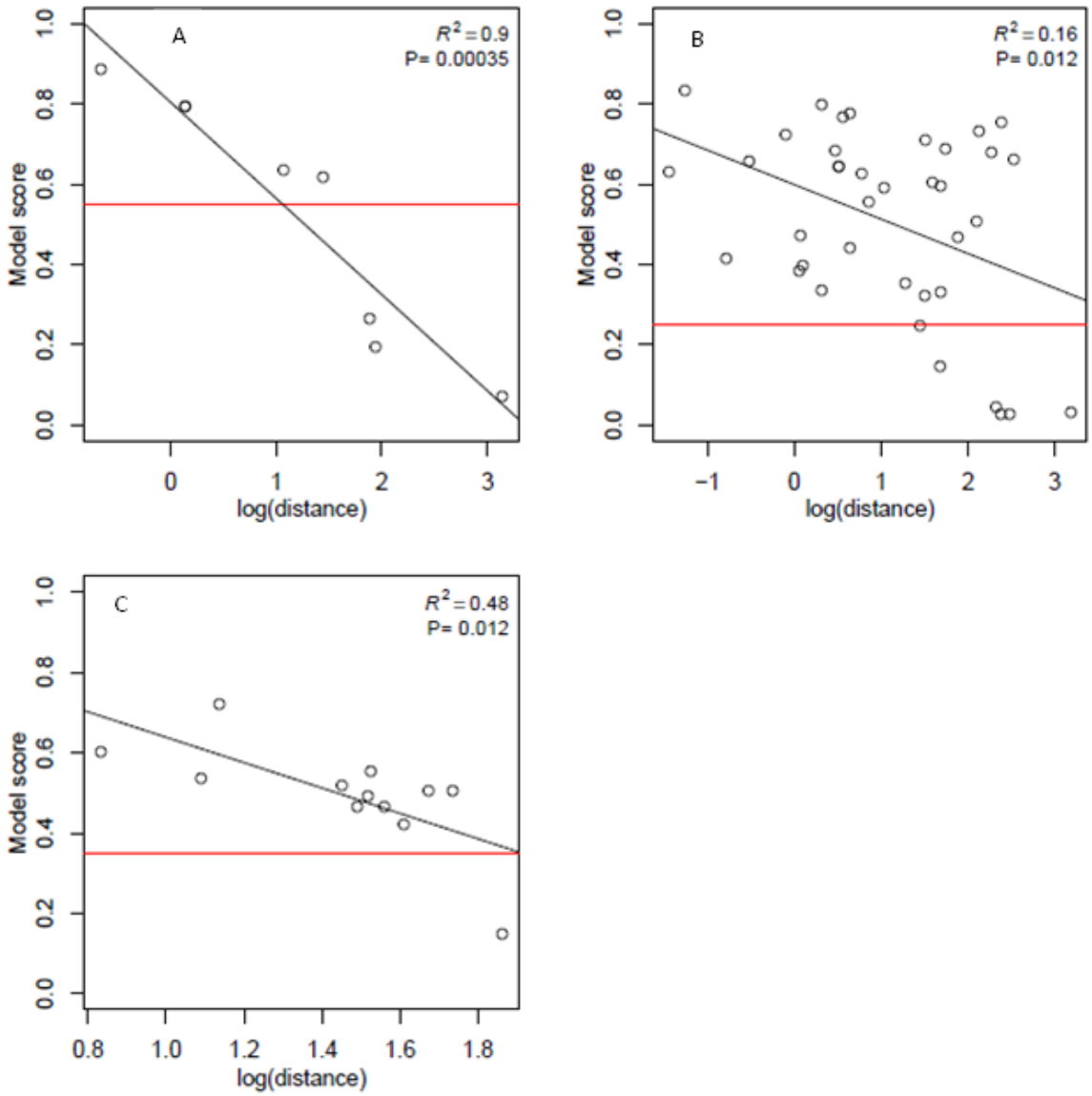
4.3.4 Comparison of Standard Models (Bioclim) and Tailored Models

When predictions of standard and tailored models were compared with a threshold of suitability applied, the results varied substantially (Figure 15; Table 7). Although predicted areas of suitable habitat were not consistently greater for one set of models than the other, models differed in the percentage of habitat predicted by 43% to 82%, in all cases resulting in a difference of over 1000 km^2 of suitable habitat (Table 7). This result highlights the challenges of applying distribution modeling in applied conservation - model predictions can vary widely with limited statistical support for choosing one over another.

Table 7: Comparison of the Extent of Suitable Habitat Predicted by Models Generated Using Subset and All Biogeographic Variables

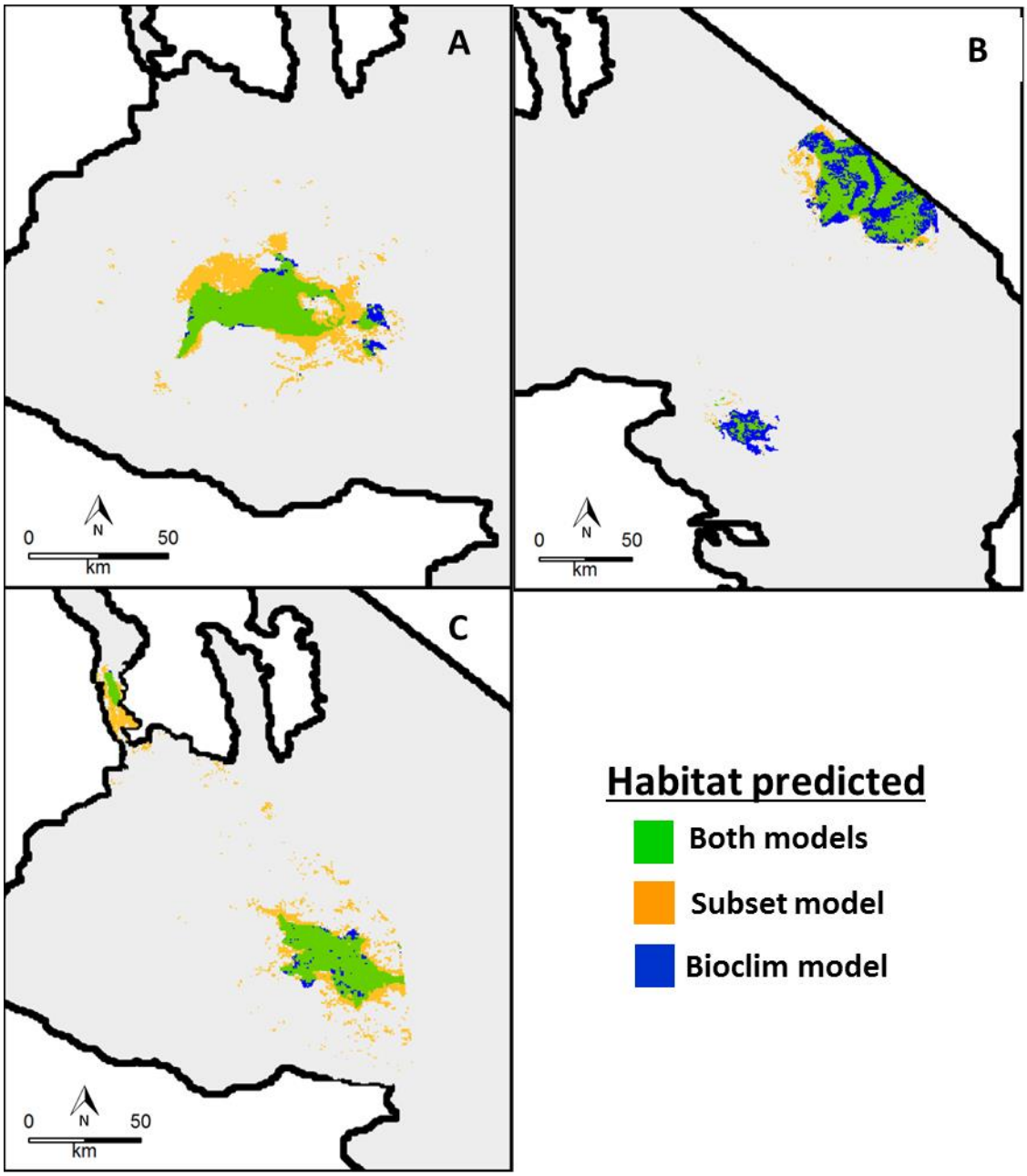
	Predicted suitable habitat (km^2)			
Species	**Subset model only**	**Bioclim model only**	**Both models**	**% increase, larger prediction**
Mentzelia tridentata	1085	110	1180	176%
Eriophyllum mohavense	1045	108	1037	182%
Grusonia parishii	394	1442	2034	143%

Figure 13: Relationship between Maxent Model Scores and the Minimum Distance to a Known Observation for Independent Field Observations



Red line indicates MSS threshold used to demarcate predicted suitable habitat. Panels depict results for (A) *Eriophyllum mohavense*, (B) *Grusonia parishii*, and (C) *Mentzelia tridentata*.

Figure 14: Maps Depicting Differences in Model Predictions



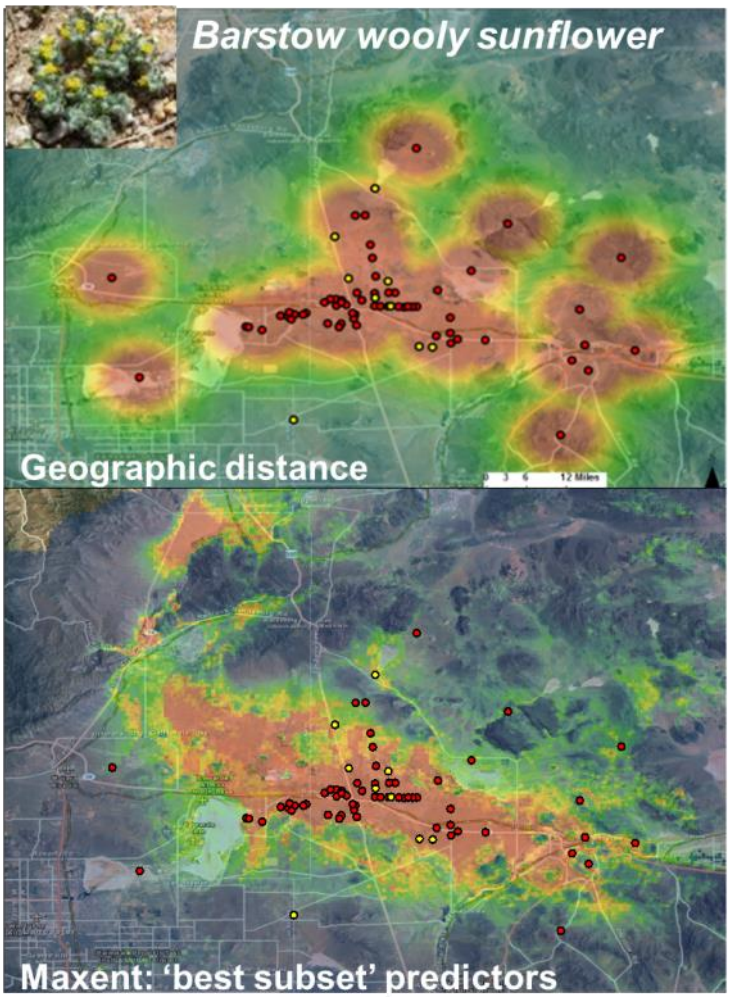
Differences in model predictions (with threshold) for the standard approach using bioclimatic variables and a tailored approach using a selected subset of predictor variables. Areas depicted in green were predicted by both modeling approaches.

4.4 Discussion of Model Assessment

These findings highlight important issues in modeling rare plant species and emphasize that SDMs should be used with caution in applied conservation settings, particularly when used to establish hard line conservation boundaries. As the SDMs generally performed only as well as

or slightly better than null models based on geographic distance, these results suggest that there is a lack of statistical power in many distribution models of rare species. It is entirely possible that distribution models are identifying key climatic variables associated with a species geographic range, but if models based on distance from known occurrences perform just as well, it suggests that spatial autocorrelation may be a factor in high fit of SDMs to the distributions of geographically restricted species. To illustrate this, the prediction of a model based on geographic distance and a SDM based on environmental variables is presented for *Eriophyllum mohavense* in Figure 15. The fine-grained predictions of the SDM for this species may indicate important aspects of habitat similarity, but since they do not capture the distribution better than the geographic distance model, it is difficult to argue that the SDM should be used in deciding what areas to conserve. The more conservative approach would be to emphasize areas near known occupied habitat indicated by the geographic distance model, supplemented by areas predicted by the SDMs.

Figure 15: Visual Comparison of Geographic Distance and Maxent Model for *Eriophyllum mohavense*, the Barstow Woolly Sunflower



Warmer colors (yellow and red represent areas of higher predicted suitability).

CHAPTER 5:
Using Models to Identify Hot Spots of Rare Species Richness

5.1 Introduction and Methods

One important component of balancing the demands for renewable energy with the need for biological conservation is to identify places with large numbers of rare species. These "hot spots" of species richness tend to have high conservation value, at least for this one objective. To identify areas that might support suitable conditions for high rare plant richness, species distribution models were built for 151 rare plant species whose documented occurrences allowed the research team to identify at least 5 populations and overlay the results. Using the Worldclim Bioclim dataset, maps were made of where these plants were predicted to occur across the DRECP area. This area is the recent focus of rapid development and conservation planning. Predictions for California Rare Plant Rank (CRPR) 1 species (those primarily endemic to California) and CRPR 2 species (those rare in California but more common beyond) were overlaid in order to identify predicted regions of rare plant diversity in the California Deserts. Models were built using the 19 Worldclim Bioclim variables across the full background of the DRECP area. Thresholds of suitability were based on MSS (maximum sensitivity plus specificity). Models were overlaid across CRPR Rank 1 and Rank 2 separately.

5.2 Results and Discussion

Several patterns emerge from examination of the maps of predicted diversity (Figure 16). First, western areas of the desert abutting mountain ranges are identified as areas of high richness. This highlights how these areas support both true desert species and species from other habitats that extend to the edge of California's Mojave and Sonoran Deserts. Secondly, the Clark and Kingston mountain ranges in eastern California, much of which are included in the Mojave National Preserve, are identified as centers of richness both for endemic and non-endemic species. The Preserve's ranges host many species that normally occur outside of California, but also occur in these mountains.

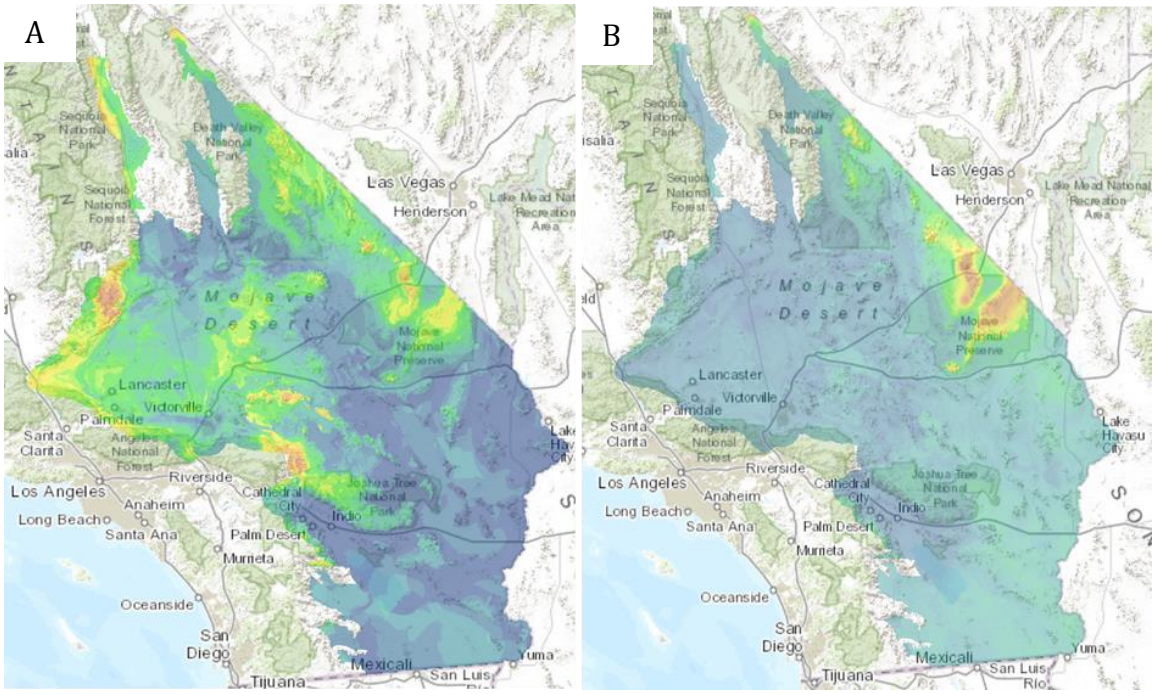
Another intriguing area of predicted high richness is the Ord and Lavabed mountain ranges southwest of Barstow. This area falls outside of National Park/National Preserve areas and currently is known to support a number of rare California endemics, such as the creamy blazing star (*Mentzelia tridentata*), Mohave monkey flower (*Mimulus mohavensis*), and Mojave menodora (*Menodora spinescens var. mohavensis*), and is predicted to have suitable conditions for several other rare species. Based on the simple maps presented here, this area might support additional rare species not currently documented in those locations, or might be a region that could act as a refuge for plants from other areas forced to shift their ranges as a result of climate change.

Predictive maps such as the ones accompanying this report represent valuable tools that can help guide field-based efforts to document plant diversity. They can identify unanticipated locations where rare species might be found. They can also be used to help predict where

appropriate habitat for rare plants could occur over large areas that are infeasible to survey on foot. In addition, they provide a means for predicting where species might occur in the future, under scenarios of climate change, something that cannot be accomplished through field surveys.

However, predictive maps are based on imperfect data--known localities that represent only a subset of each species' real distribution. They are not substitutes for on-the-ground exploration by experienced botanists. It is one thing to use a species distribution model to identify likely areas to hunt for new rare plant occurrences, and another thing entirely to use the predictions of a model to decide which parcels of land to preserve and which to develop. Finally, models cannot predict the distribution of a species that has never been described, and new species are described every year in the California desert. These models are useful tools that can be used to guide research and focus field exploration based on what is known today, and what might likely occur in the future.

Figure 16: Predicted Rare Plant Richness



Areas in Warmer Colors (yellows and reds) are areas of higher predicted rare plant richness. The map on the left (A) depicts predicted richness for California Rare Plant Rank 1 species, while the map on the right (B) depicts predicted richness for Rank 2 species.

CHAPTER 6: Conclusions

A significant challenge in analyzing the biological resource impacts of solar energy development in the Mojave and Colorado Desert Region is the lack of detailed distribution information for sensitive plants and animals. This knowledge is fundamental to the assessment of the impacts of utility-scale solar energy development within both the regional and local contexts. The known occurrences of species within the desert region currently are limited by survey time and often biased by anthropogenic interests. This report integrates the inclusion of additional sources of species occurrence data with a rigorous habitat suitability modeling approach, including field-testing of models, in order to obtain novel habitat distribution maps for a suite of rare Mojave plant species.

Although species distribution models can be important tools for conservation planning, their limitations must be recognized and included in model interpretation (Wiens et al. 2009, Franklin 2010, Dawson et al. 2011). Models are limited in their ability to predict occurrences by uncertainties in basic ecology and biology, the quality of observational data, and quality and choice of environmental variables. As noted above, species distribution modeling is particularly challenging for rare and poorly surveyed species. Use of geographic models for site development or plan mitigation should be done cautiously due to model uncertainty, and ideally in conjunction with field surveys assessing model accuracy. In cases where plants are only active for a portion of the year or only aboveground in a subset of years, ground-truthing surveys will need to be conducted multiple times over multiple years before a high likelihood of absence can be determined.

Rare species are often the focus of conservation-oriented application of SDMs, yet they pose several challenges to the statistical methods commonly deployed, as discussed above. The challenges posed by rare species are due to the fact that by definition rare species have few occurrences and/or restricted geographic ranges (Rabinowitz 1981). Important challenges to SDM applications include 1) limited environmental and/or geographic ranges, 2) scarcity of occurrence data, and 3) lack of random occurrence data. These three factors require expertise and caution in the construction of SDMs for rare species and necessitate care in the interpretation of model results.

First, limited environmental ranges of rare plant species are due to habitat specialization or adaptation to a narrow range of climatic, biological, and/or soil conditions. These can affect model performance and lead to inflation of statistics used for model assessment. Where their specific required conditions are uncommon, habitat specialists have very narrow ranges, despite sometimes being locally common. Where suitable habitat is widely distributed in small patches, limited dispersal can still confine habitat specialists to a subset of putatively suitable locations, i.e., geographic limitation. Both the ecological specialization of habitat specialists and limited geographic range size can influence the performance of SDMs by constraining the ability of models to predict occurrence beyond the occupied range of habitat conditions (McPherson et al. 2004, Segurado and Araujo 2004, Elith et al. 2006).

Interestingly, habitat specialization can provide the opportunity for the generation of high-quality models for select species that have few known occurrences. This is because, where species have very narrow environmental tolerances, relatively fewer records may be sufficient to characterize their distributions (Kadmon et al. 2003). Hernandez et al. (2006) found that Maxent performed the most reliably with small sample sizes (5, 10, and 25 occurrences). Accuracy of models was higher for specialist species that had smaller geographic ranges and limited environmental tolerance (Hernandez et al. 2006). However, the necessary strong correlation between occurrences and a set of environmental predictors for habitat specialists can lead to spurious inflation in the statistics used to evaluate SDMs (Boone and Krohn 2002, Kadmon et al. 2003, Thuiller et al. 2004, Luoto et al. 2005). Assessment of models for habitat specialists must been done with care and acknowledgement of the potential for inflated confidence in model predictions, particularly well beyond the geographic range of the target species. For this and other reasons detailed in Chapter 4, we strongly suggest using geographic distance as an additional constraint on model predictions.

Second, there are significant challenges in **data availability** for rare plants including lack of occurrence data (i.e., small sample size with points either widely dispersed or narrowly clustered), which limits the accuracy of model predictions regardless of the modeling method used (e.g., Maxent vs. RandomForests) (McPherson et al. 2004). Furthermore, the vast majority of available data are presence only and do not include absences (Graham et al. 2004). In general, the quality of model predictions is directly related to the quality of data they are built on, with models based on robust sample sizes outperforming those based on few records (Pearce and Ferrier 2000, Kadmon et al. 2003).

Third, datasets on rare species occurrence often include spatial bias explicitly because sampling has been non-random; for example, when only in easily accessed areas, or those of management interest, are sampled. Montoya et al. (2009) found negative correlation between the aggregation of presences and species range size. In comparison with three other commonly applied modeling methods, test statistics assume independence of samples, and inflation of model performance can occur when training and test data are not truly independent (Araujo and Guisan 2006). Rare species are more likely to be spatially auto correlated; Veloz (2009) found that spatial autocorrelation of sampling effort between test and training data inflated model scores. As discussed in Chapter 4, spatial sorting bias, which is the difference between geographic distance from testing-presence to training-presence sites and the geographic distance from testing-absence to training-presence sites (Hijmans 2012), can disproportionally affect SDMs for rare species and can lead to poor model calibration (Phillips et al. 2009).

Despite these limitations in the generation of SDMs and their interpretation, SDMs are increasingly used in conservation to shape reserve design and to guide mitigation of the ecological costs of development and climate change (Wiens et al. 2009, Porfirio et al. 2014). Therefore, the central goal of this study was to explore methods for the optimization of SDMs for rare desert plants and to generate a set of finely tuned models based on the best possible data and field surveys for a suite of rare California desert plants potentially affected by renewable energy development. The report closes by outlining the direct management

implications of this modeling and field validation study for rare plants in the California deserts and beyond.

6.1 Management Implications for Renewable Energy

6.1.1 Are species distribution models useful at identifying novel occurrences?

For the majority of the focal species in this study, model-guided field surveys located new occurrences, 66 in total across 7 focal species. This suggests that SDMs are a useful component of an approach to identify sites to include in field surveys in the majority of cases. They can provide biologists with suggested areas to survey when assessing sites for new solar energy facilities or monitoring existing ones. However, in many cases, model results were confounded with geographic proximity, suggesting that simple biological and conservation principles, such as the idea that new occurrences are likely to be found near existing occurrences, may be nearly as informative for rare species as highly parameterized statistical models. Expert knowledge was also important in limiting search areas to areas that are ecologically suitable for rare species. Therefore, a hierarchical approach that incorporates three aspects-- preliminary modeling, reduction of search area via expert opinion, and field surveys--is recommended.

6.1.2 Is field ground truthing necessary to ascertain confidence in model predictions?

For rare species in desert habitats, ground truthing may be impractical. With truly rare species, few new occurrences are likely to be found and model predictions beyond known occupied habitat are likely to be exceedingly rare. Although ground-truthing efforts are important for general validation of SDM methods, in individual applied conservation planning efforts, careful statistical evaluation is more likely to provide practical validation of model accuracy in a time-efficient manner. However, without ground truthing, model results should be interpreted conservatively, especially for areas of novel prediction. In addition, to be effective, ground-truthing must be conducted when plant species are active and all necessary identifying characteristics are present. These facts greatly influence the feasibility and cost of field-ground truthing.

6.1.3 How should field ground truthing be conducted for annual species?

Field ground truthing for annual species must be conducted in multiple years in order to validate models and confirm occurrences. For plant species that are only active for a portion of the year, or only aboveground in a subset of years, surveys need to be conducted multiple times over multiple years before a high likelihood of absence can be determined. Many of the novel occurrences for annual species located by this study would not have been found if surveys were conducted only in a single year. For example, several *Eriophyllum mohavense* and *Mimulus mohavense* occurrences were only observed in 2011, a year in which annual species were generally more abundant in the northwestern Mojave. Critically, this finding highlights the fact that absence of annual species cannot be determined via a single survey. Rather, it can only be assumed after several years of appropriately timed surveys, specific to each study species.

6.1.4 Is rigorous selection of environmental variables beneficial compared to a standard variable selection approach?

Model comparisons showed that for the selected target rare species, identification of the best subset of environmental variables did not provide a significant improvement in model scores compared to use of all environmental variables. However, predictions of models based on a subset versus all environmental variables often led to different amounts of habitat and habitat predicted in different areas. This highlights the inherent uncertainty in distribution modeling. Multiple modeling approaches may yield models with similar scores but different results, highlighting the importance of understanding the biases in particular modeling approaches, or, alternatively using and combining results from multiple modeling methods.

6.1.5 Are SDMs effective in determining the distributions of rare desert plants for conservation planning in the California Deserts?

This study found that SDMs should be applied with caution in the applied conservation of rare desert plant species. Even when built on optimized occurrence data and with relatively detailed environmental data, the models generated generally performed only as well or slightly better than null models based on geographic distance.

6.1.6 Are regional model predictions broadly applicable?

Models generated for regional planning are applicable at the regional scale and have limited applicability at the local scale. Environmental variables used in this work ranged from a scale of 250 m to 1 km. Combined with uncertainty in the locations of plant species ranging from 10 m to 1 km, the results are by necessity of course-scale relative to the scale at which the focal plant species respond to environmental variation. The resultant mapped predictions may be relevant for regional planning and for identification of broad areas of habitat, but would not be suitable for fine-scale habitat predictions (~10 m) within individual development sites or conservation reserves. This is an inherent trade-off in making predictions over broad areas where only coarse data may available, versus fine-scaled modeling within a restricted area where detailed environmental variables may be available.

6.1.7 Can species distribution model predictions for multiple species be used together to inform field efforts to predict where habitat for multiple rare species may occur over large areas?

Yes. One means of addressing uncertainty in distribution modeling is to combine results across species to create composite maps of predicted suitability for suites of rare species. This approach can help identify areas that may be promising for field surveys of rare species, or documenting areas of predicted high diversity of rare species. They may also be useful in predicting where suites of species may occur under climate change scenarios. However, composite models, like individual species models, are dependent on locality data quality and can have reduced predictive capacity for species or suites of species with incomplete occurrence data. Composite models, for example, may increase bias toward well-surveyed areas and fail to identify important but under-surveyed areas unless steps are taken to address this bias.

6.1.8 How does geographic distance inform where rare species are likely to occur?

The findings in this report suggest that the likelihood of occurrence for many rare species is highest close to known locations. Thus, areas with high-predicted probability of occurrence that are near occupied habitat may be attributed the highest conservation value. Modeling can supplement proximity data by identifying high priority novel areas for surveys, by incorporating results into other planning efforts (e.g., combining with expert opinion maps), or by being cautiously used to identify potential habitat within a region. In addition, models can be informative for addressing questions that cannot be addressed easily by other means (e.g., movement with climate change).

GLOSSARY

Term	Definition
BCM	Basin Characterization Model
CE	California Endangered
CCH	The Consortium of California Herbaria
CNDDB	California Natural Diversity Database
CRPR	California Rare Plant Ranks
DEM	Digital Elevation Model
DRECP	Desert Renewable Energy Conservation Plan
EO	Element Occurrence (CNDDB)
FE	Federally Endangered
FT	Federally Threatened
GIS	Geographic Information Systems
HCP	Habitat Conservation Plan
MSS	Maximum Sensitivity plus Specificity
NCCP	Natural Community Conservation Plan
NDVI	normalized difference vegetation index
NPS	National Park Service
REAT	Renewable Energy Action Team
SDM	Species distribution model
SSURGO	Soil Survey Geographic

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APPENDIX A:
Draft Models for DRECP

Species distribution models for nine rare plant species were provided to Conservation Biology Institute for inclusion on DataBasin at the request of the DRECP in January of 2013 (Table 3.2). Detailed information on environmental variables, methods, and model diagnostics, are available on DataBasin in the DRECP Working Group supporting document "UCD_McIntrye and Moore Maxent Models for DRECP." Datasets, mapping tools and model scores are available for reference for each species on DataBasin.

For example, *Cymopterus deserticola*
http://databasin.org/datasets/399514da4a7d474189875eb332994914.

In addition, models were prepared for the DRECP for *Mimulus mohavensis* and *Eriophyllum mohavense* that summarize predicted habitat distribution for each species in a simple visual format for DRECP participant discussion.

These Maxent generated distribution models were built using an approach that emphasized the ability of models to predict the results of field-based surveys for rare species. As a result, this approach emphasizes ability to predict unknown populations, rather than the ability to accurately describe the known distribution. Furthermore, these models were evaluated for their ability to distinguish occurrences from non-occurrences within the known geographic region where a species occurs (defined as a 20km buffer around the known range), and then model results were projected out to the larger DRECP region. This approach emphasizes the uncertainty in discriminating habitat from non-habitat in regions where the species is not known to occur.

For both species, model results are provided for the known range (model training area) and the entire DRECP (model projection area). The raw model results and a thresholded (using the 10% training presence threshold) result are also provided.

<u>Models for both species were assessed based on:</u>

1) AUC_{cv}- Cross-validated unadjusted AUC scores based on 100 replicate draws from occurrence data reducing the number of localities within 3km of one another.

2) AUC_{pwd}-validated AUC scores adjusted based on a pairwise geographic distance correction (Hijmans 2012) repeated 100 times

***<u>Mimulus mohavensis</u>*<u>:</u>**
AUC_{cv}: 0.901
AUC_{pwd}: 0.711
10% training threshold: 0. 40155

Predictor variables used: 19 Bioclim variables calculated from the 270m resolution BCM climate model (Flint and Flint 2012b)

***Eriophyllum mohavense*:**
AUC_{cv}: 0.855
AUC_{pwd}: 0.651
10% training threshold: 0.236657

Predictor variables used: average albedo, slope complexity, ave NDVI, ratio fall:spring NDVI, Elevation, Northness, Soil PH, Bioclim 2 (mean diurnal range), Bioclim 6 (Min temp of coldest month), Bioclim 7 (temp annual range), Bioclim 10 (mean temp warmest quarter), Bioclim 12 (annual precip), Bio 16 (precip of wettest quarter), Bio 18 (precipitation of warmest quarter)

Figure A-1: Binary Habitat Suitability for *Mimulus mohavensis*

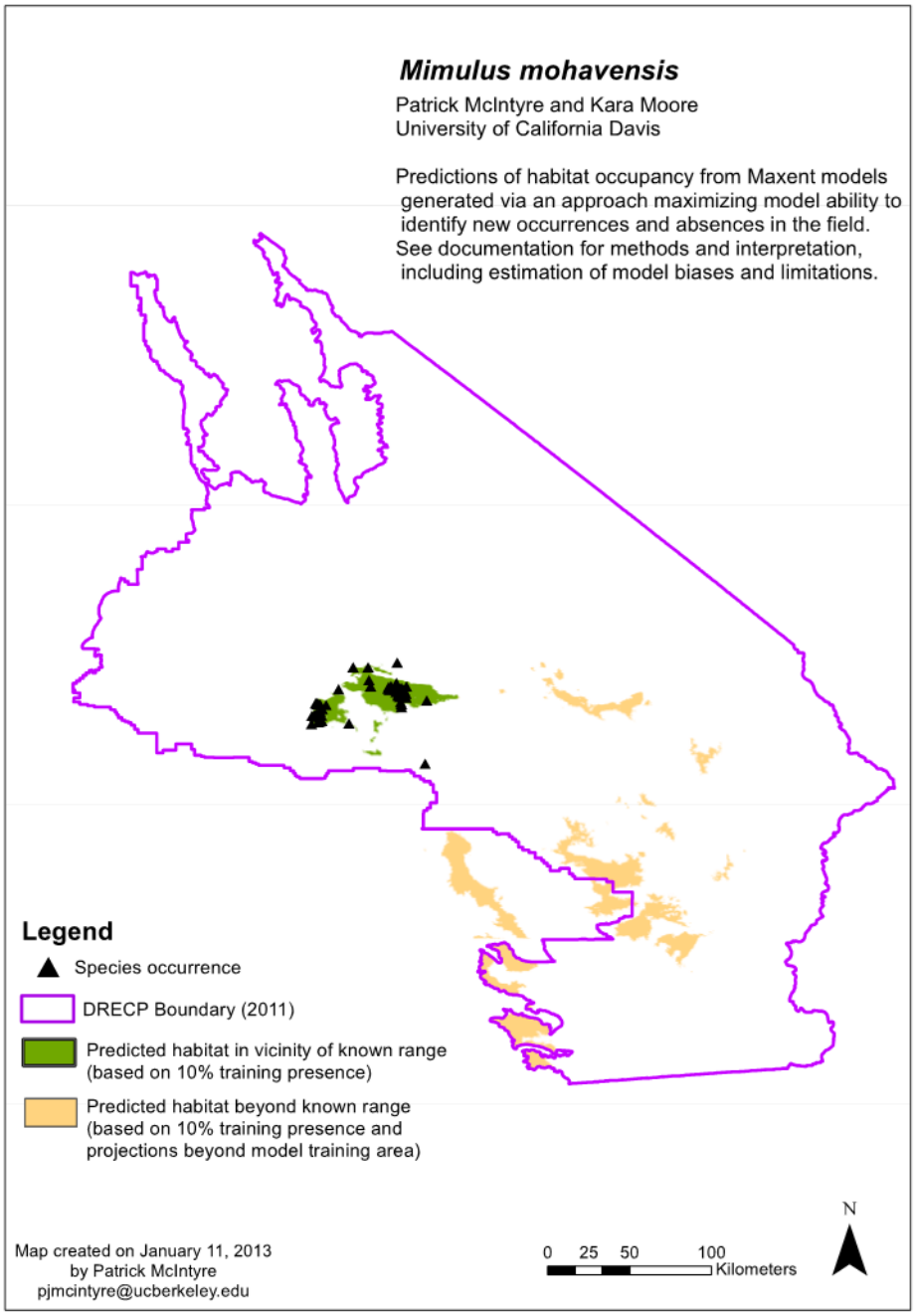

Figure A-2: Continuous Habitat Suitability for *Mimulus mohavensis*

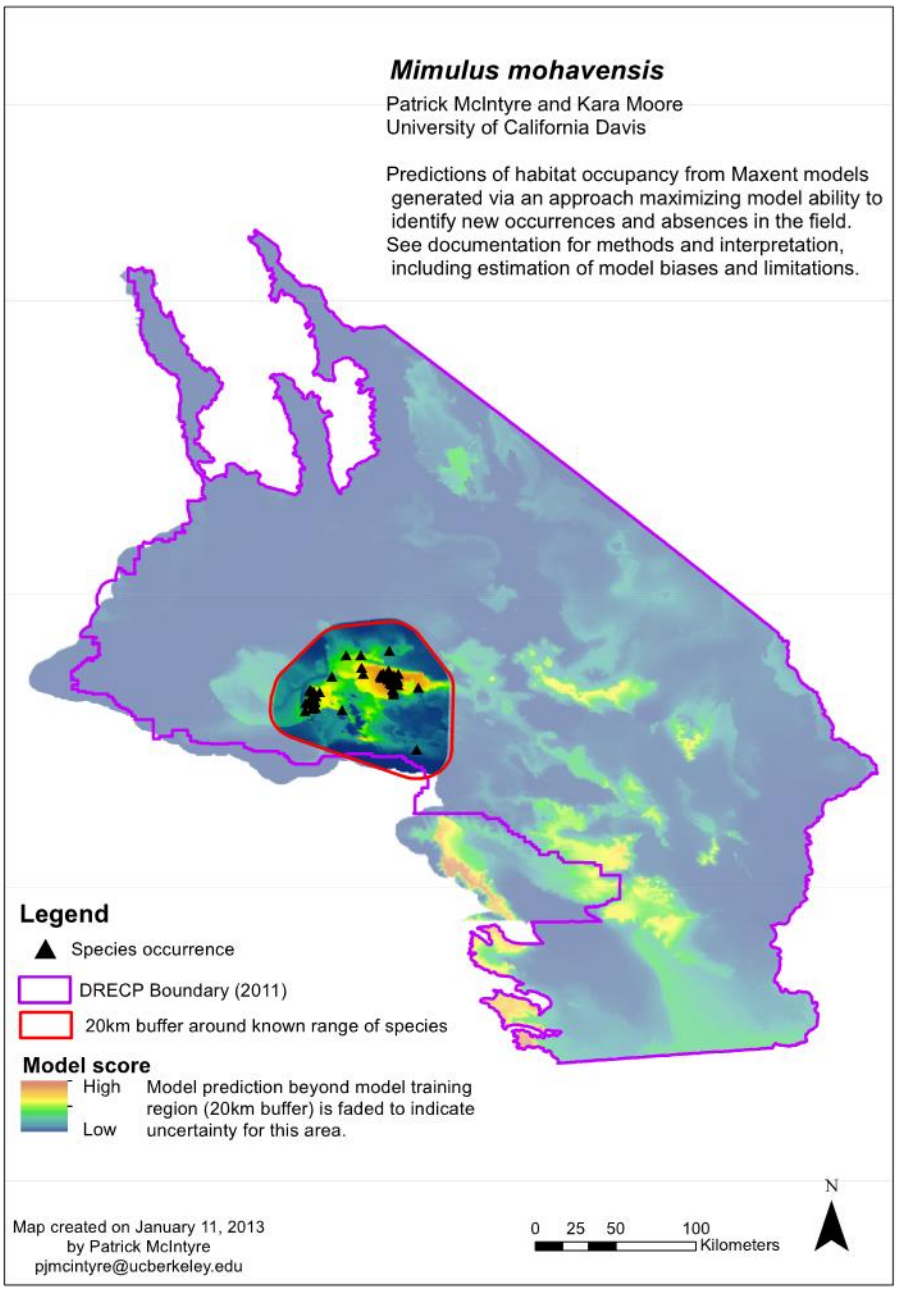

Figure A-3: Binary Habitat Suitability for *Eriophyllum mohavense*

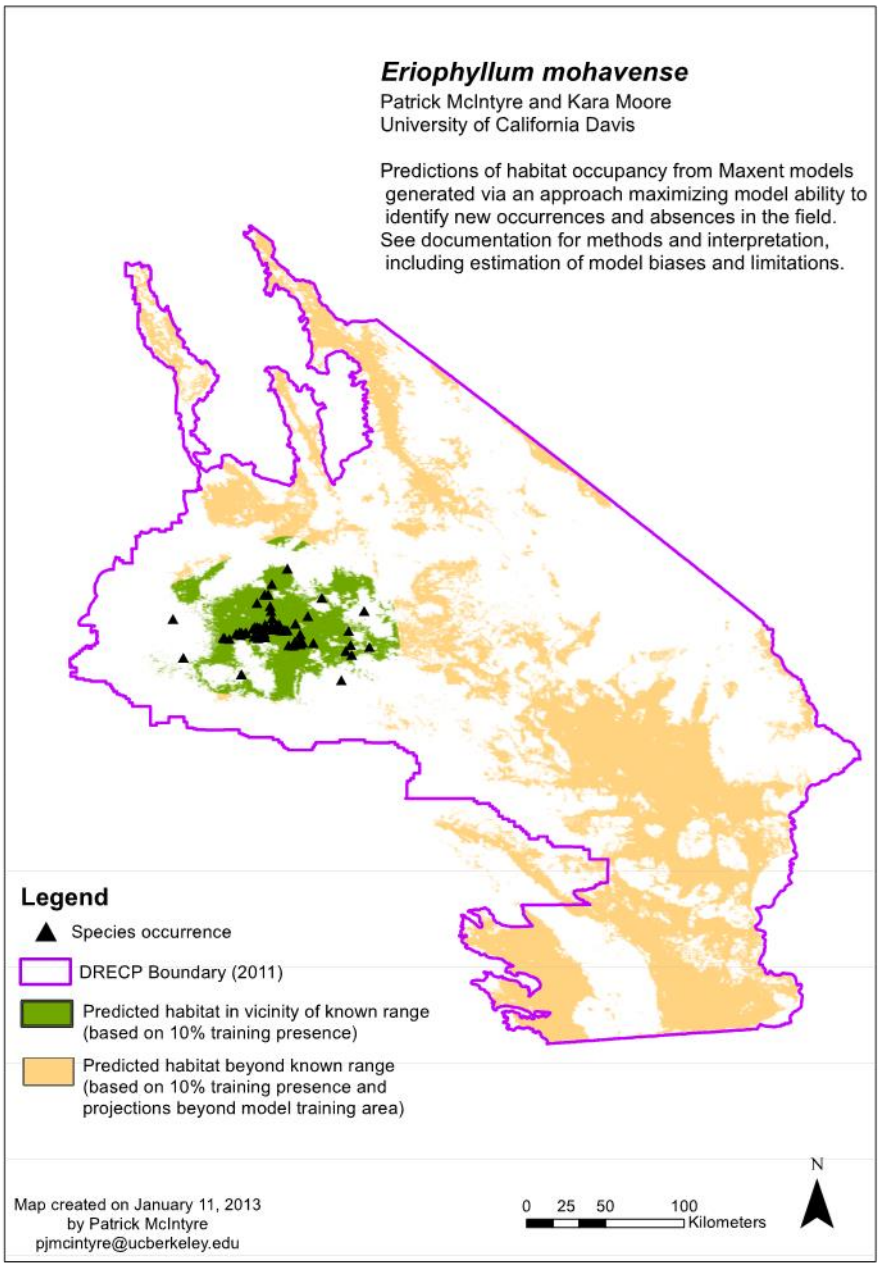

Figure A-4: Continuous Habitat Suitability for *Eriophyllum mohavense*

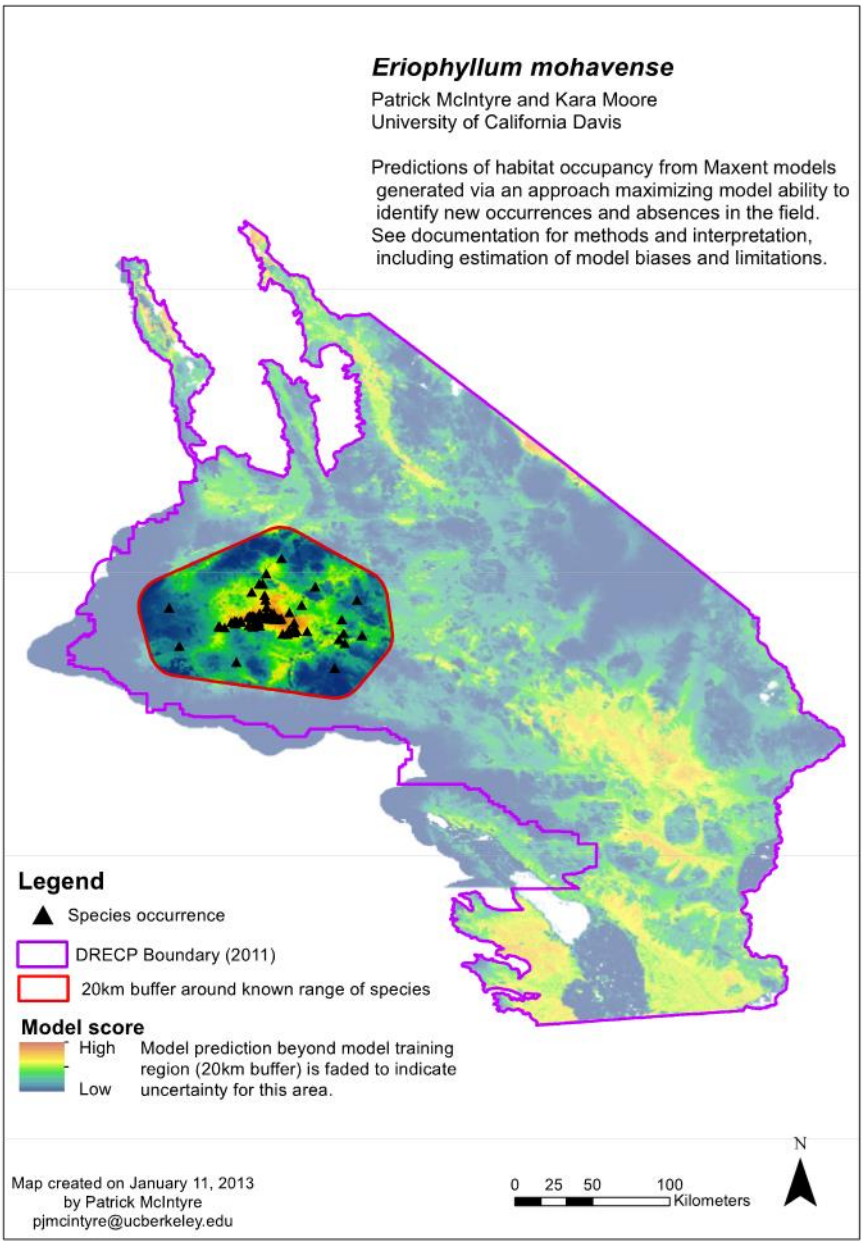

Figure A-5: Binary Habitat Suitability for *Castela emoryi*

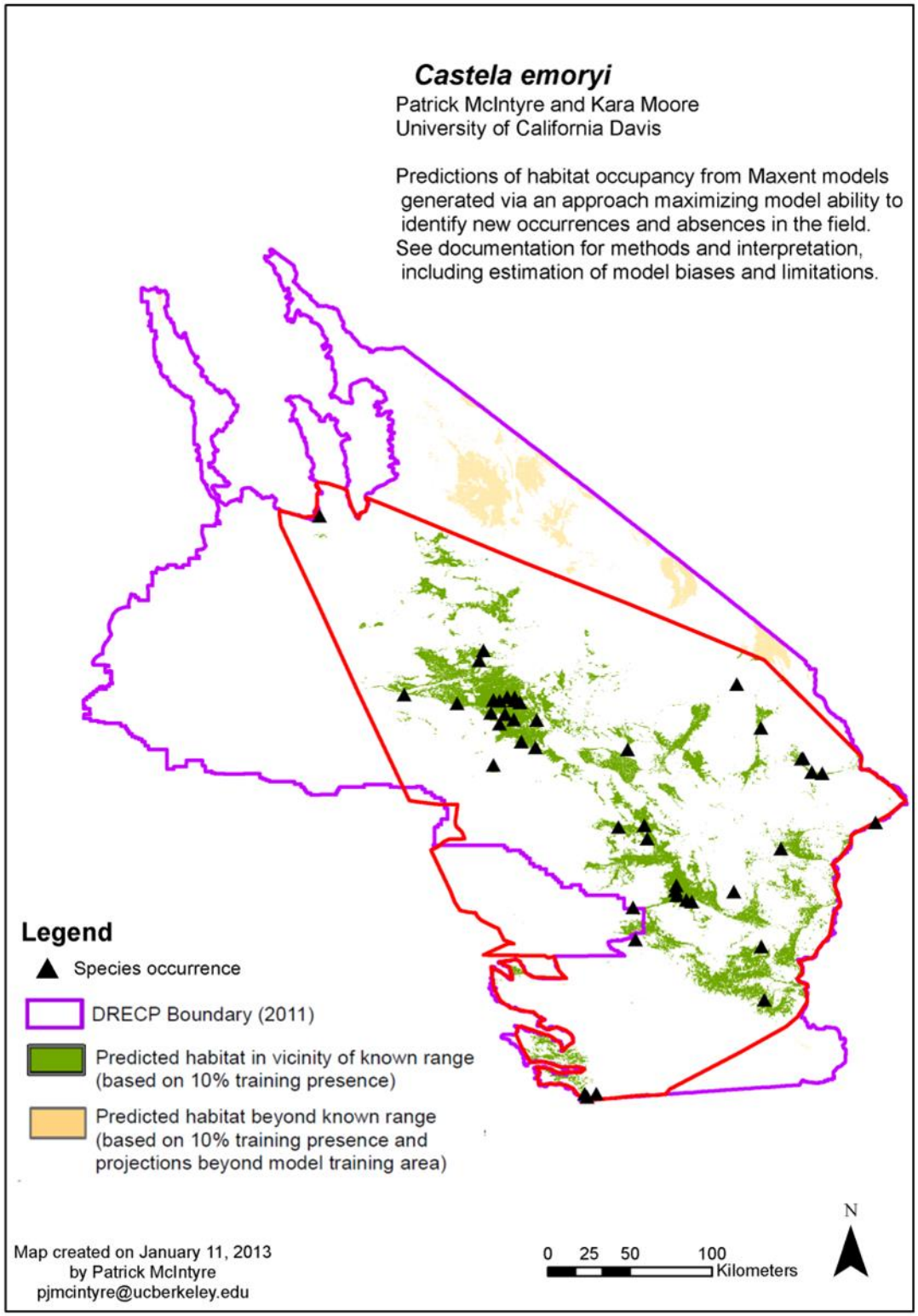

Figure A-6: Continuous Habitat Suitability for *Castela emoryi*

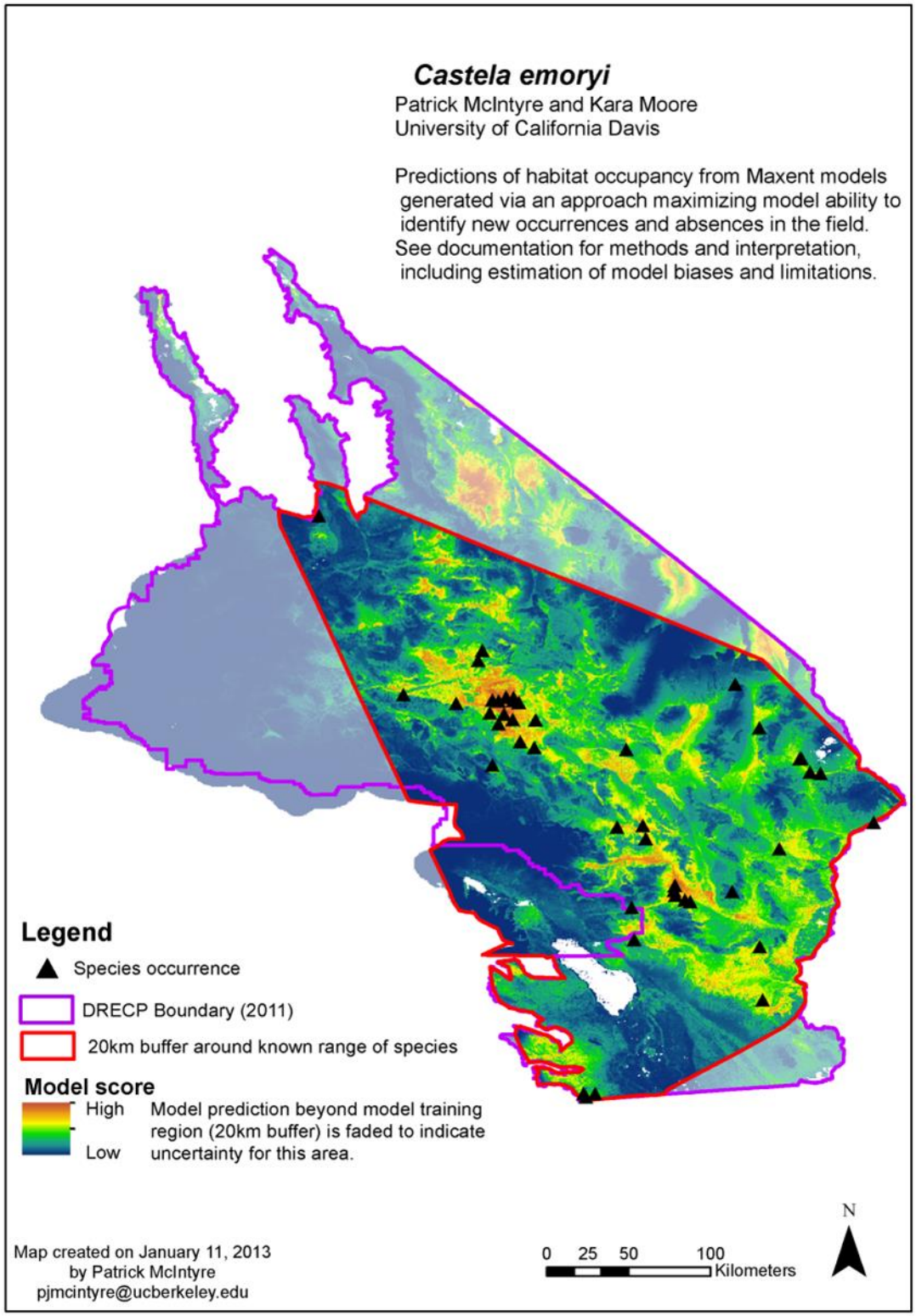

Figure A-7: Binary Habitat Suitability for *Grusonia parishii*

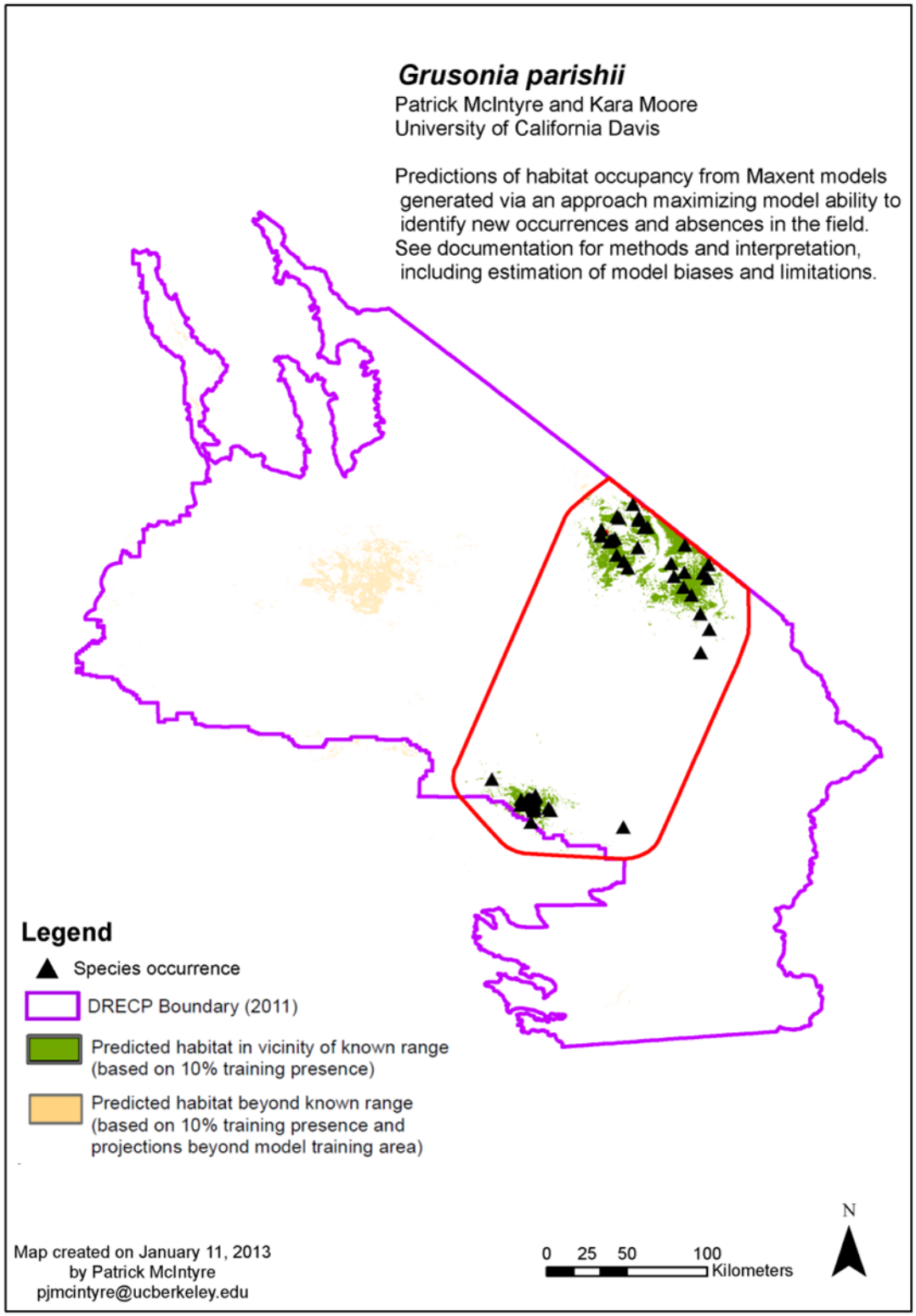

Figure A-9: Binary Habitat Suitability for *Mentzelia tridentata*

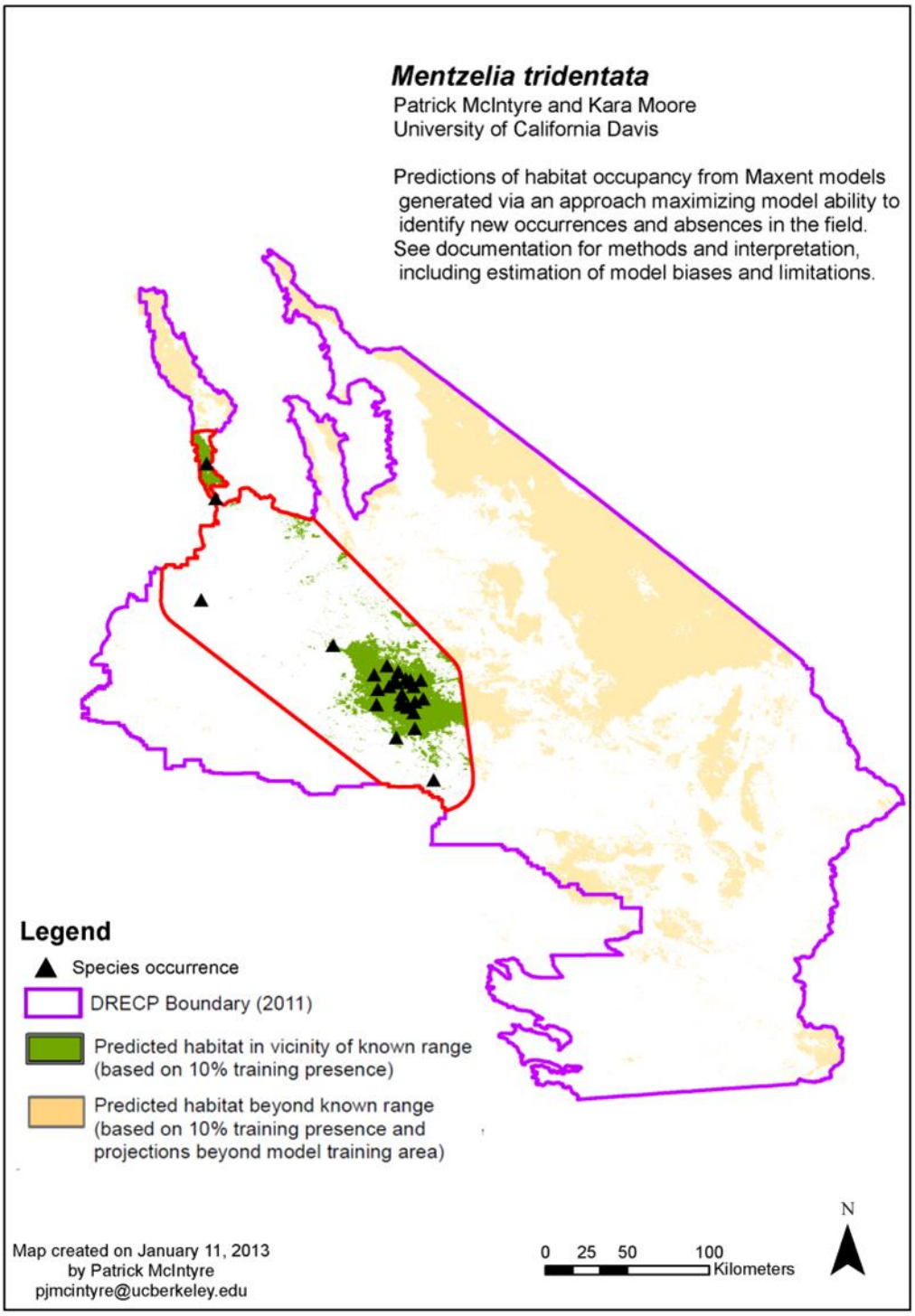

Figure A-10: Continuous Habitat Suitability for *Mentzelia tridentata*

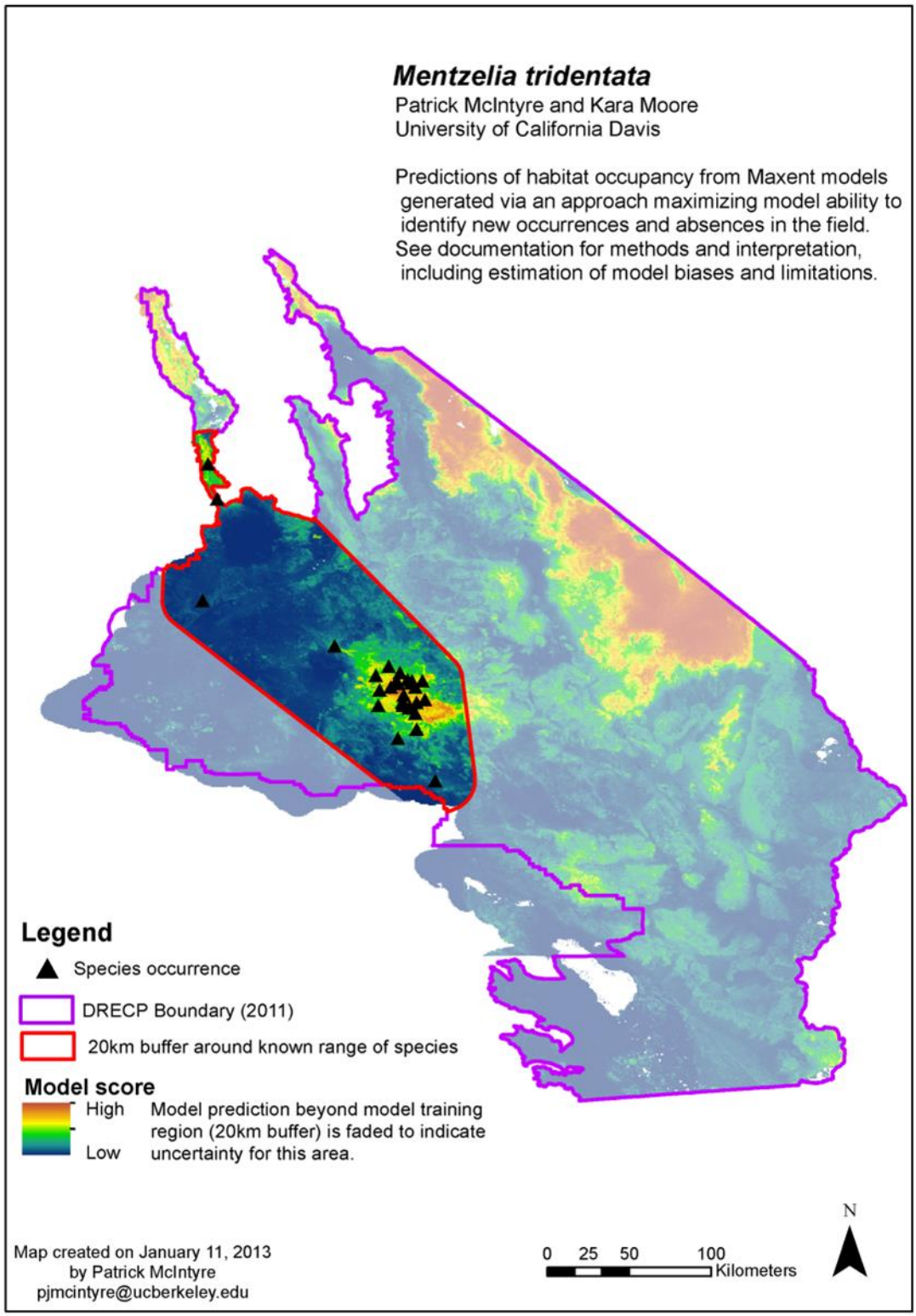

Figure A-11: Binary Habitat Suitability for *Penstemon albomarginatus*

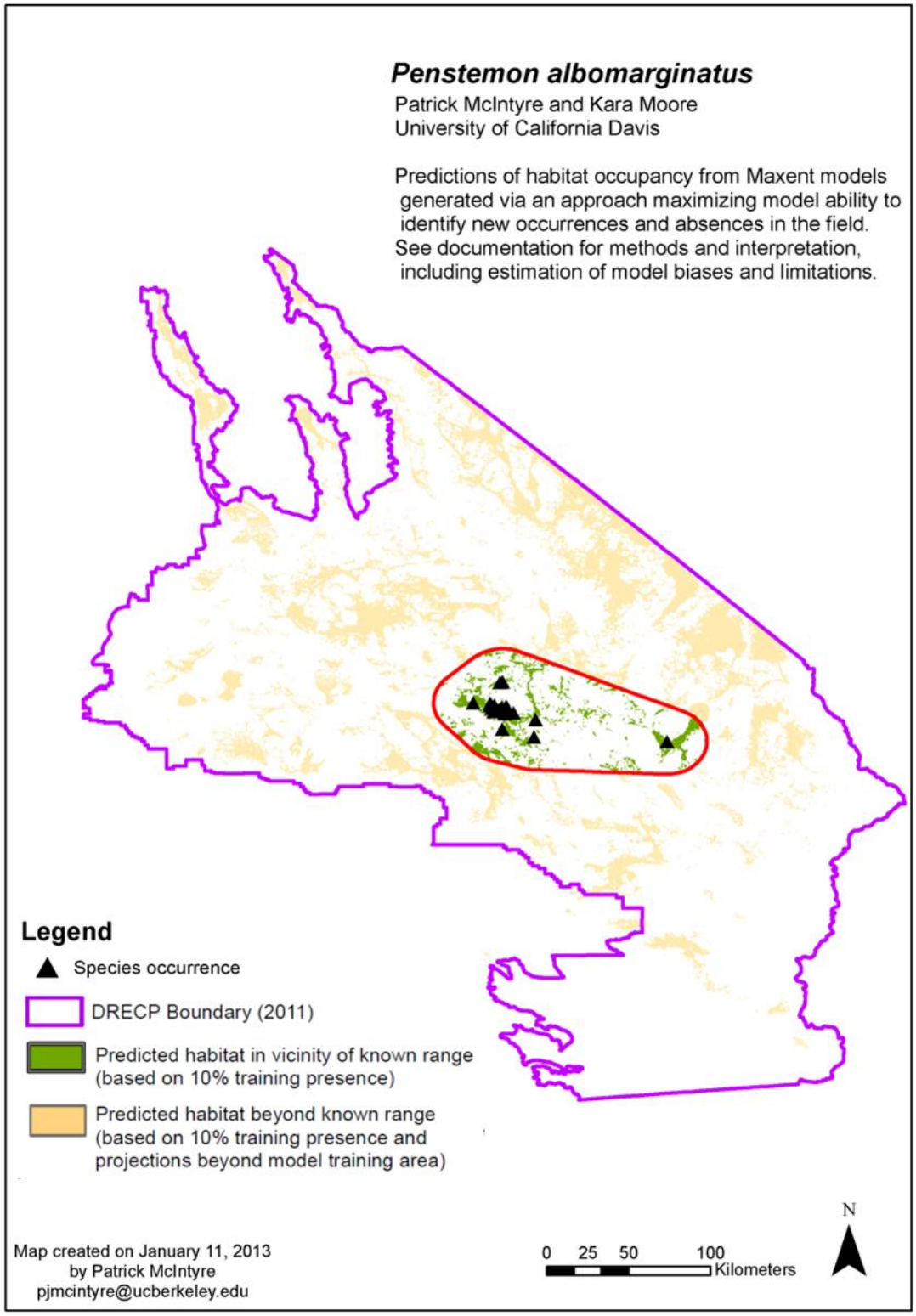

Figure A-12: Continuous Habitat Suitability for *Penstemon albomarginatus*

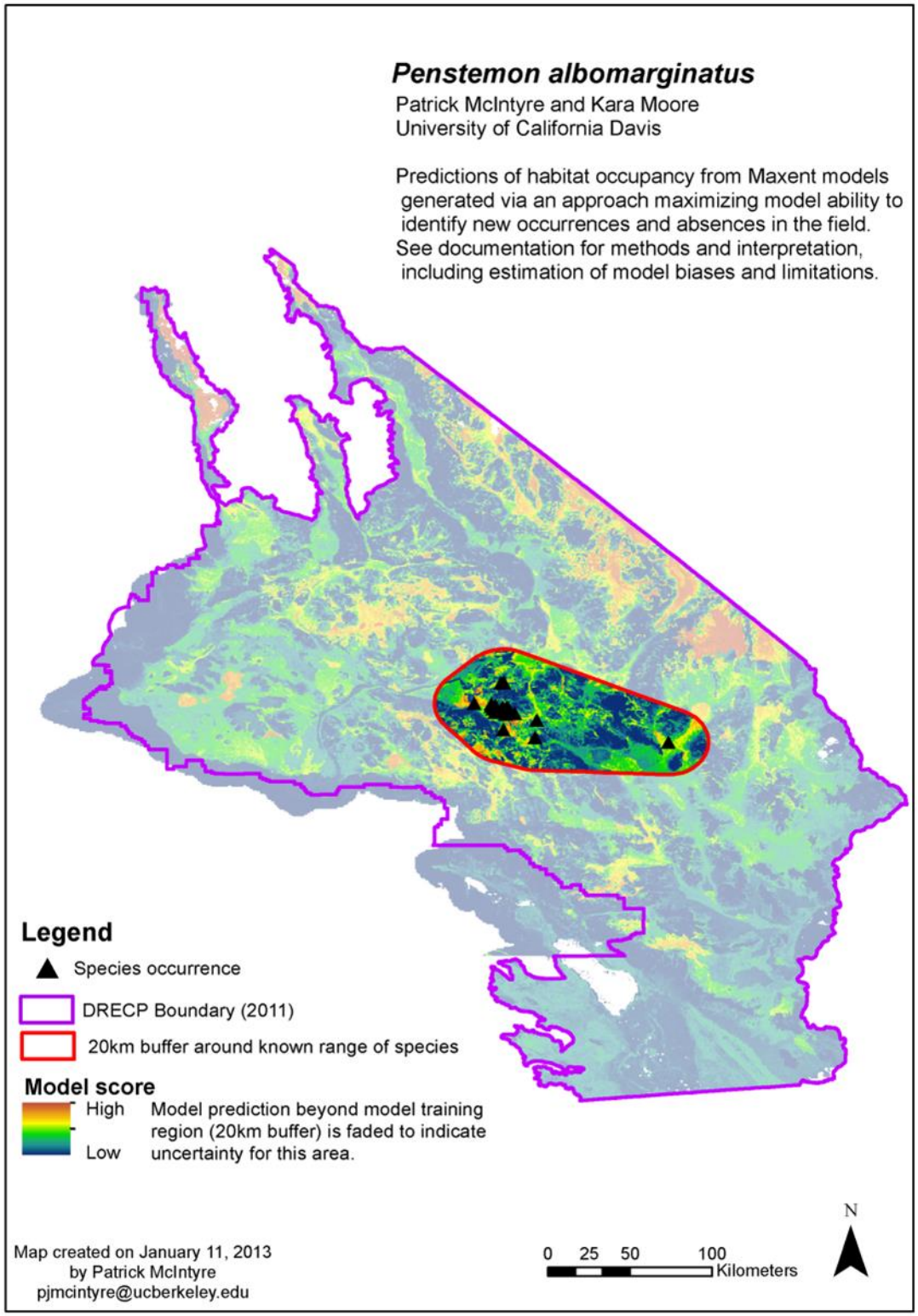

Figure A-13: Binary Habitat Suitability for *Cymopterus deserticola*

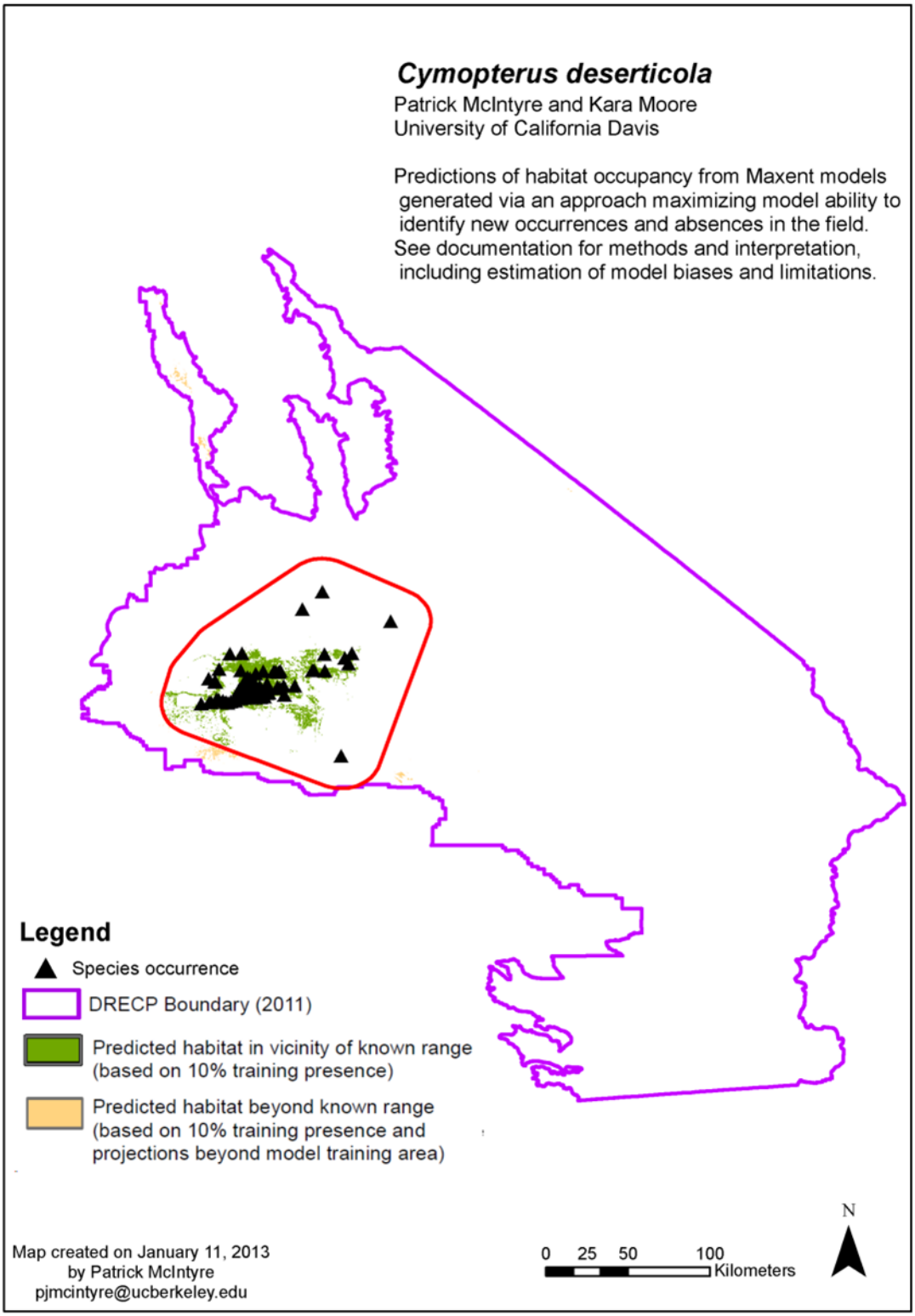

Figure A-14: Continuous Habitat Suitability for *Cymopterus deserticola*

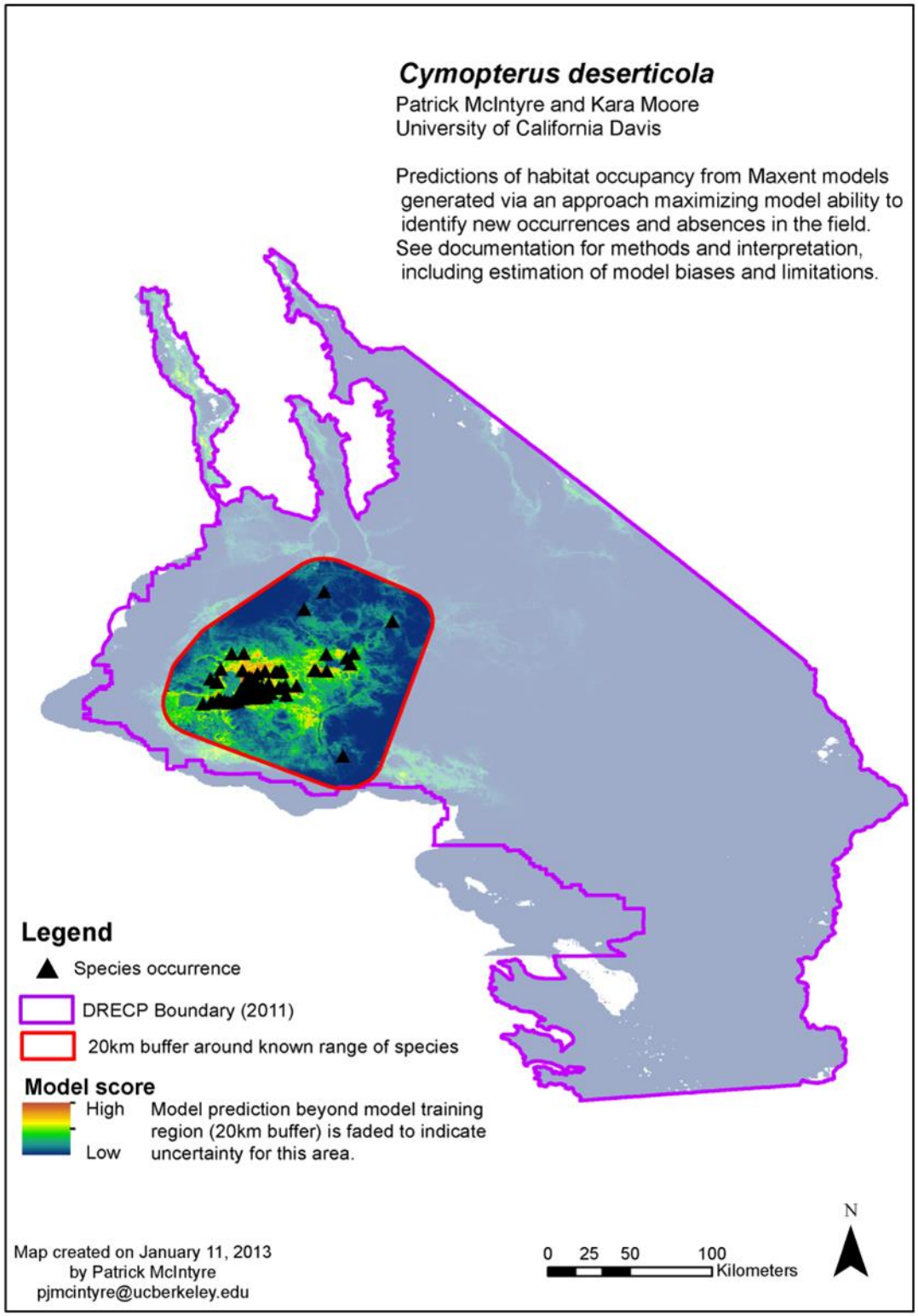

Figure A-15: Binary Habitat Suitability for *Asclepias nyctaginifolia*

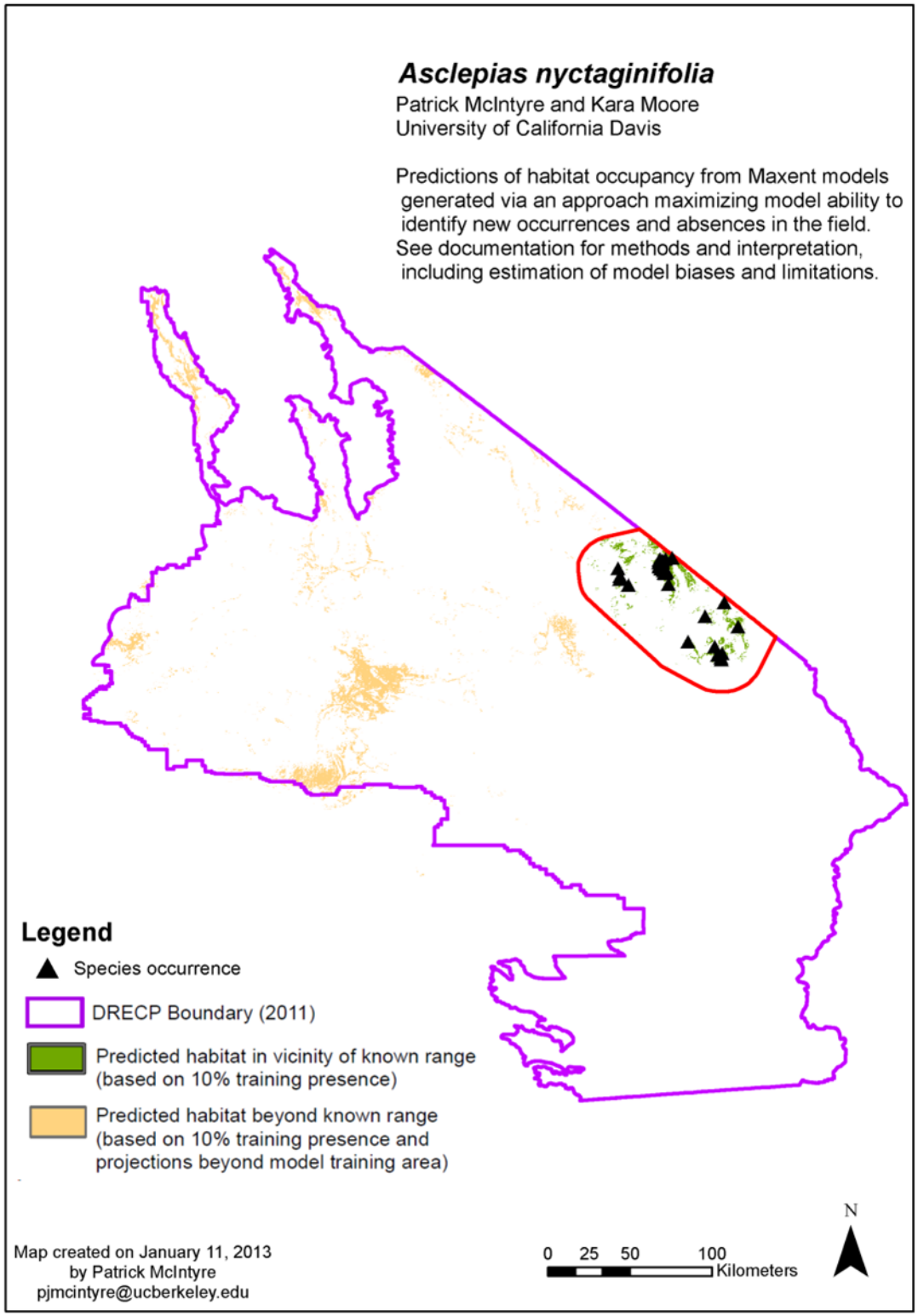
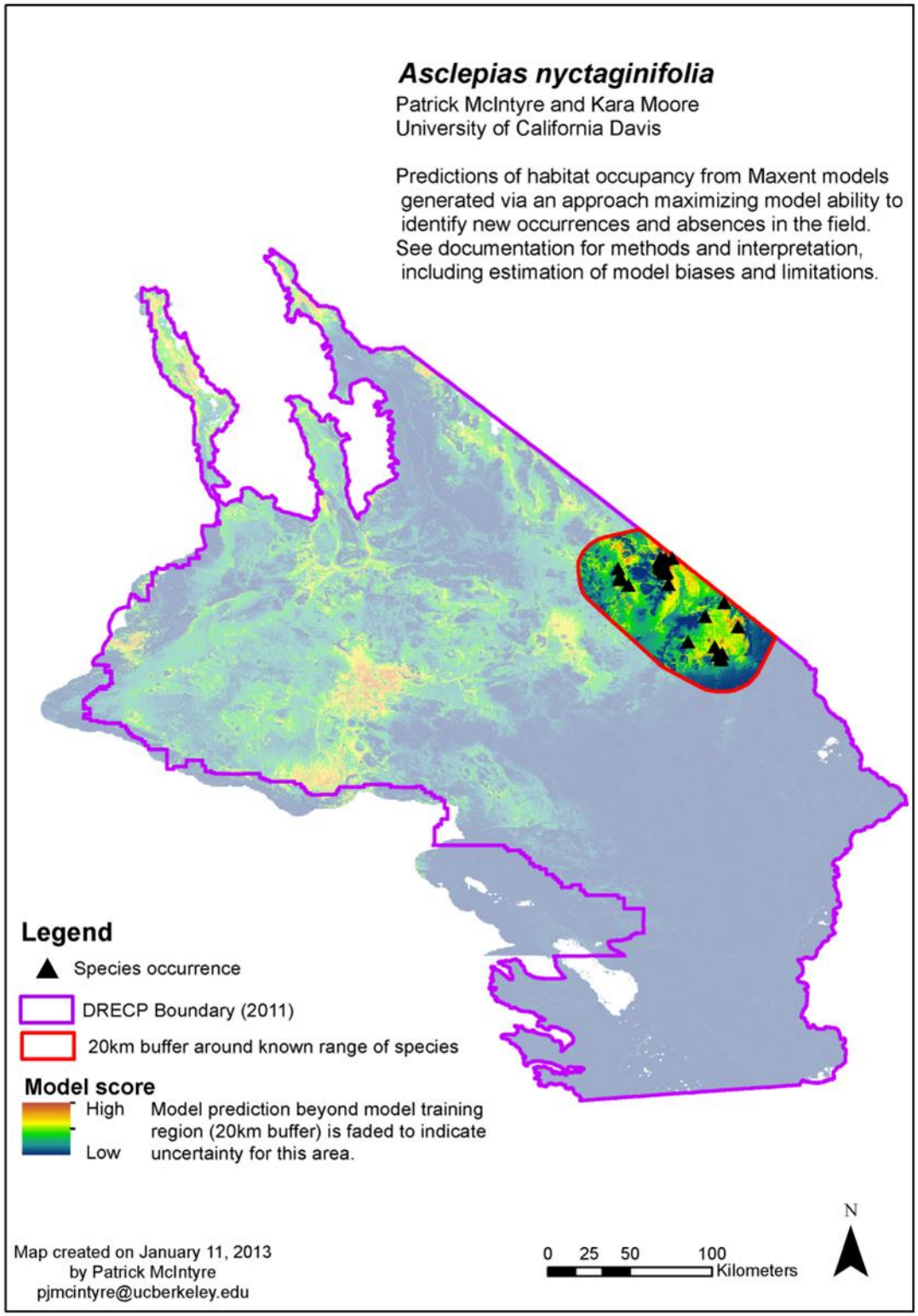
Figure A-16: Continuous Habitat Suitability for *Asclepias nyctaginifolia*