Energy Research and Development Division
FINAL PROJECT REPORT

CUMULATIVE BIOLOGICAL IMPACTS FRAMEWORK FOR SOLAR ENERGY PROJECTS IN THE CALIFORNIA DESERT

Prepared for: California Energy Commission
Prepared by: University of California, Santa Barbara

DECEMBER 2013
CEC-500-2015-062

PREPARED BY:

Primary Authors:
Frank W. Davis
Jason Kreitler
Oliver Soong
David Stoms
Stephanie Dashiell
Carrie Schloss
Lee Hannah
Whitney Wilkinson
John Dingman

Bren School of Environmental Science and Management
2400 Bren Hall
University of California, Santa Barbara
Santa Barbara, CA 93106-5131
Phone: 805-893-3438| Fax: 805-893-7612

Contract Number: 500-10-021

Prepared for:

California Energy Commission

Simone Brant
Contract Manager

Aleecia Gutierrez
Office Manager
Energy Generation Research Office

Laurie ten Hope
Deputy Director
ENERGY RESEARCH AND DEVELOPMENT DIVISION

Robert P. Oglesby
Executive Director

DISCLAIMER

This report was prepared as the result of work sponsored by the California Energy Commission. It does not necessarily represent the views of the Energy Commission, its employees or the State of California. The Energy Commission, the State of California, its employees, contractors and subcontractors make no warranty, express or implied, and assume no legal liability for the information in this report; nor does any party represent that the uses of this information will not infringe upon privately owned rights. This report has not been approved or disapproved by the California Energy Commission nor has the California Energy Commission passed upon the accuracy or adequacy of the information in this report.

ACKNOWLEDGEMENTS

This project was funded under California Energy Commission Contract #500-10-021. The research team thanks Energy Commission staff Misa Milliron and Simone Brant for managing and providing administrative support and guidance to the project.

The research team is grateful to Kara Moore O'Leary, University of California at Davis, for sharing data and research insights on desert plant species, and to Ben Best (National Center for Ecological Analysis and Synthesis) for help with species distribution models. Thanks to Conservation Biology Institute personnel Wayne Spencer, Jim Strittholt, Rebecca Degagne, Jerre Stallcup and Mike Gough for their collaboration and advice on species distribution models and for providing use of DataBasin for sharing project data. Thanks to Larry Powell of the Mojave Desert Ecosystem Program for help implementing a project SharePoint site for data sharing and model visualization. The team is grateful to Mike Howard and staff at Dudek for sharing data and insights on species distribution modeling for desert species, and to U.S. Fish and Wildlife Service biologist Cat Darst for facilitating access to data from the Desert Tortoise Recovery Program. Thanks to Jim Thorne at UC Davis for providing access to land use change scenarios. The team also thanks the following individuals who spent a significant amount of time providing advice and commenting on draft research products: Laura Crane, Dick Cameron, Brian Cohen and John Randall (The Nature Conservancy of California); Ileene Anderson (Center for Biological Diversity); Susan Lee and Amy Morris (Aspen Environmental Group), Ryan Drobek (Center for Energy Efficiency and Renewable Technologies), Todd Keeler-Wolf and Diana Hickson (California Department of Fish and Wildlife), and Ashley Conrad-Saydah (California Environmental Protection Agency).

Finally, the team would like to acknowledge the excellent contract administration support provided by staff of the Earth Research Institute, notably Kathy Scheideman, John Sanchez, Jeri O'Mahoney and Cecilia Sousa.

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.

The Energy Research and Development Division conducts public interest research, development, and demonstration (RD&D) projects to benefit California.

The Energy Research and Development Division strives to conduct the most promising public interest energy research by partnering with RD&D entities, including individuals, businesses, utilities, and public or private research institutions.

Energy Research and Development Division funding efforts are focused on the following RD&D program areas:

- Buildings End-Use Energy Efficiency
- Energy Innovations Small Grants
- Energy-Related Environmental Research
- Energy Systems Integration
- Environmentally Preferred Advanced Generation
- Industrial/Agricultural/Water End-Use Energy Efficiency
- Renewable Energy Technologies
- Transportation

Cumulative Biological Impacts Framework for Solor Energy Projects in the California Desert is the final report for the Cumulative Biological Impacts Framework for Solar Energy Projects in the California Desert project (contract number 500-10-021) conducted by University of California, Santa Barbara Bren School of Environemntal Science and Management. The information from this project contributes to Energy Research and Development Division's Energy-Related Environmental Research Program.

For more information about the Energy Research and Development Division, please visit the Energy Commission's website at www.energy.ca.gov/research/ or contact the Energy Commission at 916-327-1551.

ABSTRACT

This project developed analytical approaches, tools and geospatial data to support conservation planning for renewable energy development in the California deserts. Research focused on geographical analysis to avoid, minimize and mitigate the cumulative biological effects of utility-scale solar energy development. A hierarchical logic model was created to map the compatibility of new solar energy projects with current biological conservation values. The research indicated that the extent of compatible areas is much greater than the estimated land area required to achieve 2040 greenhouse gas reduction goals. Species distribution models were produced for 65 animal and plant species that were of potential conservation significance to the Desert Renewable Energy Conservation Plan process. These models mapped historical and projected future habitat suitability using 270 meter resolution climate grids. The results were integrated into analytical frameworks to locate potential sites for offsetting project impacts and evaluating the cumulative effects of multiple solar energy projects. Examples applying these frameworks in the Western Mojave Desert ecoregion show the potential of these publicly-available tools to assist regional planning efforts. Results also highlight the necessity to explicitly consider projected land use change and climate change when prioritizing areas for conservation and mitigation offsets. Project data, software and model results are all available online.

Keywords: biodiversity, climate change, Desert Renewable Energy Conservation Plan**,** land use change, Maxent, Mojave Desert, Sonoran Desert, species distribution models, Zonation

Please use the following citation for this report:

Davis, Frank; Jason Kreitler, Oliver Soong; David Stoms; Stephanie Dashiell; Carrie Schloss; Lee Hannah; Whitney Wilkinson; John Dingman. (University of California, Santa Barbara). 2013. ***Cumulative Biological Impacts Framework for Solar Energy Projects in the California Desert.*** California Energy Commission. Publication number: CEC-500-2015-062.

TABLE OF CONTENTS

Acknowledgements i

PREFACE ii

ABSTRACT iii

TABLE OF CONTENTS iv

LIST OF FIGURES vi

LIST OF TABLES viii

EXECUTIVE SUMMARY 1

Project Benefits 3

CHAPTER 1: Introduction 4

1.1 Utility-scale Solar Energy and Biological Impacts 4

1.2 Project Scope 5

CHAPTER 2: Siting Solar Energy Development to Minimize Biological Impacts 8

2.1 Methods 9

2.1.1 Choice of study area, data type, and spatial resolution 9

2.1.2 Logic model 10

2.1.3 On-site Impacts 11

2.1.4 Off-site Impacts 13

2.1.5 Spatial modeling, validation and testing 15

2.1.6 Initial model modifications 16

2.1.7 Peer review of initial model and final revisions 18

2.1.8 Comparison to similar models 18

2.2 Results 21

2.2.1 Compatibility scores in urban areas 21

2.2.2 Compatibility scores by land manager 21

2.2.3 Model results in Solar Energy Zones (SEZs) 22

CHAPTER 3: Species Distribution Models for Desert Conservation Planning 23

3.1 Introduction 23

3.2 Species Selection 24
3.3 Species Locality Data for Species Distribution Modeling 24
3.4 Environmental Variables 27
3.5 Maxent Species Distribution Models 32
3.5.1 Model evaluation 33
3.6 Maximum Likelihood Models 34
3.7 Results 34
3.7.1 Maxent models 34
3.7.2 Maxlike models 38
3.8 Model Limitations and Caveats 42
CHAPTER 4: Mid-century Projections of Species Distributions 43
4.1 Climate Change Futures for the California Desert 43
4.2 Projected Changes in Species Distributions 46
CHAPTER 5: A Planning Support Tool for Offsetting the Impacts of Energy Development 52
5.1 Background 52
5.2 MOJAVSET – A Planning Support Tool for Offsetting the Impacts of Solar Energy Development in the California Deserts 54
5.3 Western Mojave Worked Example to Illustrate the Use of Mojavset for Mitigation Offsets. 56
5.3.1 Location, offset decisions, data, and species covered 56
5.3.2 Proposed utility scale solar projects 57
5.3.3 Conservation Features 58
5.3.4 Mojavset parameters for the test case 58
5.3.5 Projected impacts and offset scenarios 58
5.4 Discussion 63
5.4.1 Climate change and mitigation offsets 65
CHAPTER 6: Modeling Cumulative Effects of Solar Energy Development 66
6.1 Background 66
6.1.1 CEA for Renewable Energy Development in Arid Environments 66

6.2 Overview of the Cumulative Effects Assessment Framework Developed for this Project 67

6.3 Worked Example for the Western Mojave Subregion 72

6.3.1 Models of current and future conditions 72

6.3.2 Changes in biodiversity and areas of high conservation value 73

6.4 Discussion 80

6.4.1 Climate change and cumulative effects analysis 83

GLOSSARY 84

REFERENCES 85

Appendix A: Details of GIS Compatability Modeling.....

Appendix B: Summary of Maxent Models.....

Appendix C: Mojavset Users Manual.....

LIST OF FIGURES

Figure 1: Map of project study area 6

Figure 2: Flowchart of project tasks and activities. 7

Figure 3: Logic model used to map site compatibility with utility-scale solar projects 10

Figure 4: Top level of the logic network 11

Figure 5: Logic for on-site degradation. 12

Figure 6: Logic for impacted native vegetative cover. 13

Figure 7: Logic for habitat fragmentation. 14

Figure 8: Logic for off-site impact. 15

Figure 9: Recovery function for vegetative cover derived from Webb et al. (2009). 16

Figure 10: Locations of random points used for validation of compatibility modeling 17

Figure 11: Comparison of degradation models by UCSB and the Human Footprint (Leu et al. 2008). 20

Figure 12: Comparison of degradation models by UCSB and TNC. 20

Figure 13: Examples of 270m downscaled climate grids used for Maxent model parameterization (1981-2010) and hindcasting (1951-1980). 30

Figure 14: (left) Map sources for CWHR habitat types....31

Figure 15: Maxent scores for Barstow woolly sunflower for the calibration period (1981-2010) .36

Figure 16: Summary of SDM model robustness (best vs. mean bootstrapped AUC) 38

Figure 17: Maxlike vs. Maxent models for Mohave ground squirrel, including maxlike probabilities 40

Figure 18: Maxlike vs. Maxent models for Barstow woolly sunflower, including Maxlike probabilities 41

Figure 19: Historical and projected mid-century precipitation for the warmest quarter and maximum daily temperatures for the warmest month. 44

Figure 20: Modeled summer (JJA) maximum daily temperatures (maxT_warm-Bio5) and minimum daily winter (DJF) temperatures for two historical periods 45

Figure 21: Mid-century (2040-2069) projections for Growing Degree days....46

Figure 22: Composited view of current and projected future habitat distribution for Barstow woolly sunflower 47

Figure 23: Representative examples of current vs. mid-century habitat areas for four study species....49

Figure 24: Frequency distributions of proportion stable range for 65 study species 50

Figure 25: Frequency distribution of the ratio of future to current suitable habitat area within the study region. 51

Figure 26: Map illustrating the use of the utility curve in Zonation....53

Figure 27: General workflow of the Mojaveset. 55

Figure 28: Location map of the Western Mojave study area 57

Figure 29: Western Mojave ecological subsection with species richness and proposed utility scale solar development locations. 59

Figure 30: Direct offset sites (red) for hypothetical solar energy projects (gray) using a 2:1 offset ratio 62

Figure 31: Maximum conservation gains offset solution (red) using a 2:1 offset ratio for a hypothetical set of solar energy projects (gray). 63

Figure32: Processing flow for cumulative effects analysis....71

Figure 33: Map of the case study area showing a hypothetical set of solar projects as well as designated protected lands that were treated differently in the Zonation model of land conservation value. 74

Figure 34: Ecological condition as represented in four models....76

Figure 35: Species distribution models for the Mojave ground squirrel....77

Figure 36: Barplots summarizing changes in modeled species distributions as a result of proposed solar development and projected climate and land use change....78

Figure 37: Species richness patterns produced by summing condition-weighted....79

Figure 38: Distribution of conservation value based on 17 focal species....81

Figure 39: Change in Zonation removal rank based on comparison of the baseline model to mid-century model....82

LIST OF TABLES

Table 1: Mean scores with and without urban lands....21

Table 2: Area of most compatible land with and without urban lands....21

Table 3: Mean scores by land manager....22

Table 4: Wildlife species for which species distribution models were produced....25

Table 5: Plant species for which species distribution models were produced....26

Table 6: Environmental variables used for species distribution modeling....29

Table 7: Mean and maximum contribution of environmental variables to 65....37

Table 8: Species list, summary of modeled solar development impact, and offsets achieved for each species based on Direct Offset vs. Maximum Biodiversity objectives....60

Table 9: Impact site and offset site reports....61

Table 10: Typology of cumulative effects: sources, pathways, and effects....69

Table 11: List of species consider in the cumulative effects analysis....75

EXECUTIVE SUMMARY

Increased interest in utility-scale renewable energy projects in the California deserts has raised concerns about potential impacts on biological resources. Many areas of high energy potential are in fragile environments that are easily disturbed and hard to restore. This project developed data, analytical approaches and tools to support conservation planning for renewable energy development in the California deserts. Specific objectives included identifying areas to minimize conflict between desert species and ecological communities vs. renewable energy development, production of new geospatial data for species distribution models, species habitat distribution modeling under current and projected future climate and land use, and development of practical approaches for locating potential mitigation offset areas and evaluating cumulative ecological effects of multiple solar projects.

An assessment method was developed for modeling the relative degree of compatibility of new solar energy projects in the Mojave and Sonoran Deserts of southern California with biological conservation values. The resulting hierarchical logic model considers both onsite and offsite impacts of solar energy projects and gives higher scores to areas that are expected to have lower overall biological impacts. After excluding urban areas, where sites have relatively low biological value but may still be incompatible with solar development, 741,000 – 988,000 acres (300,000 – 400,000 hectacres) of land were mapped as having high compatibility with solar development. The California Energy Commission estimates that 62,000 acres (25,000 hectacres) of utility-scale solar projects will be required in the Desert Renewable Energy Conservation Plan (DRECP) area with 8.7 gigawatts of installed capacity to achieve 2040 greenhouse gas reduction goals.

Species distribution models were produced for 65 species (25 terrestrial wildlife species, 40 plant species) of conservation significance to the DRECP process. Models were produced using Maximum Entropy and, for a subset of 10 species, Maximum Likelihood algorithms. Several new environmental data layers were created specifically for this project to improve the resolution and quality of species distribution models, including 270 meter-resolution grids of seven important bioclimatic variables for the periods 1951-1980, 1981-2010, and 2040-2069.

Maximum Entropy performed better than Maximum Likelihood for species with relatively few observation data. Maximum Entropy distribution models for most species showed good to very good performance. The lowest performing models were for wide-ranging bird species and the highest for rare plant species. In general, models were consistent with biological knowledge of the species in terms of variable selection and influence.

To study implications of climate change on cumulative effects assessments and on species distributions and conservation priorities, recent outputs from three global climate models and two widely used models from the earlier assessment were statistically downscaled to 270 meter resolution and results were used to derive bioclimatic variables used in the SDMs. The models were based on "business as usual" emission factors and model projections were analyzed for 2040-2069.

Depending on the model, maximum daily temperatures in the warmest month and minimum daily temperatures in the coldest month are projected to increase approximately 2.5-3.5 °C for 2040-2069 compared to 1981-2010. Summer precipitation is projected to remain similar or increase slightly compared to the 1981-2010 historical reference period. These projected changes drive significant shifts in modeled species distributions. For most species, the majority of area mapped as suitable today is projected to be unsuitable by mid-century, and the majority of the area modeled as suitable in mid-century is currently mapped as unsuitable.

The projected species distributions are subject to multiple assumptions and sources of uncertainty, and results from model hindcasting recommend caution in applying the Maximum Entropy models to forecasted future habitats. Nevertheless, attempts to offset habitat losses from energy development must consider climate-driven changes in the distribution of suitable habitats in identifying offset sites. The results also indicate the need to consider connectivity between current and future habitats in evaluating cumulative impacts of habitat loss or restoration efforts associated with renewable energy development. Prioritizing areas where current and projected future habitats overlap (i.e., "stable" habitats) is probably the most reliable and simplest way to address climate change for multiple species.

A mitigation offsets model and implementing software were developed to explicitly address the following questions:

- Which sites(s) could most cost-effectively offset spatially delineated and unavoidable impacts of solar energy development?
- Where should offsets be sited if they are constrained to a specified geographic region (e.g., a DRECP sub-region)?
- How do sites selected to offset impacts to species directly affected by the projects compare to sites selected to maximize biodiversity conservation gain for the full set of conservation features?

A set of modeling tools was produced that provide decision support for the four steps (avoid, minimize, restore, offset) of the mitigation hierarchy. Named Mojavset, these tools generate maps of potential offset sites and information about those sites for a user-defined set of energy projects. To demonstrate Mojavset, proposed and permitted solar projects were evaluated in the Western Mojave subregion of the DRECP study area.

An approach to cumulative effects assessment is presented that is a compromise between the desire to capture current knowledge and understanding of the ecology of desert species at appropriate spatial and time scales, with the requirement for a relatively simple and repeatable, spatially explicit process that can be applied to multiple species across a large planning region using available data. Energy development is assessed as onsite and offsite impacts on species' habitat extent, location and condition, and species-specific effects are integrated across multiple species of concern. Effects of energy development are considered as both current and projected future climate and land use change. The approach is readily implemented by linking the tools produced for this project including: a) the hierarchical logic model for evaluating site condition (Chapter 2), b) species distribution models (Chapters 3 and 4), and Zonation results for multiple species that integrate projected change in climate and land use (Chapters 5 and 6).

The approach is demonstrated with an example for 17 species of high conservation importance in the Western Mojave study subregion. Modeled impacts from the currently approved and proposed solar projects in this subregion have a relatively small impact on the study species or overall biodiversity patterns. The impact of projected land use change (based on current county General Plans) associated with residential development is potentially much greater than solar development in this DRECP subregion. Furthermore, projected mid-century climate is significantly different from today's climate and the difference produces large changes in modeled distributions of the study species, which in turn changes modeled biodiversity conservation value across large areas.

Project Benefits

Products of this research benefit California in numerous ways. Several hundred new public geospatial data layers have been created for the California deserts to characterize climate, habitat conditions, and current and projected future species distributions. These data can help support ongoing conservation planning and ecological research. A method has been developed for multi-criterion analysis of site compatibility with renewable energy development and used to produce a new solar development compatibility layer for the DRECP region. Public software has been produced to help planners identify areas that could serve to offset unavoidable biological impacts of renewal energy development. A cumulative assessment framework has been designed that takes advantage of these public data layers and software tools. This framework offers an explicit, repeatable approach for evaluating the combined effects of multiple solar energy projects on desert species while also including scenarios of future climate and land use. Collectively, project data, software and methods can support conservation planning for renewable energy development in the California deserts that is compatible with maintaining native species and their habitats.

CHAPTER 1: Introduction

1.1 Utility-scale Solar Energy and Biological Impacts

Expanded interest in utility-scale renewable energy projects in the California deserts and elsewhere has raised concerns about potential impacts on biological resources. Many areas of high energy potential are in fragile environments that are easily disturbed and hard to restore. Understanding the impacts of large energy projects and associated infrastructure is still in its infancy (Lovich and Ennen 2011). Utility scale solar projects have less implementation track record than wind energy projects, but possible effects include habitat loss and fragmentation; alteration of water sources; elimination of crucial seasonal habitats for some wildlife species; disruption of wildlife movement patterns, connectivity and associated loss of gene flow; wildlife avoidance of project areas due to noise or human activity; promotion of invasive species that take advantage of disturbed sites; wildlife mortality on service roads; bird collisions with infrastructure and electrocutions from new transmission lines; and increasing predation as a result of additional prey perches on powerline poles (Hernandez et al. 2014).

It is imperative for policymakers and developers to better understand *both project-level and cumulative effects* of large scale solar energy development in desert environments (Lovich and Ennen 2011). The Council for Environmental Quality defines cumulative effects as "... the impact on the environment which results from the incremental impact of the action when added to other past, present, and reasonably foreseeable future actions regardless of what agency (Federal or non-Federal) or person undertakes such actions" (40 CFR 1508.7). More simply put, cumulative effects result from the combined effect of multiple activities over space or time (MacDonald 2000).

The National Environmental Policy Act (NEPA) prescribes a mitigation hierarchy: avoid, minimize, restore, or offset in descending order of preference. The bustle of planning activity for renewable energy in the West has focused on avoiding crucial habitats and minimizing impact on significant biological resources. California has also done considerable assessment and planning for renewable energy development. The Renewable Energy Transmission Initiative (RETI) is planning the infrastructure to tie renewable energy projects to the grid. Phase 1A grouped promising renewable energy sites into Competitive Renewable Energy Zones (CREZ) that excluded protected areas. Phase 1B assessed CREZs in terms of economic and environmental factors, which were quantified according to eight criteria that were designed to identify those CREZs which: disturb the least amount of land per unit of energy output; minimize potential conflicts with areas of special environmental concern; minimize potential impacts on wildlife and significant species; and maximize the use of previously disturbed lands. The eight ranking scores for each CREZ were then summed to provide a total ranking score of relative environmental concern.

Executive Order S-14-08 created a Renewable Energy Action Team (REAT) consisting of the California Department of Fish and Wildlife, the California Energy Commission, U. S. Fish and

Wildlife Service, and Bureau of Land Management. One of the key functions of the REAT is to develop the Desert Renewable Energy Conservation Plan (DRECP). DRECP will identify Initial Development Focus Areas (DFAs) with low biological value in the Mojave and Colorado Deserts and corresponding areas for species conservation to provide offset for project impacts. The plan will also address habitat linkages, environmental gradients, ecological functions, and climate change adaptation.

Many other conservation and/or renewable energy planning efforts are underway or completed in the California Deserts. Of particular significance, the Bureau of Land Management produced a programmatic environmental impact statement for solar energy on public domain lands in the West, including the California Deserts (http://solareis.anl.gov/documents/fpeis/). A consortium of NGO environmental groups has developed their own siting criteria for renewable energy projects. Many conservation plans have identified priority areas to be preserved in this region, notably The Nature Conservancy (TNC) ecoregional portfolios, Western Riverside NCCP/HCP, the West Mojave Plan Habitat Conservation Plan, and the Coachella Valley Natural Communities Conservation Plan/Habitat Conservation Plan. The Nature Conservancy has also pioneered a methodology for identifying offset sites for a no-net loss of conservation features (Kiesecker et al. 2009).

1.2 Project Scope

Improved habitat suitability models and conservation planning tools can help overcome major obstacles in the regulatory planning process. Such models must go beyond compilations of existing data layers to help identify important habitat areas for multiple species, at fine scales and incorporating possible influences of urban development and climate change.

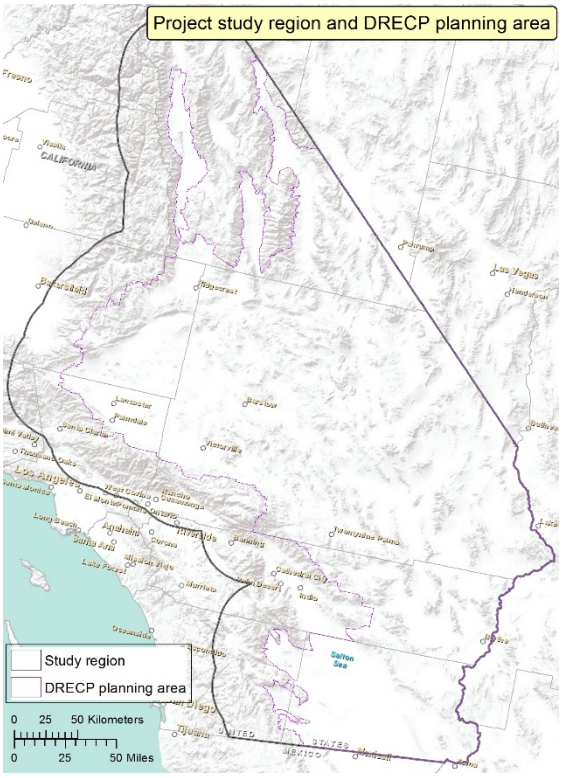
The goal of this project was to develop data, analytical approaches and tools to support conservation planning for renewable energy development in the California deserts and similar environments elsewhere. Specific objectives included identification of areas to minimize conflict between desert species and ecological communities vs. renewable energy development, production of new geospatial data for species distribution models, modeling of species distributions under current and projected future climate and land use, and investigating approaches for locating potential mitigation offset areas and for evaluating cumulative impacts of multiple projects.

The project study area encompasses the planning region for the DRECP (Figure 1) plus a 40 km buffer extended beyond the DRECP region boundary. Due to data limitations the buffer was not extended into Arizona, Nevada, or Mexico.

The project study design was initially refined through consultation with key consultants (Dudek, Aspen Environmental Group, Conservation Biology Institute), environmental groups (The Nature Conservancy), and agencies (BLM). Several stakeholder meetings of the DRECP and a meeting of a Mojave Desert GIS users group were attended by the project team. The team also spoke with investigators on other PIER projects concerned with species modeling and possibilities for sharing species observation and environmental data. The research was then organized around two main tasks: Production of enhanced habitat suitability models; and,

development of a Cumulative Impacts Assessment Framework that included a siting model to avoid or minimize impact, a model for siting mitigation offsets, and a cumulative impact assessment model (Figure 2).

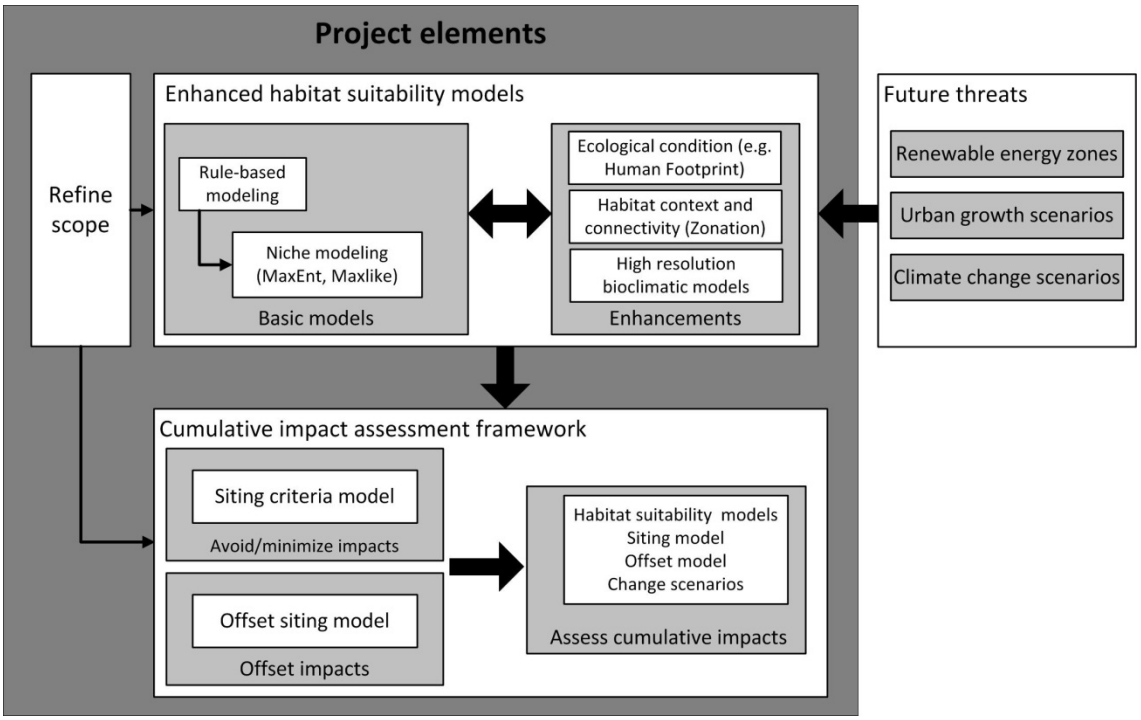
Figure 1: Map of project study area



Includes the DRECP planning region (purple line) and a 40 km buffer around the region, restricted to California.

Chapter 2 presents a siting criteria model for solar energy development to minimize biological impacts. Chapter 3 describes the production of habitat suitability models (referred to as species distribution models (SDMs)) for 65 plant and animal species of conservation interest in the study region. Chapter 4 presents scenarios of distributions for these same species in mid-century based on downscaled climate model forecasts developed for this project as well as projected land use change. Chapter 5 describes an offset siting tool to identify candidate areas for offsetting unavoidable impacts of energy development, and Chapter 6 presents the cumulative impact assessment framework, which applies products and tools described in Chapters 2-5 to model cumulative effects of solar energy development in the context of forecasted climate change and land use change. An example is presented for the Western Mojave subregion of the DRECP planning region. The main body of the report is followed by References and technical appendices.

Figure 2: Flowchart of project tasks and activities.



CHAPTER 2:
Siting Solar Energy Development to Minimize Biological Impacts

Areas of high solar energy potential are often in fragile environments that are easily disturbed and hard to restore. The best way to minimize environmental impacts in accordance with the National Environmental Policy Act (NEPA) is to find project sites that avoid the potential for impact from even occurring. However, the pressure to develop renewable energy is so recent that conservation planning in such areas has not been completed. Once conservation plans are completed, they will ideally identify the sites of greatest ecological importance that should be off-limits to energy projects. In the interim, there is a real need to map sites that energy developers and conservation interests can agree have low potential conservation value and thus can be developed while avoiding conflict in the review and permitting process.

Developers generally accept that some sites will become off-limits to protect imperiled species, but they prefer that the map of remaining lands identify the relative potential for conflict/risk rather than classify areas as suitable or unsuitable for solar projects based solely on conservation value. They prefer to be informed of the decision risk and then make an informed business decision that considers all relevant factors.

This chapter presents an assessment method for modeling the relative degree of compatibility of new solar energy projects in the Mojave and Sonoran Deserts of southern California with biological conservation values. Developing projects on low compatibility lands increases the risk of biodiversity loss and the risk that solar developers would face stiff opposition from conservation interests or high mitigation costs from siting projects. Although the two forms of risk are perceived from opposite directions, both share a similar measure of the potential for conflict. The range of values runs from most compatible to most potential conflict (i.e., least compatible). The compatibility indicator proposed here ranges from most to least compatible, highlighting site potential for concurrently meeting renewable energy and biological conservation goals. Use of the most compatible sites corresponds to the "no regrets" strategy recommended by an independent science advisory group (Spencer et al. 2010).

In developing the GIS tools to model compatibility, the logic model assumed that highly degraded sites close to infrastructure would have the least potential value for biodiversity conservation (Audubon California et al. 2009; Kiesecker et al. 2010). Because of the extensive geographic domain, the analysis is dependent upon standardized, publicly available spatial land use/land cover data.

Coarse-resolution land use mapping tends to miss some existing disturbances, such as off-road vehicle tracks through the desert. For the purposes of mapping risk, however, such errors are less treacherous, at least to conservationists, than commission errors by which the model may incorrectly identify a site as being highly degraded and of low conservation value (Andreasen et al. 2001). *For this project, a conservative approach has been taken in applying spatial data to minimize errors of commission*. For solar developers, the risk of omission errors represents missed

opportunities, whereas commission errors might lead to wasted effort pursuing sites that encounter resistance later in the process. In the modeling, scores have been scaled by the following standard:

Higher score = more compatible = more likely suitable for solar development

This chapter lays out the logic of the model as well as the spatial data inputs, assumptions, and processing to foster acceptance by stakeholders. It also presents results of validation against photo plots and comparisons with similar models by The Nature Conservancy and USGS. The model was vetted with knowledgeable stakeholders in terms of:

- The logic of how the criteria were assembled and combined;
- The spatial data—were there better sources? Were any key data missing?
- Usefulness of the products—did the model provide stakeholders with the right level of detail and accuracy?

This model only addresses potential conflict with biological resources based on ecological condition and is not a complete assessment of suitability for solar energy development. However, the model can be used by developers in conjunction with models of other constraints (e.g., steep terrain, parcelization, visibility) and opportunities (e.g., solar insolation, proximity to transmission capacity) in order to make preliminary siting decisions.

The model is not a comprehensive assessment of biological conservation value. No biological observations or species distribution models were used in constructing this model. The Desert Renewable Energy Conservation Plan (DRECP) process (http://www.drecp.org/) is currently conducting such a planning process. The product developed here is intended to complement the DRECP.

2.1 Methods

2.1.1 Choice of study area, data type, and spatial resolution

This study was charged with assessing the California deserts but was not constrained by any particular planning boundary. Therefore the boundary of the American Semi-Desert and Desert province (#322) of the US Forest Service ECOMAP was used to delineate the basic area (http://www.fs.fed.us/r5/projects/ecoregions/ca_sections.htm). This boundary was buffered by 20 kilometers to minimize omissions of potential solar energy sites while excluding the major population centers of southern California. As a final step, the buffered desert province was clipped to the boundary of counties for which detailed land cover mapping was available from the Farmland Mapping and Monitoring Program (FMMP); Inyo County had not been mapped and was therefore excluded in the analyses described in this chapter.

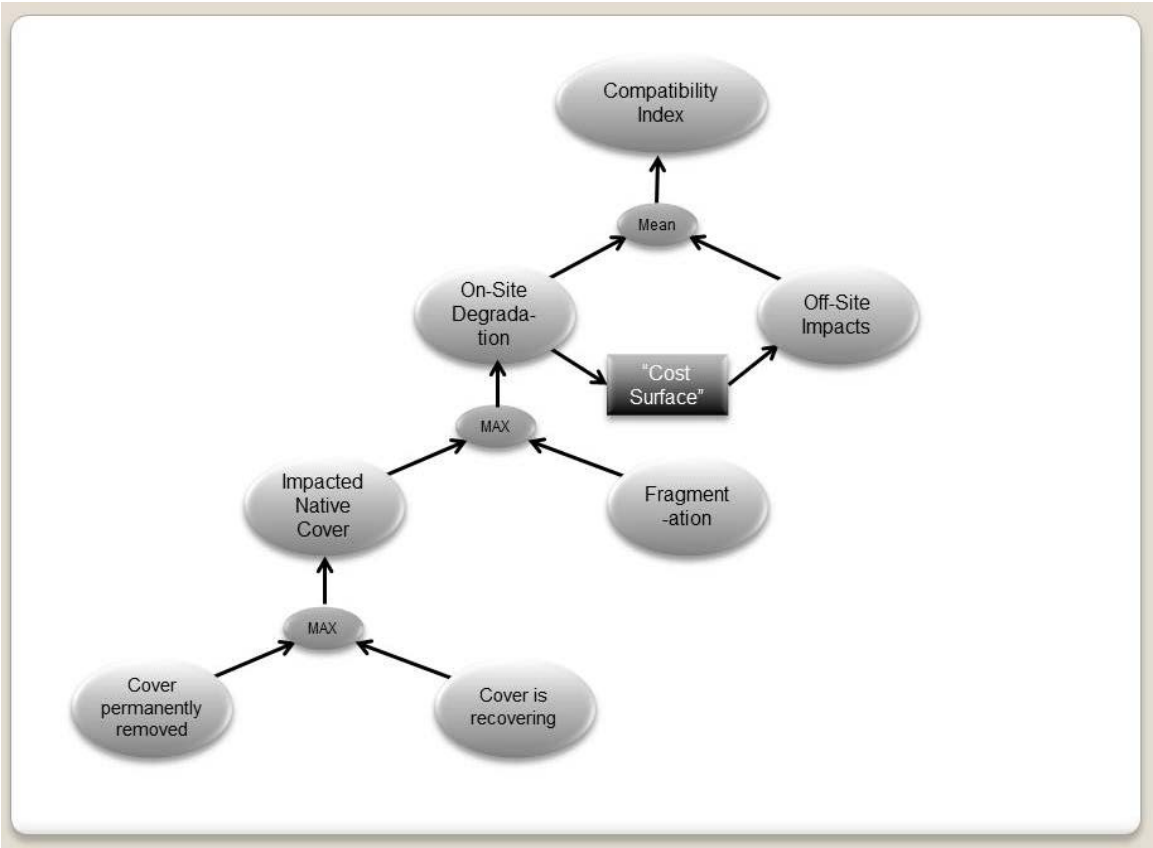
All spatial data were processed in grid or raster format at 90m resolution. This was the highest common resolution at which other data sets were available (e.g., climate). For purposes of

identifying compatible sites for solar energy projects, which typically require a minimum of 15 hectares, this resolution was considered adequate.

2.1.2 Logic model

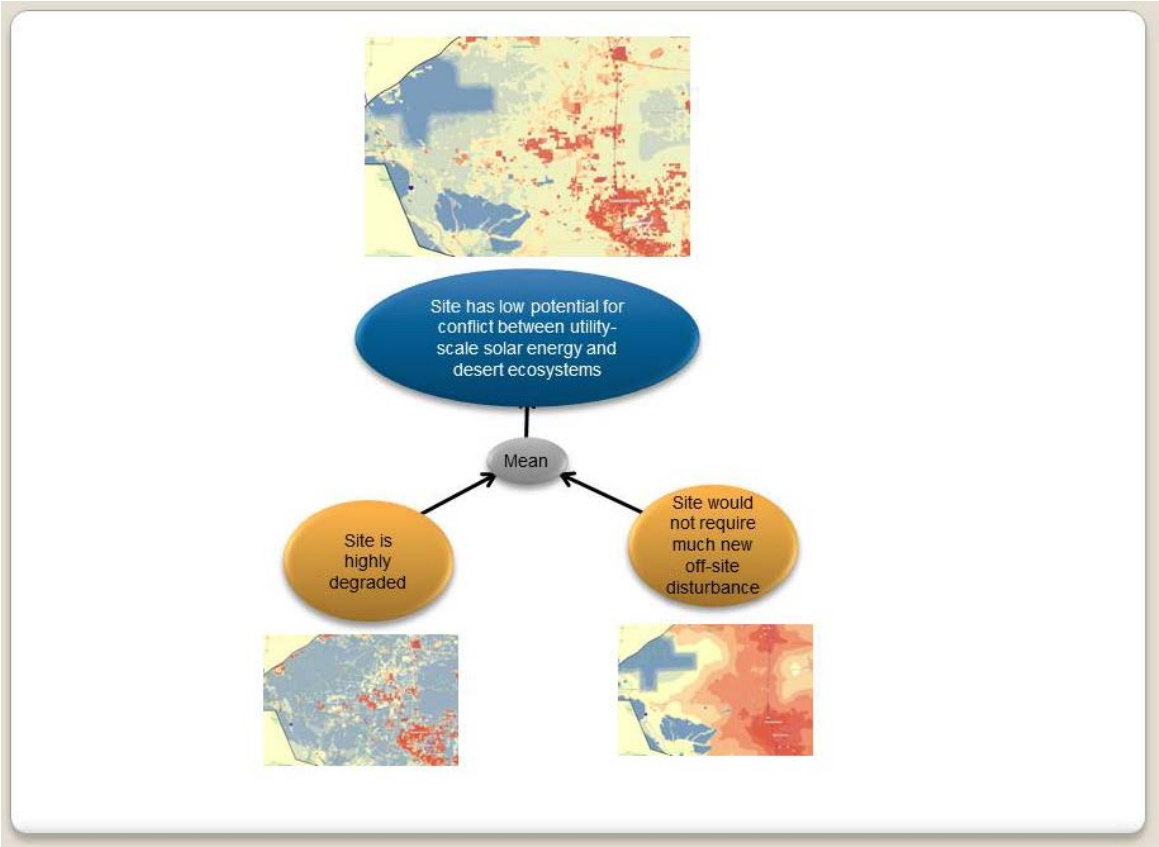
A hierarchical logic model or logic network provides a structured approach for organizing evidence to evaluate site compatibility. In fragile ecosystems such as the California deserts, any lands in pristine condition may ultimately prove to have significant conservation value. The best way to minimize impacts in this case is to site projects on lands that are already degraded and that are relatively close to infrastructure. The logic model developed here evaluates compatibility based on a hierarchy of evidence regarding current site condition as well as the condition of off-site areas likely to be affected by a project (Figure 3).

Figure 3: Logic model used to map site compatibility with utility-scale solar projects.



The first level of the logic network for evaluating compatibility evaluates the expected effect of a solar project on the current level of degradation (on-site impact) and how much additional degradation would be generated by connecting the site to existing road/substation/transmission line infrastructure (off-site impact) (Figure 4).

Figure 4: Top level of the logic network



Showing overall rating of biological risk based on-site degradation and off-site disturbance. In map inserts, red indicates least compatible with solar development, and blue is the most compatible. Only the western Mojave Desert is shown to allow details to be seen.

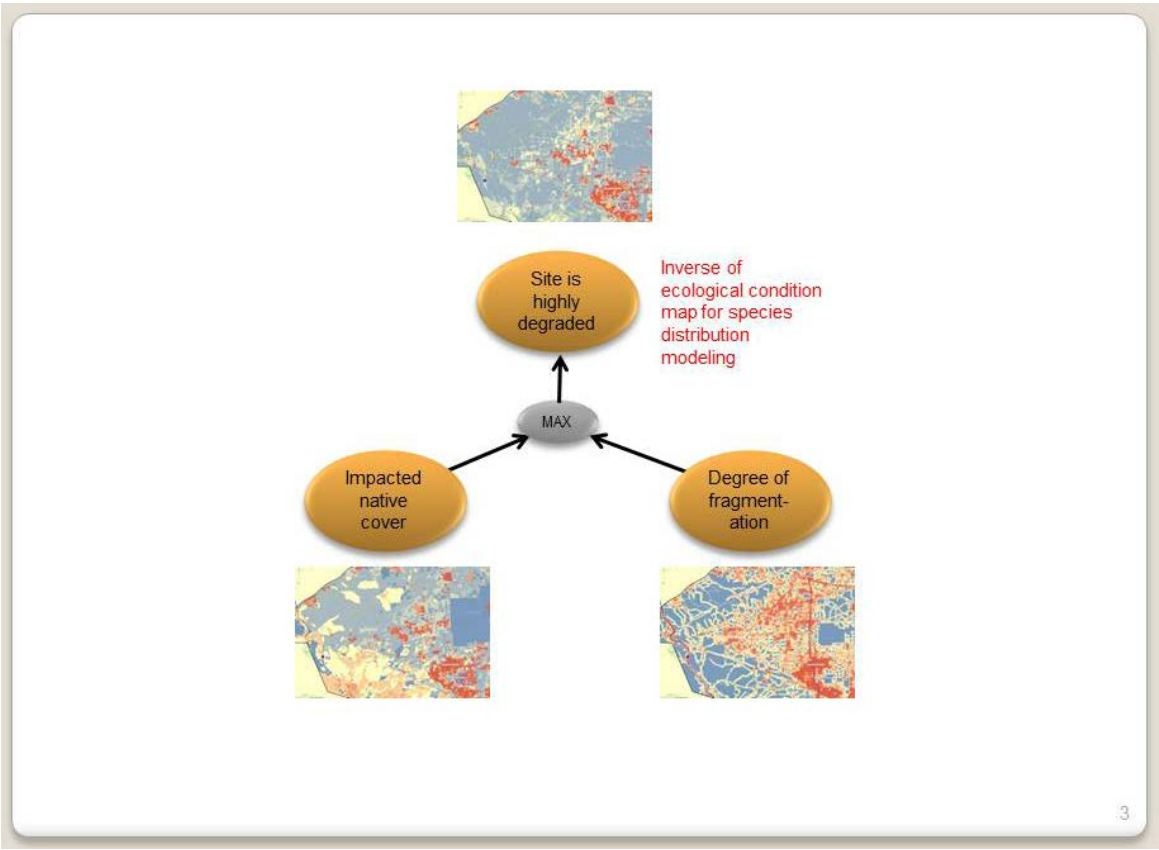
2.1.3 On-site Impacts

Analysts frequently model ecological condition directly from various human activities such as building roads, urban development, and agriculture. In this study, the level of degradation was modeled with reference to removal of vegetative cover (impacted native cover) and degree of habitat fragmentation (Figure 5). Scores were scaled such that the highest scores represented the degraded sites, which are the best for solar development from the perspective of minimizing biological impact. Ideally modeling would have included soil compaction and damage to biological soil crusts that take long time periods to recover (Webb et al. 2009), but appropriate data were not available.

Loss or reduction of vegetative cover can be considered either effectively permanent, such as urban development, heavily contaminated sites, and utilities, or temporary such as where vegetation is recovering from past disturbance such as farming (Webb et al. 2009) (Figure 6). Although native vegetative cover may eventually recover from farming, the soil crust is removed by plowing and therefore would tend to be of lower conservation priority.

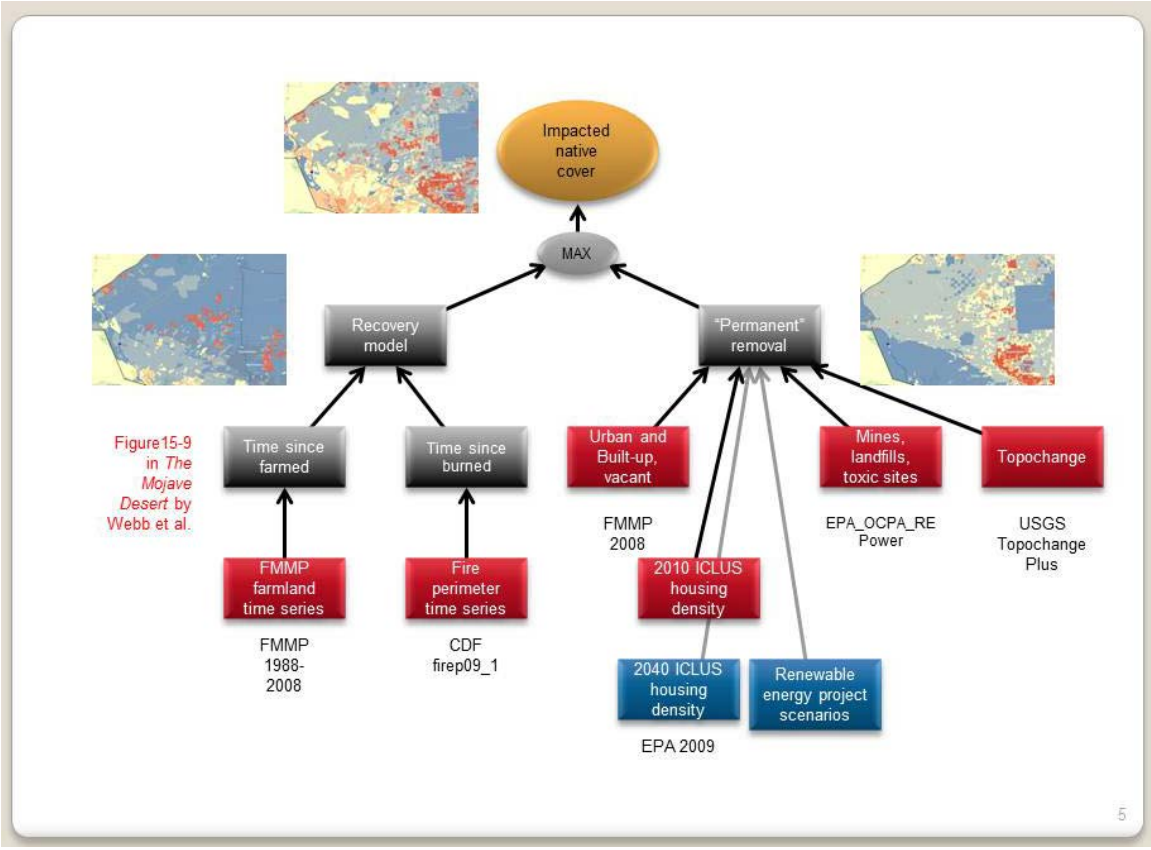
Repeated fire in mid-elevation desert shrubland can allow invasive annual grasses to establish and alter the fire regime, particularly after wet years (Brooks and Matchett 2006). To model ecological condition in future time periods, such as for modeling cumulative impacts, urban growth scenarios and renewable energy projects (blue boxes in Figure 6) can be substituted for current land uses.

Figure 5: Logic for on-site degradation.



Fragmentation is caused by linear features such as roads and railroads, transmission lines, and large canals or aqueducts (Figure 7). Future transmission lines (blue box) can be incorporated for modeling cumulative impacts.

Figure 6: Logic for impacted native vegetative cover.



Red boxes are data inputs. Gray boxes are intermediate outputs. Blue boxes represent urban growth and energy scenarios.

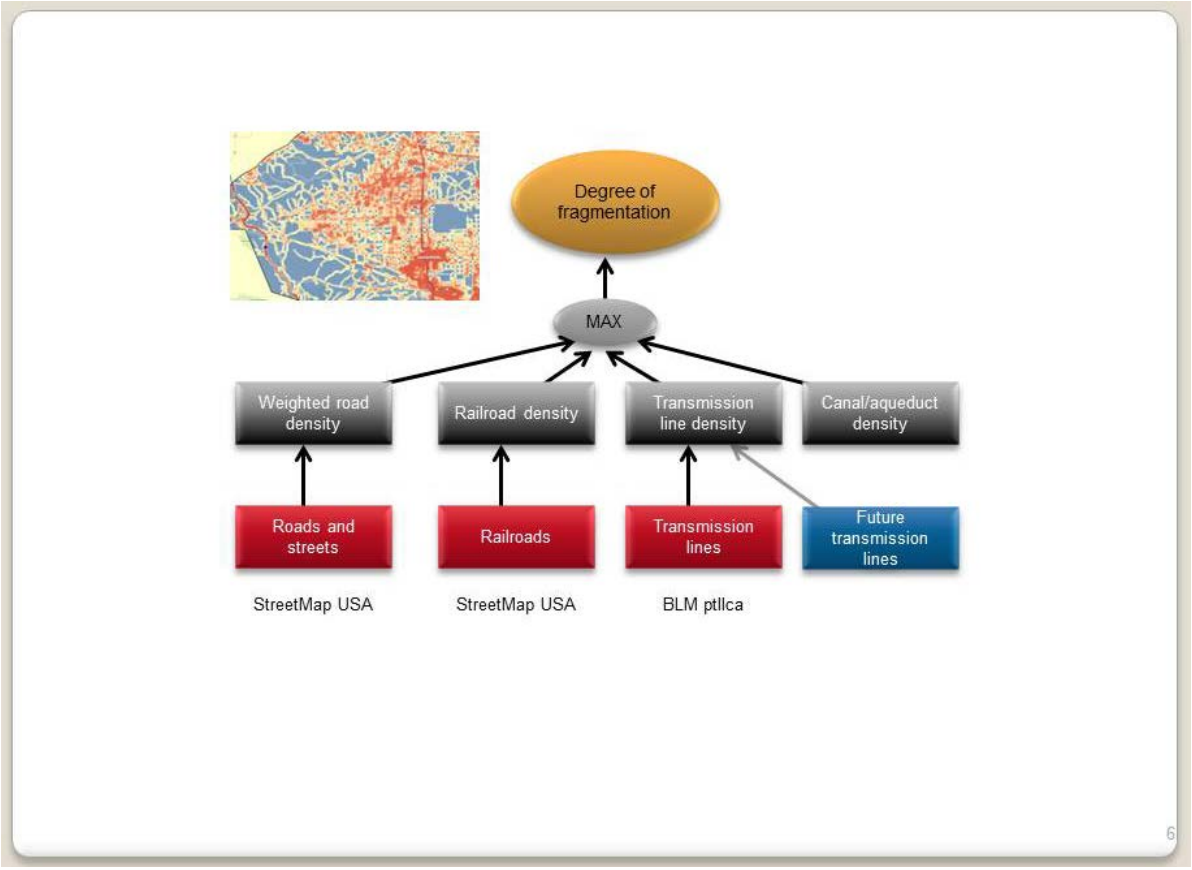
2.1.4 Off-site Impacts

Most suitability and constraints analyses of renewable energy projects attempt to minimize geographic distance from existing infrastructure as a surrogate for capital costs and permitting challenges (Carrión et al. 2008; Charabi and Gastli 2011; Janke 2010). From an ecological perspective, connecting energy production sites from a greater distance also potentially causes more impacts. However, just as sites vary in their current condition and the degree that solar development would cause new impacts, the landscape through which new access roads and collector and trunklines would be constructed also varies. For this product, the off-site impact was calculated as a "cost-distance" over a cost surface based upon the inverse of the condition layer (Figure 8).

Stakeholders were concerned about the relative cost of sites in different parts of the desert. In more heavily modified areas of the desert, even sites in the best condition might be moderately degraded. To adjust for this effect, condition scores were standardized by ecological subregions (ECOMAP subsections). Scores below the mean for the subregion were divided by two to make them less compatible with development (i.e., higher conflict) than would otherwise be the case. This step has no effect on the sites modeled as most compatible with development.

Cost-distance combines both the geographic distance of crossing a grid cell and the cost or additional ecological impact of doing so, summed over all cells in the least-cost pathway. Cost-distances were generated separately from paved highways, existing electrical substations, and existing transmission lines. The cost surface treated lands that are off-limits to connect new power projects, such as parks and wilderness (i.e., RETI Category I exclusion areas), and were treated as barriers that were assigned very high costs. Designated critical habitat areas for listed species are not off-limits to infrastructure projects but crossing them would be incompatible with biodiversity; a high cost was assigned to them.

Figure 7: Logic for habitat fragmentation.

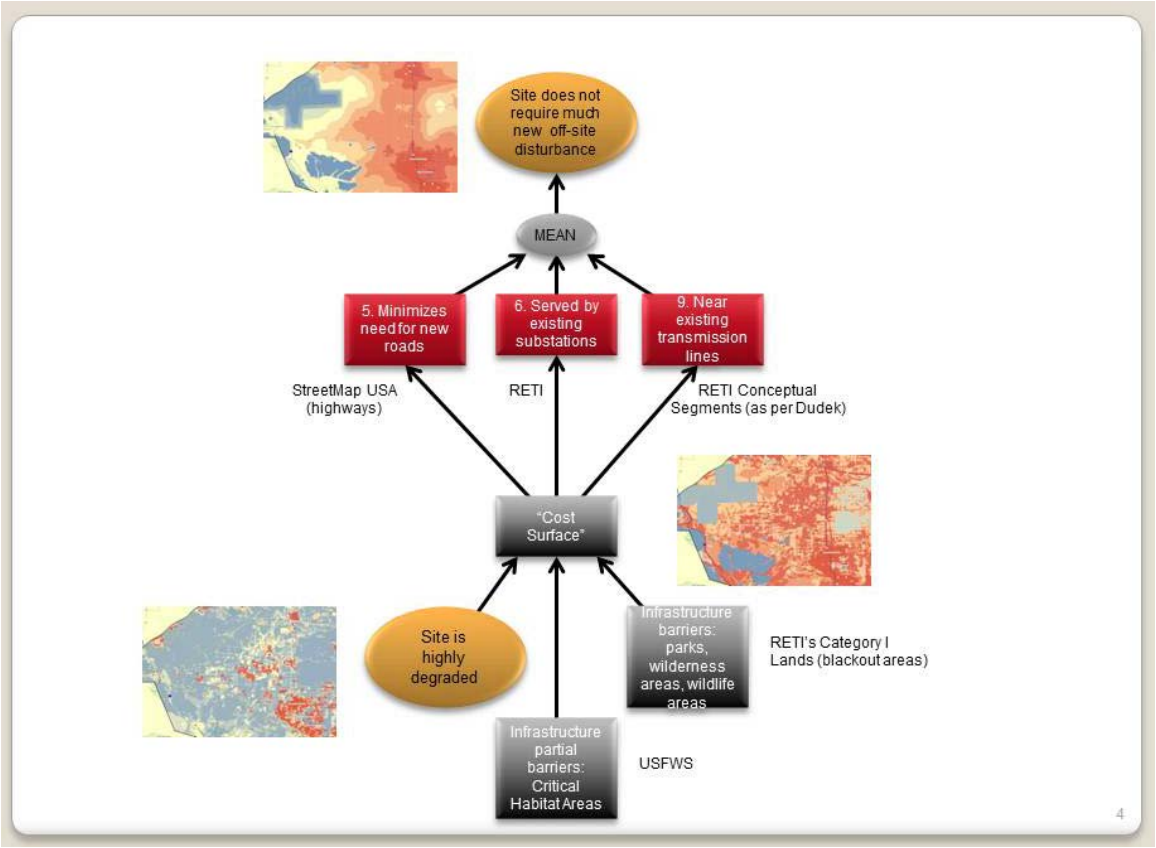


The blue box with gray arrow represents future transmission lines to determine future habitat fragmentation in energy scenarios.

In the case of off-site impacts, the highest compatibility would be for sites whose connection pathway was already degraded, so the cost surface was scaled with the least-degraded sites as the highest cost. The cost-distance scores (roads, substations, and transmission lines) were aggregated by averaging them. Note that the overall cost-distance score represents the lowest possible cumulative impact to connect a site. The actual pathway for access roads and connector lines may follow a higher impact route, especially if the financial cost is lower. Some solar technologies require large amounts of water so proximity to municipal wastewater treatment

plants is sometimes recommended as well. This criterion was not included in the current version of the model.

Figure 8: Logic for off-site impact.



Cost-distance is calculated separately for highways, existing substations, and transmission lines.

2.1.5 Spatial modeling, validation and testing

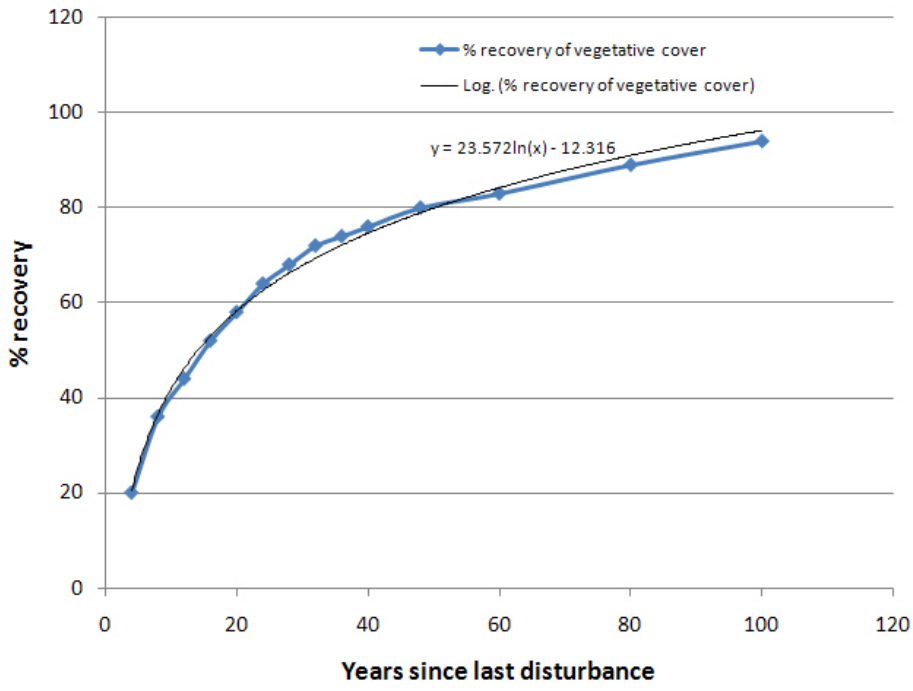
The logic diagrams were translated into spatial modeling tools with ArcGIS 9.3 ModelBuilder (See Appendix A for Details of GIS compatibility modeling).

To model recovery of vegetative cover following agriculture, the natural log recovery function presented by Webb et al. (2009) was adopted (Figure 9).

Validation is challenging because the model outcome is not directly measureable in the field. On the other hand, stakeholders can rightly be skeptical of the product if there is not some level of quality assurance. The degradation/condition layer developed here was evaluated at a set of 381 random points against photointerpretation from 2009-2010 NAIP natural color imagery with 1 m spatial resolution (Figure 10). Each random location was used as the center point of a 90 m radius photo- plot. For each point, the overall level of disturbance of the land (none, slight, substantial, complete transformation) was recorded. If land was disturbed, the land use

associated with the disturbance was recorded, if discernable (see Appendix A for details on coding).

Figure 9: Recovery function for vegetative cover derived from Webb et al. (2009).



To test the modeled degree of fragmentation, the number of highways, roads (paved and unpaved), transmission lines, and railways visible in the imagery was counted and weighted in each category similar to the modeled version. These points were then compared with the modeled predictions of On-site Degradation, Impacted Native Cover, and Degree of Fragmentation. General patterns of agreement were quantified for the points identified to be located on land with some level of disturbance. Out of the 381 sample points, 284 showed no discernable land use disturbance.

2.1.6 Initial model modifications

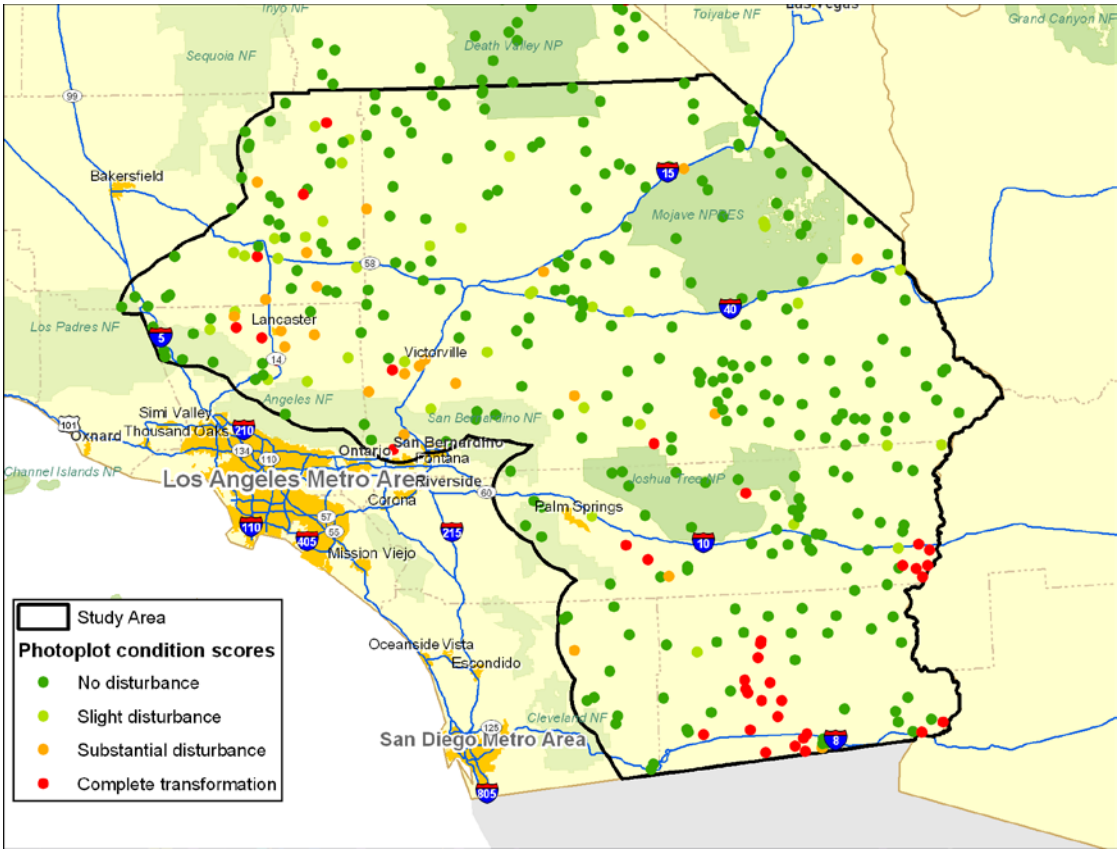
Investigating the mismatches between plots and the initial modeling led to several modifications of the model:

- Farmland of Local Importance in FMMP mapping was removed from the Ag Disturbance model (Figure 6). In the desert counties, this class was generally used for agricultural soils that were not being irrigated or cultivated. Hence they were in better ecological condition than other farmland.
- Burned areas were generally not evident in the orthophotography, and therefore the recovery modeling led to higher scores than the photointerpretation for those plots.

As a result, fire recovery was downweighted relative to agricultural recovery (Figure 6).

- Utility lines were dropped from the "Permanent" Removal model to avoid double-counting with fragmentation (Figure 6).
- Some large mines were detected in the photointerpretation that were outside of areas mapped for FMMP and are not tracked by EPA. A map of significant topographic change from USGS was obtained to model these sites (Kiesecker et al. 2011) and was included in the Permanent Removal model (Figure 6).
- There are several large canals and aqueducts in the study area that are 8-25 meters across that were not accounted for in the initial modeling. These were added to the Fragmentation model (Figure 7).

Figure 10: Locations of random points used for validation of compatibility modeling



Colored by coding for impacted native cover.

Overall, the on-site degradation model agrees strongly with the photoplot data in the no impact and high impact classes (Appendix A). The model does best at identifying highly degraded sites. The model also performs well at not falsely including highly degraded sites in areas identified in the photoplots as having no discernable impact. However, in general, *the model tends to predict a greater degree of degradation across the landscape than was discerned in the photoplots*. Specifically, the Impacted Native Cover model agrees most strongly with the photoplot data (Appendix A). The observed discrepancies could be due to the fact that past fire and agricultural impacts were not discernable in the orthophotography. In the case of fragmentation, disagreement could be due to the small search radius used in photointerpretation (90m) compared to GIS modeling (450m) (Appendix A).

In the interest of finding the most parsimonious model, the correlations between some of the spatial data layers were calculated to see whether highly correlated criteria could be removed from the model. Sites closest to infrastructure may also tend to be the most degraded, although not all degraded sites are located close to all forms of infrastructure. However, the correlation between on-site degradation and off-site impact was only 0.36, indicating that they were not highly redundant. Cost-distance includes geographic distance so the former is generally correlated with the latter, but in this case the correlation between Euclidean distance and cost-distance was only 0.19.

2.1.7 Peer review of initial model and final revisions

Initial model results were distributed to a representative group of stakeholders on August 11, 2011. The package included a white paper that described the logic, data, GIS analysis steps, validation process, and revision, plus a Google Earth visualization of the model's intermediate and final results. Reviewers were asked to provide feedback on the process, the products, and how the final compatibility layer could be applied in the DRECP process.

On August 25, 2011 a web meeting was hosted for feedback from nine reviewers from environmental groups and consulting firms. A few others, including agency staff, submitted additional written or verbal comments. The list of reviewers and their affiliations is provided in Appendix A. These comments ranged from data sources to the calculation methods to documentation and publication of results. The main changes in the model from this review include: changing how wildfire was modeled to better reflect the threat of invasive annual grasses, reducing the score of the Vacant or Disturbed class in the FMMP data based on visual inspection of a large sample in the orthophotography, rescaling the fragmentation scores to reduce its influence, adding U.S. Fish and Wildlife Service Critical Habitat designations in the cost surface, standardizing on-site degradation scores within subregions as part of the cost surface modeling, and rescaling the off-site disturbance values based on the cost-distance analysis.

2.1.8 Comparison to similar models

There have been other efforts to map human impact in this study area that have used similar input data and methods. The model developed here was compared to two others - the Human Footprint in the West (Leu et al. 2008) and a model of land degradation produced by The Nature Conservancy (TNC) of California (Cameron et al. 2012). The Human Footprint (HF)

initial scores had been binned equally into 10 classes, which were grouped into four larger groups roughly corresponding to the photointerpreted coding (Appendix A). The HF classes for low impact (1) and high impact (8-10) matched well with the photoplots. However, the mid-range classes often indicated a greater impact than was observed in the photos. As a result, the HF could be a reasonable choice for modeling compatible sites with high degradation.

TNC's overall score was a combination of land use (0 undisturbed or 1 urban/agriculture, then smoothed by averaging cell values within a 810 m search radius of each cell and assigning that value to the focal cell) and fragmentation, weighted four to one respectively (Cameron et al. 2012). Their study area was slightly different than so the number of points for comparison differs accordingly. *Similar to the Human Footprint, TNC's model did best at representing no impact and high impact classes, but less well at the mid-ranges (Appendix A).* Overall agreement with the photoplot data was considerably higher for the TNC model than for the Human Footprint. The method developed here for calculating fragmentation as a weighted line density was very similar to TNC's. Like the project team's results, TNC's fragmentation scores did best in the lowest fragmentation class, but had relatively poor agreement in more fragmented classes (Appendix A). Some of this discrepancy is probably related to the small search radius used in the photo interpretation (90m) compared to the GIS modeling (450m). It is also possible that the team's binning of TNC fragmentation scores into classes was not optimal for maximizing agreement, although this is probably a relatively minor effect.

The spatial distribution of degraded land from on-site degradation model was also compared with both Human Footprint in the West (Figure 11) and TNC (Figure 12) to determine where the indices were consistent or inconsistent in identifying the most degraded class. All three maps were transformed into the same degradation classes used for the photoplots.

In general, models tend to have highest agreement in the eastern part of the desert region where there is little impact due to fragmentation, urban development or agriculture. The models show some disagreement in the extent of highly degraded areas, especially around Lancaster and Victorville, where HF picked up more highly degraded areas than the project model and where TNC mapped less degradation. In comparison with the TNC model, there is some disagreement surrounding agricultural areas. This is due to the fact that agriculture is dynamic and often shifts locations from year to year, so that the publication year of input data can significantly affect model results. Furthermore, due to the grouping of values into four broad classes, the disagreement shown in the comparison maps does not necessarily signify that there is a large discrepancy in the values assigned. Finally, the HF and TNC models did not model off-site impact for connecting solar projects to the existing infrastructure, so their products are not exactly comparable to the compatibility index map.

Figure 11: Comparison of degradation models by UCSB and the Human Footprint (Leu et al. 2008).

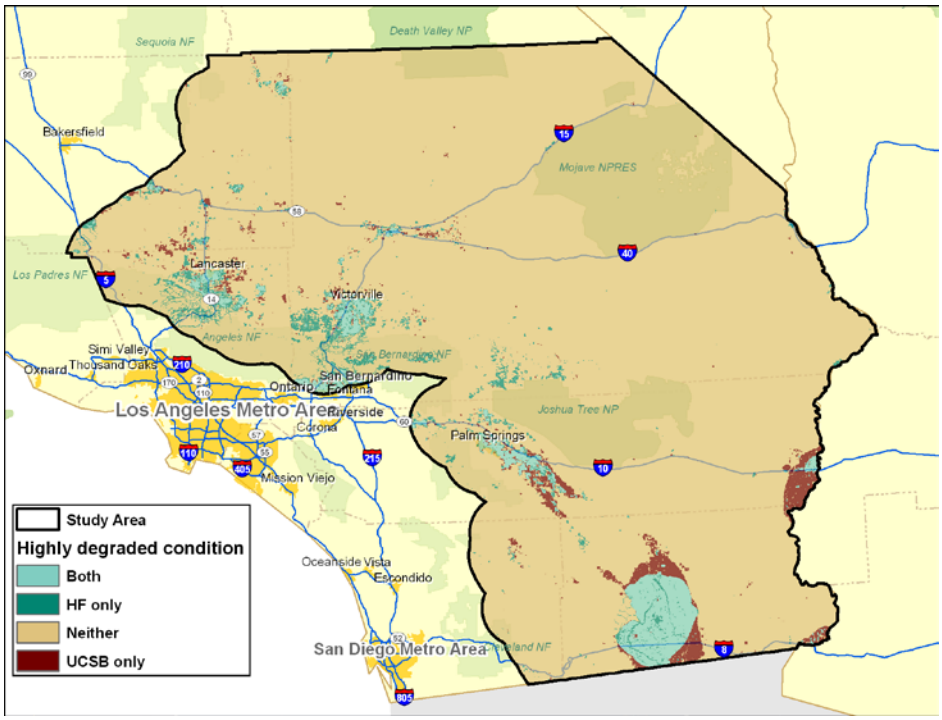
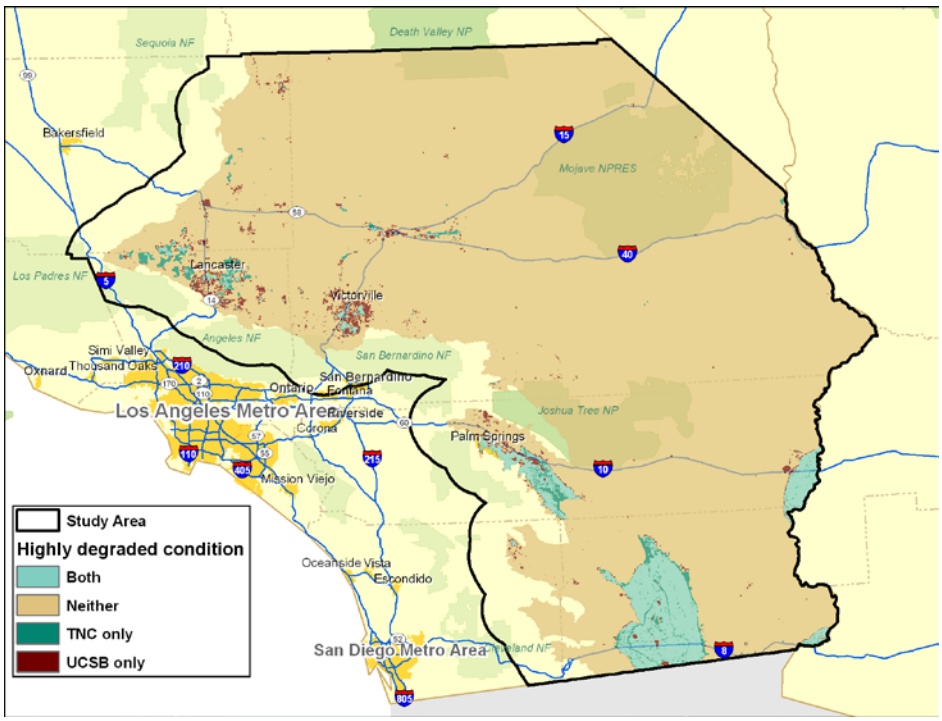


Figure 12: Comparison of degradation models by UCSB and TNC.



2.2 Results

2.2.1 Compatibility scores in urban areas

Because the purpose for this project was to model compatibility with biological resources, and not overall suitability for solar energy projects, urban areas were included in the model and rated as highly degraded and therefore as highly compatible. Urban areas, however, are generally agreed to be unsuitable for utility-scale solar energy. Therefore the compatibility scores were summarized both with and without urban areas to identify the most compatible area that is also potentially available for solar development. Urban land was defined and delineated used the map from the 2000 US Census of urbanized area and urban clusters. Removing urban areas from the model lowered the scores by an average of one point (Table 1).

Table 1: Mean scores with and without urban lands.

Land base	Mean on-site degradation score	Mean off-site impact score	Mean compatibility score
All lands	11.0	34.0	22.0
All non-urban lands	9.8	33.1	20.9

Perhaps of greater interest is the area of land that is both most compatible and available outside of urban areas. Because compatibility scores are relative, two threshold scores were used to define "most compatible"—scores > 70 and more conservatively, scores > 90. Nearly 400,000 hectares were modeled above the higher threshold and 542,000 hectares at the lower threshold (Table 2). After excluding urban areas, roughly 75 percent of all lands remain at both thresholds. Thus there appears to be a sizeable area of degraded land close to infrastructure yet outside of towns. For reference, the California Energy Commission estimates that 25,000 ha of utility-scale solar projects will be required in the DRECP area with 8.7 GW of installed capacity to achieve 2040 greenhouse gas reduction goals (California Energy Commission 2012).

Table 2: Area of most compatible land with and without urban lands.

Land base	Area (hectares) with compatibility score > 90	Area (hectares) with compatibility score > 70
All lands	392,460	541,652
All non-urban lands	290,241	416,095

2.2.2 Compatibility scores by land manager

The criteria that characterize condition/degradation tend to emphasize private rather than public lands, despite the high level of interest in public lands for developing solar energy projects. For comparative purposes, on-site degradation, off-site impact scores, and

compatibility scores were summarized by major category of land owners or managers as represented in the Protected Areas Database of the United States v1 (Table 3). Indeed, private land had much higher average scores in all three ratings than any public land agency. BLM lands, which are the focus of permit applications on public lands, appear to be in very good ecological condition, but have some sites that result in a higher compatibility score than national parks.

Table 3: Mean scores by land manager.

Land manager	Mean on-site degradation score	Mean off-site impact score	Mean compatibility score
Private land	31.4	66.0	47.6
State of California (3100 - 3500)	3.4	2.9	2.9
National Park Service (not available for solar projects) (1600)	3.0	0.8	1.8
Bureau of Land Management (1100)	3.5	27.5	15.2
U. S. Forest Service (1400)	15.8	37.8	25.6
U. S. Fish and Wildlife Service (not available for solar projects) (1300)	3.3	21.8	12.2
Department of Defense (not available for solar projects) (1500)	3.7	33.3	18.0
Native American Lands (2200)	21.0	30.0	24.2

2.2.3 Model results in Solar Energy Zones (SEZs)

The BLM Solar Programmatic Environmental Impact Statement (Solar PEIS, BLM/DOE 2010) designated Solar Energy Zones (SEZs, http://solareis.anl.gov/sez/index.cfm) on public lands in California and other states. Their logic was similar in trying to minimize conflicts with natural and cultural resources; therefore one would not expect SEZs to be relatively far from existing infrastructure nor on pristine land. On-site degradation Scores, off-site impacts Scores, and final compatibility scores from this project were summarized within the set of SEZs in the California Deserts (Appendix A). SEZs tend to score low for on-site degradation, i.e. they are in relatively good ecological condition; however, being close to existing transmission lines and highways, SEZs received relatively high scores for off-site Impacts. This highlights an important tradeoff on public lands where lands suitable for solar energy tend to be in less-degraded condition than private lands, but may at least be close to existing infrastructure to minimize offsite impacts.

CHAPTER 3:
Species Distribution Models for Desert Conservation Planning

3.1 Introduction

Effective conservation planning for biodiversity depends critically on knowledge of the ecology and distribution of focal species, ecological communities and ecosystems (Scott 2002; Scott et al. 1993). Unfortunately such knowledge is generally woefully incomplete, especially for bioregional, multi-species planning over large regions that have not been thoroughly surveyed or mapped such as the DRECP planning area (Spencer et al. 2010).

In recent years, new geospatial data, computational tools and modeling approaches have stimulated a resurgence of interest in modeling species habitats and range limits over large areas based on the association of known species occurrences to mapped environmental predictors. The resulting species distribution models (SDMs) are being applied to diverse questions in ecology, evolution and conservation and are widely used to forecast changes in species distribution under environmental change (Elith et al. 2006; Franklin et al. 2013; Franklin and Miller 2009).

This chapter summarizes methods and findings for SDMs produced at UCSB to support conservation planning in the California deserts. Models were developed for 45 plant species and 20 animal species selected because they were being considered for covered species status in the DRECP or because they were identified by the DRECP Independent Science Advisers as other important species to consider (Spencer et al. 2010) (Table 4). "Covered Species" are plants and animals identified in the DRECP Plan for which conservation and management are provided and take (as defined by the U.S. Endangered Species Act) would be authorized over the permit period. A revised draft Covered Species List was released by the REAT in June 2013 (http://www.drecp.org/documents/docs/DRECP_Draft_CSL_Memo_Methods_and_List_June_17_2013.pdf). The list for this project includes 18 of these species (Table 4 and Table 5).

The SDMs are integrated with geospatial data on ecological condition (Chapter 2) to evaluate cumulative impacts of solar energy development, other land use change, and climate change (Chapter 6) and to identify areas of possible importance for mitigation offsets (Chapter 5). In producing these models, several new environmental data layers were developed for current conditions that improved model performance for a number of species. High-resolution projections of mid-century climatic conditions were also produced to analyze the implications of regional climate change on the distribution and extent of species' habitats (see Chapter 4). Various statistical modeling approaches were considered including two reported here: Maximum Entropy Modeling (Fitzpatrick et al. 2013; Phillips et al. 2006) and Maximum Likelihood Modeling (Fitzpatrick et al. 2013).

Details of the species distribution models are provided in Appendix B. *The project team emphasizes that the models described here were not produced at the request of the DRECP REAT process.*

Other groups have been contracted to deliver such models to the REAT. The models described here were produced as part of this project's overall objective of developing a framework for assessing the cumulative effects of solar energy development.

3.2 Species Selection

Sixty-five taxa (20 native terrestrial vertebrates, 45 native vascular plants) were selected for distribution models (Table 4 and Table 5). As noted above, nearly all of these species were highlighted 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 18 are included in the Draft Covered Species List issued by the REAT on June 17, 2013. The team will use common names when referring to these species. Scientific names are provided in Table 4.

The 65 selected species represent a mix of species, sub-species or varieties ranging from taxa whose distributions are entirely or nearly wholly restricted to the study region (e.g., Mojave ground squirrel) to others with much broader distributions (e.g., Swainson's hawk, American badger), to narrowly restricted species whose distribution is mainly outside of or at the margins of the study area (e.g., San Bernadino aster). Many are narrow habitat specialists associated with rare desert habitats such as freshwater emergent wetlands (e.g., black rail), desert riparian areas (e.g., Southwest willow flycatcher), distinct substrates such as active sand dunes (e.g., Mojave fringe-toed lizard) or limestone outcrops (e.g., scaly cloak fern). Most species are also of high conservation concern and either legally protected by federal and/or state endangered species laws or identified as species of concern by the California Native Plant Society or other groups.

The Joshua tree was included because of its role as a foundation species (Ellison et al. 2005) and perhaps keystone species (Spencer et al. 2010) where it occurs.

3.3 Species Locality Data for Species Distribution Modeling

The two main data sources for modeling species distributions were the California Natural Diversity Database (CNDDB, http://www.dfg.ca.gov/biogeodata/cnddb/) and, for birds, eBird (http://ebird.org/content/ebird/).

Many of the observations in CNDDB are recorded as polygons rather than points. Only polygon occurrences less than 1 km^2 in area were used here. Species were assumed to be present in all grid cells intersected by the polygon (rather than using the polygon centroid). Where locational accuracy information was available, data with a spatial uncertainty greater than 250-500m were excluded.

For those species known to occur in locations outside of California, only that part of their distribution that fell within the buffered DRECP model domain was modeled.

Table 4: Wildlife species for which species distribution models were produced.

Species	Common name	DRECP covered species (6/17/13)	Status
Phrynosoma mcallii	Flat-tail horned lizard	✓	CSC, BLM sensitive
Uma scoparia	Mojave fringe-toed lizard	✓	CSC, BLM sensitive
Agelaius tricolor	Tricolored blackbird	✓	CSC, BLM sensitive
Asio otus	Long-eared owl		CSC
Athene cunicularia	Burrowing owl	✓	CSC, BLM sensitive
Buteo regalis	Ferruginous hawk		BLM sensitive
Gopherus agassizii	Agassizi's Desert tortoise	✓	ESA,CESA threatened
Buteo swainsoni	Swainson's hawk	✓	CESA threatened
Empidonax traillii ssp. extimus	Southwestern willow flycatcher	✓	ESA, CESA
Falco columbarius	Merlin		
Falco mexicanus	Prairie falcon		
Lanius ludovicianus	Loggerhead shrike		CSC
Laterallus jamaicensis coturniculus	California black rail	✓	CESA threatened
Melanerpes uropygialis	Gila woodpecker	✓	CESA
Toxostoma bendirei	Bendire's thrasher	✓	BLM sensitive
Toxostoma lecontei	Le Conte's thrasher		CSC
Vireo bellii pusillus	Least Bell's vireo	✓	ESA, CESA
Chaetodipus fallax pallidus	Pallid San Diego pocket mouse		CSC
Taxidea taxus	American badger		
Xerospermophilus mohavensis	Mohave ground squirrel	✓	CESA

Table 5: Plant species for which species distribution models were produced.

Scientific name	Common name	DRECP CSL 6/17/13	Federal	State	CNPS
Abronia villosa var aurita	Chaparral sand-verbena		E		1.B.1
Acmispon argyraeus var multicaulis	Scrub lotus				1.B.3
Allium nevadense	Nevada onion				2.3
Androstephium breviflorum	Small-flowered androstephium				2.2
Arctomecon merriamii	White bear poppy				2.2
Asclepias nyctaginifolia	Mojave milkweed				2.1
Astragalus cimae var cimae	Cima milk-vetch				1.B.2
Astragalus insularis var harwoodii	Harwood's milk-vetch				2.2
Astragalus tidestromii	Tidestrom's milk-vetch				2.2
Astrolepis cochisensis ssp cochisensis	Scaly cloak fern				2.3
Boechera shockleyi	Shockley's rock-cress				2.2
Calochortus striatus	Alkali mariposa-lily	✓			1.B.2
Castela emoryi	Emory's crucifixion-thorn				2.2
Chorizanthe parryi var parryi	Parry's spineflower		C		1.B.1
Cordylanthus parviflorus	Small-flowered bird's-beak				2.3
Coryphantha alversonii	Alverson's foxtail cactus				4.3
Coryphantha chlorantha	Desert pincushion				2.1
Cymopterus deserticola	Desert cymopterus	✓			1.B.2
Cymopterus gilmanii	Gilman's cymopterus				2.3
Cymopterus multinervatus	Purple-nerve cymopterus				2.2
Delphinium recurvatum	Recurved larkspur				1.B.2
Enneapogon desvauxii	Nine-awned pappus grass				2.2
Eriastrum harwoodii	Harwood's eriastrum				1.B.2
Erioneuron pilosum	Hairy erioneuron				2.3
Eriophyllum mohavense	Barstow woolly sunflower	✓			1.3.2
Eschscholzia minutiflora ssp	Red Rock poppy				1.B.2

Scientific name	Common name	DRECP CSL 6/17/13	Federal	State	CNPS
twisselmannii					
Grusonia parishii	Parish's club-cholla				2.2
Layia heterotricha	Pale-yellow layia				1.B.1
Mentzelia tridentata	Creamy blazing star				1.B.3
Mimulus mohavensis	Mojave monkeyflower	✓			1.B.2
Monardella robisonii	Robison's monardella				1.B.3
Muhlenbergia appressa	Appressed muhly				2.2
Opuntia basilaris var treleasei	Bakersfield cactus	✓	E	E	1.B.1
Pellaea truncate	Spiny cliff-brake				2.3
Penstemon albomarginatus	White-margined beardtongue	✓			1.B.1
Penstemon stephensii	Stephens' beardtongue				1.B.3
Penstemon utahensis	Utah beardtongue				2.3
Phacelia nashiana	Charlotte's phacelia				1.B.2
Psorothamnus fremontii var attenuates	Narrow-leaved psorothamnus				2.3
Sanvitalia abertii	Abert's sanvitalia				2.2
Senna covesii	Cove's cassia				2.2
Sphaeralcea rusbyi var eremicola	Rusby's desert-mallow				1.B.2
Stipa (Achnatherum) arida	Mormon needle grass				2.3
Symphyotrichum defoliatum	San Bernardino aster				1.B.2
Yucca brevifolia	Joshua tree				

3.4 Environmental Variables

There are myriad abiotic and biotic factors that influence a species' distribution and abundance. In selecting available data and creating new layers the following criteria were considered when including an environmental factor:

- Known or expected to be a significant habitat factor affecting the distribution of one or more of the species under consideration;
- Available at spatial resolution deemed adequate to support distribution modeling;
- Available for the entire study area;
- Best available data in terms of accuracy and currency.

Appendix B summarizes the environmental layers used in modeling distributions for each species. The set of variables that was used to model a species' distribution was based on available ecological studies and life history accounts for that species.

Climate variables such as temperature and precipitation influence and are influenced by organisms through specific climate factors such as minimum temperature, growing degree days, seasonal distribution of precipitation, and so on. These biologically important variables are often referred to as "bioclimatic" factors. Grids of bioclimatic variables thought to be especially important to desert organisms (Table 6) were produced at 270m resolution by downscaling 800m historical climate data for 1950–2010 available for the USA from PRISM (Daly et al. 2008) as monthly maps (http://www.prism.oregonstate.edu/). The downscaling approach applied a spatial Gradient and Inverse Distance Squared weighting (GIDS) to monthly point data by developing multiple regressions for every fine-resolution cell for every month. Parameter weighting is based on the location and elevation of the coarse-resolution cells surrounding each fine-resolution cell to predict the climate variable of the fine-resolution cell. This procedure improves the spatial representation of air temperature and is essentially a 'draping' of the climate variable over the landscape (Franklin et al. 2013). The modified GIDS technique generally improves the estimate of the climate variable by better resolving the deterministic influence of location and topography on climate. Figure 13 illustrates results for minimum temperatures.

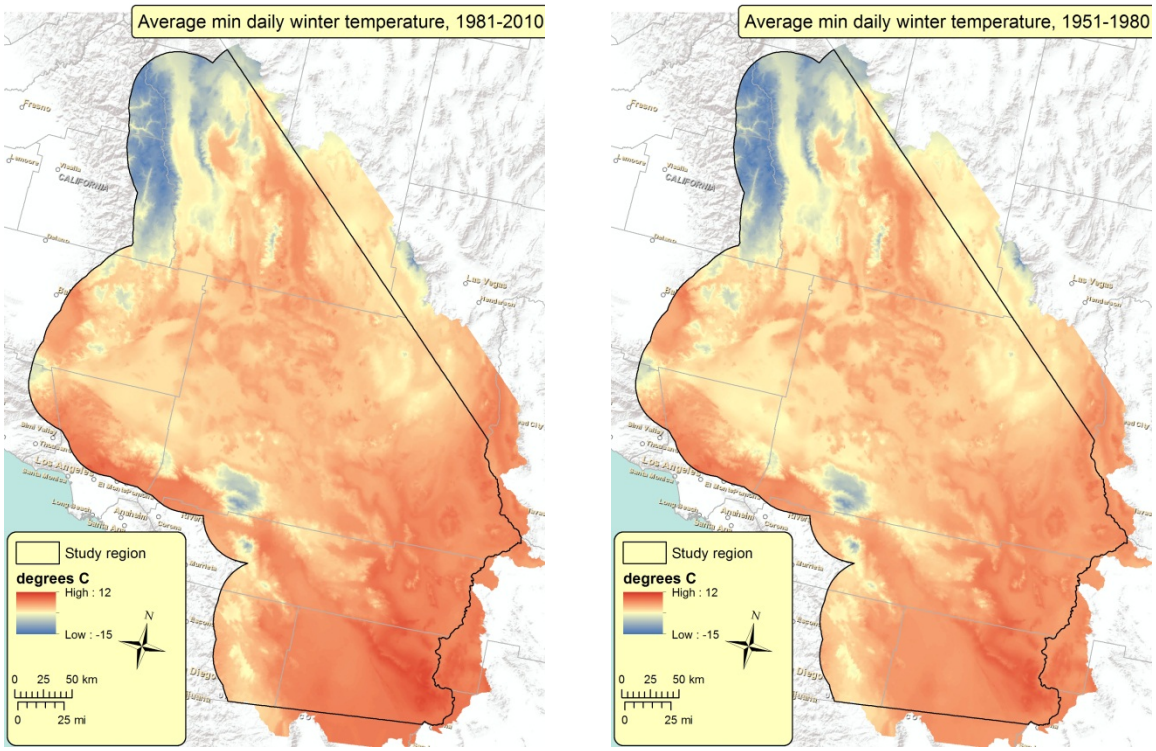
Table 6: Environmental variables used for species distribution modeling.

Variable type	Variable	Description
topoclimate	Spring solar radiation	Integrated solar radiation (WH/m^2, ESRI Spatial Analyst Area Solar Radiation). Derived from the interior of 30m NED DEM tiles buffered to 300m. Integrated from 2012-02-29 to 2012-05-30. Average integrated value in each 270m pixel.
bioclimate	Temperature seasonality	Temperature Seasonality (Coef. of Var of monthly mean temperatures, x100)
bioclimate	Maximum temperature	Max Temperature of Warmest Period (°C, x10)
bioclimate	Minimum temperature	Min Temperature of Coldest Period (°C, x10)
bioclimate	Annual precipitation	Annual Precipitation (mm)
bioclimate	Warm quarter precipitation	Precipitation of Warmest Quarter (mm)
bioclimate	Growing Degree Days	Growing Degree Days above 5°C (cumulative temp.)
bioclimate	Aridity	Aridity Index (FAO definition: bio_12/bio_23, x100). bio_23: Potential Evapotranspiration (mm/annual).
soil	Soil field capacity	Soil field capacity (MPa), produced by A. & L. Flint (USGS, Sacramento), derived from SSURGO or STATSGO where SSURGO was unavailable.
soil	Soil porosity	Soil porosity, produced by A. & L. Flint (USGS, Sacramento)
soil	Soil thickness	Soil thickness, produced by A. & L. Flint (USGS, Sacramento)
soil	Available water holding capacity	Soil available water storage (cm) from 0-50cm, derived from SSURGO or STATSGO where SSURGO was unavailable. The map unit area-weighted average of aws050wta in table muaggatt (a SSURGO table).
soil	pH	Soil pH (pH scale) from 0-50cm, derived from SSURGO or STATSGO where SSURGO was unavailable. The map unit area weighted average of the soil component, horizon depth weighted average of ph1to1h2o_r in table horizon.
hydrology	Water flow accumulation	Flow accumulation (ESRI Spatial Analyst Flow Accumulation), calculated from 90m HydroSHEDS flow direction rasters. 90m model data were log(x+1) transformed. Maximum of the transformed values in each 270m pixel.
hydrology	Perennial	Perennial water features, as indicated by the USGS NHD

Variable type	Variable	Description
	surface water	feature codes 39004, 39009, 39010, 39011, 39012, 45800, 46006, and 46602. Categorical presence/absence, indicating the presence of any perennial water feature within each 270m pixel.
geomorphology	Topographic relief	Topographic relief in the 270m cell estimated as the standard deviation of elevations from 30m NED DEM.
geomorphology	Playas	Playas, as the union of USGS NHD feature code 36100 and those features delineated by VegCAMP and GAP. Categorical presence/absence.
geomorphology	Dunes	Dunes. Categorical presence/absence.

Flint and Flint (2012) provide a detailed description of the interpolation method for bioclimatic variables.

Figure 13: Examples of 270m downscaled climate grids used for Maxent model parameterization (1981-2010) and hindcasting (1951-1980).

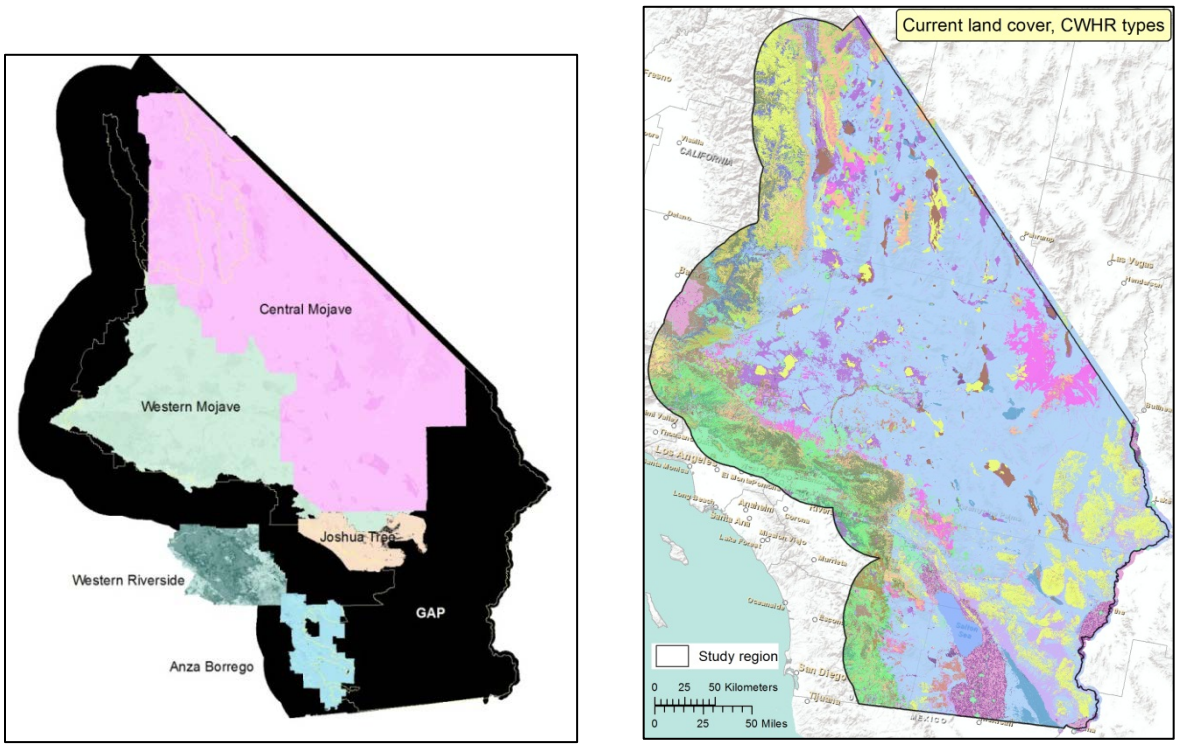


For vertebrate species, species-specific habitat suitability grids were created based on the California Wildlife Habitat Relationship System (CWHR) (http://www.dfg.ca.gov/biogeodata/cwhr/cwhr_downloads.asp#CWHR_Software). A map of wildlife habitats at 25 meter grid resolution was created by combining several map sources. Where possible the most recent vegetation maps produced or distributed by the California Department of Fish and Wildlife Vegetation Classification and Mapping Program were incorporated (see http://www.energy.ca.gov/2013publications/DRECP-1000-2013-001/DRECP-

1000-2013-001.pdf). For the remaining areas the California Gap Analysis database was used (2008 version, http://gap.uidaho.edu/index.php/california-land-cover/). Figure 14 shows the data sources used to create the composite map and the resulting map of CWHR habitat types.

For each vertebrate species, the 25m grid of CWHR habitat types was reclassified into a habitat suitability grid for the species using the arithmetic means of CWHR scores for 3 life history activities (feeding, reproduction, cover). The habitat score for reproduction was excluded for those species whose breeding areas fall outside of the study area. To account for species-specific home range or territory size, the 25m habitat suitability grid was filtered using a focal mean (the average of scores in a specified neighborhood around the cell), where the neighborhood size was set for each species to the scale of the species' home range, territory, or foraging area (Appendix B). The output was aggregated to 270m using the median value of the 25m cells contained within each 270m grid cell. The resulting habitat suitability index was included as a candidate variable for species distribution modeling using Maxent.

Figure 14: (left) Map sources for CWHR habitat types



Used to create habitat suitability grids for modeling vertebrate species distributions; (right) Map of CWHR habitat types.

3.5 Maxent Species Distribution Models

Species distribution models (SDMs) were created using Maximum Entropy (Maxent) software version 3.3.3k. (Phillips et al. 2006; Phillips and Dudík 2008). Maxent uses methods from machine learning to analyze the co-variation between the distribution of species observations and predictor variables at those same locations relative to a set of "background samples" drawn at random from the study region. The method has proven particularly effective when species occurrence data comprise presence-only records, small samples, and are not a probability based sample (Elith et al. 2011; Phillips and Dudík 2008).

For this study, a sample of 10,000 random background points was drawn for each model. Jackknife tests were conducted of predictor variable importance. The threshold criterion for converting probability to presence-absence maps was maximum training sensitivity plus specificity (Liu et al. 2013).

Some occurrence datasets were conspicuously spatially biased, reflecting uneven survey efforts related to, for example, accessibility or site-specific environmental impact analyses. Unfortunately, there is no simple way to tell whether the locational bias in samples produces an environmental bias in modeled species-environment associations. For this study, multiple observations that fell within a single 270m grid cell were treated as a single observation. To the project team's knowledge, the only means of estimating sampling effort from presence-only occurrence data that is also generally applicable to all species is by aggregating the occurrences of a superset of related species. The project team attempted to accommodate this sampling bias using the options provided with Maxent (Phillips et al. 2009). However, such crude estimates of sampling bias introduced many undesirable artifacts into the models of poorly sampled rare species. *Here only models without bias adjustment are reported, but with the strong caveat that the models could contain unknown spatial biases and must be considered untested extrapolations* (Spencer et al. 2010).

Model domain specification is a critical decision in Maxent modeling (and in species distribution modeling in general) because it defines the geographic extent and range of environmental variation for background samples and model extrapolation. If the model domain is too broad, most of the area may be highly dissimilar from areas occupied by the species, reducing the ability of Maxent to discriminate suitable habitat from the remaining relatively similar but unsuitable habitats. Moreover, the model may identify suitable habitats in areas that are not plausibly occupied by the species due to dispersal barriers or other confounding factors. On the other hand, if the model domain is too restricted, the background may not encompass sufficient environmental variation to discriminate habitat from non-habitat, and the extrapolated distribution of the species may misidentify potential habitats. Put another way, increasing the domain may allow the model to be applied over larger areas, but at the potential loss of some discrimination of local habitat quality.

As a test of SDM sensitivity to the model domain, models were fitted for each species based on a "broad" domain (the buffered DRECP region shown in Figure 14) and a "narrow" domain. These are referred to these as "broad extent" and "narrow extent" models. For plant species, the

narrow domain was defined as the set of all ecological subsections (Goudey and Smith 1994) where the species has been observed. For animal species, the narrow domain was defined as the putative range of the species within the buffered DRECP region based on CWHR range maps (http://www.dfg.ca.gov/biogeodata/cwhr/cawildlife.aspx) plus areas that are outside of the CWHR range and are within 10 km of locations where the species has been recently recorded. A comparison of broad and narrow models is provided in Appendix B. *Only broad extent models are shown and discussed in the main body of this report*.

3.5.1 Model evaluation

Model Area Under the Receiver Operating Curve (AUC) was used as one indication of model fit (Fielding and Bell 1997). This index is designed to account for the issue that the predictive skill of a model has four components: true positive (predicted and observed presence), false positive (predicted presence, observed absence), true negative (predicted and observed absence) and false negative (predicted absence, observed presence). These components depend on the threshold used to convert continuous model estimates of the likelihood of occurrence into a modeled presence or absence. The Receiver Operating Curve (ROC) plots the true positive fraction against the false positive fraction for all possible thresholds and evaluates the area under the resulting curve. The AUC evaluates to one for a perfect model and to 0.5 if the model is no better than chance (Fielding and Bell 1997). Although there have been criticisms of the use of AUC to evaluate SDMs (Lobo et al. 2008), and AUC based on a random background sample may be inflated, it is a useful comparative metric (Elith et al. 2006; Franklin et al. 2013).

Another test of SDM performance is how accurately the model predicts the presence or absence of the species in a set of samples not used to parameterize the model. Given the small sample sizes for some species, model sensitivity to input data was tested through model bootstrapping, in which the training data is selected by sampling with replacement from the presence points. Seventy percent of occurrence data was used for model training and 30 percent for testing, and this process was repeated 10 times using bootstrap sampling from all occurrence data. The average of the 10 models was used for all final analyses. Comparison of the best AUC value to the average AUC across the 10 runs provides some indication of model robustness.

Model hindcasting was performed as an additional test of model fit. Distribution models were calibrated based on occurrence and climate data and soils for the period 1981-2010 and the models were then hindcast to the period 1951-1980. CWHR habitat suitability rating was not included as a variable for vertebrates. Climate was different enough between the two periods to create discernible differences in predicted distributions. Model AUC was evaluated based on species observations collected during the 1951-1980 time interval. Small numbers of occurrence data for the earlier period limited the power of this approach for most species, so only the 19 species with at least 20 data points were assessed. For well-sampled species, the approach provides a different indicator of the ability of the models to predict species occurrence under changing environmental conditions.

Finally, models were visually inspected and compared to other SDMs by species experts in informal workshops organized by California Energy Commission staff. Results were not formally quantified, but in general experts were comfortable with - and models generally

agreed on - areas that were identified as having very high suitability and were also near known occurrences. There was also general agreement regarding areas identified as having very low habitat suitability There was less consensus among the experts and among the models about areas with intermediate habitat suitability or areas assigned high suitability that were distant from known occurrences of the species.

3.6 Maximum Likelihood Models

Maxent is just one of a large number of multivariate methods that have been applied to species distribution modeling (Elith et al. 2006). Distribution models can vary considerably with the method used, especially with presence-only data and small sample sizes. Recently, Royle et al. (2012) criticized Maxent because it does not provide direct estimates of the probability of species occurrence. As an alternative, they introduced a maximum likelihood method (Maxlike) that explicitly estimates the probability of species occurrence and the species' prevalence from presence-only data and environmental covariates. Fitzpatrick et al. (2013) compared Maxent and Maxlike models for six ant species in New England and concluded that Maxlike generally outperformed Maxent in their case study. In particular, they found that Maxent scores tended to underestimate the probability of occurrence in areas where species had been recorded, and that the two methods led to quite different probability maps.

To evaluate the sensitivity of SDM results to choice of method, Maxlike models for a subset of 10 species were produced using the R package Maxlike and two different solution procedures, simulated annealing and the quasi-Newton BFGS method (Chandler et al. 2013).

3.7 Results

3.7.1 Maxent models

Maxent models are summarized in Appendix B. Figure 15 provides examples of Maxent scores for Barstow woolly sunflower calibrated with observations and climate data for the period 1981-2010 and the same model hindcast to the period 1951-1980. The abrupt change in scores at the boundary between Kern and San Bernadino Counties reflects a change in resolution of soil maps available for those counties, and illustrates a source of uncertainty in the species models that depend on soil factors. The artifact is much less apparent once scores reach the threshold to produce the presence-absence model (Figure 15).

SDMs for most species show good to very good model performance based on AUC values, and are relatively robust based on comparison of best AUC to bootstrapped AUC values (Figure 16). For example, the best and average AUC values for Barstow woolly sunflower are 0.99 and 0.99, respectively, and the best and average AUC values for Mojave ground squirrel are 0.96 and 0.96, respectively.

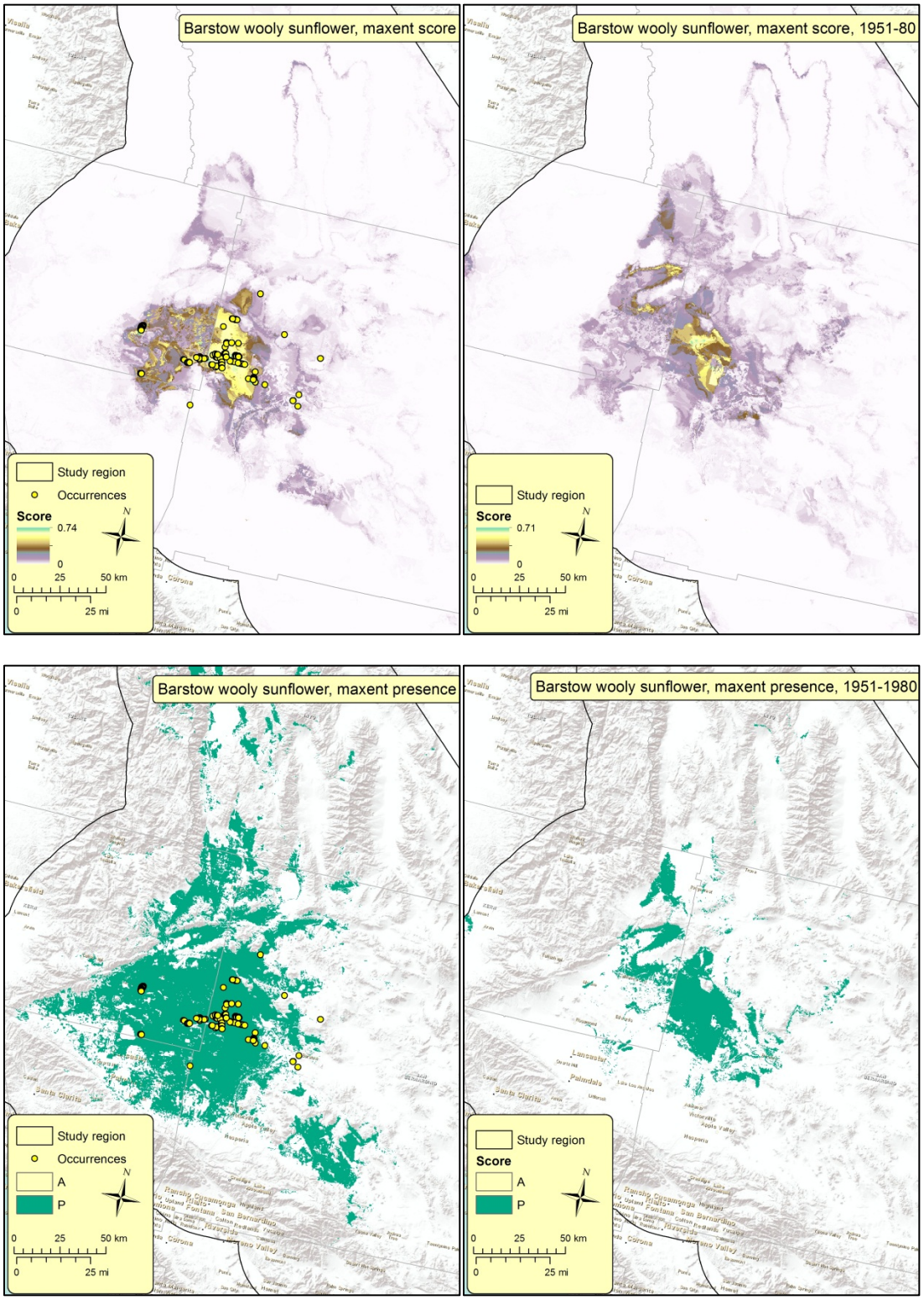
The lowest AUC values are associated with wide-ranging bird species such as Loggerhead shrike (best AUC=0.80), Le Conte's thrasher (0.81), and raptors such as Prairie falcon (0.86) and Long-eared owl (0.88). Rare plant models have the highest AUC values, a pattern observed in other studies (Syphard and Franklin 2010). For animals, models that include CWHR habitat

suitability ratings as a predictor variable generally perform better than those based on solely on climate variables (Figure 16).

Model skill in hindcasting known localities from 1951-1980 varied considerably among the 19 test species (Figure 16). AUC scores are equivalent and in a few cases even slightly higher for the earlier period. However, model skill dropped considerably for several species when hindcast, notably for most raptors and for some currently rare species such as Least Bell's vireo.

Summer precipitation was the most important predictor variable, contributing an average of 30 percent across all 65 models and accounting for over 90 percent in the model for Spiny cliff brake (Table 7). CWHR suitability was also highly influential, as were temperature seasonality and minimum temperature (Table 7). Relief was important for the subset of species models in which it was included (e.g., Desert tortoise). In general, models were consistent with biological knowledge of the species in terms of variable selection and influence.

Figure 15: Maxent scores for Barstow woolly sunflower for the calibration period (1981-2010)



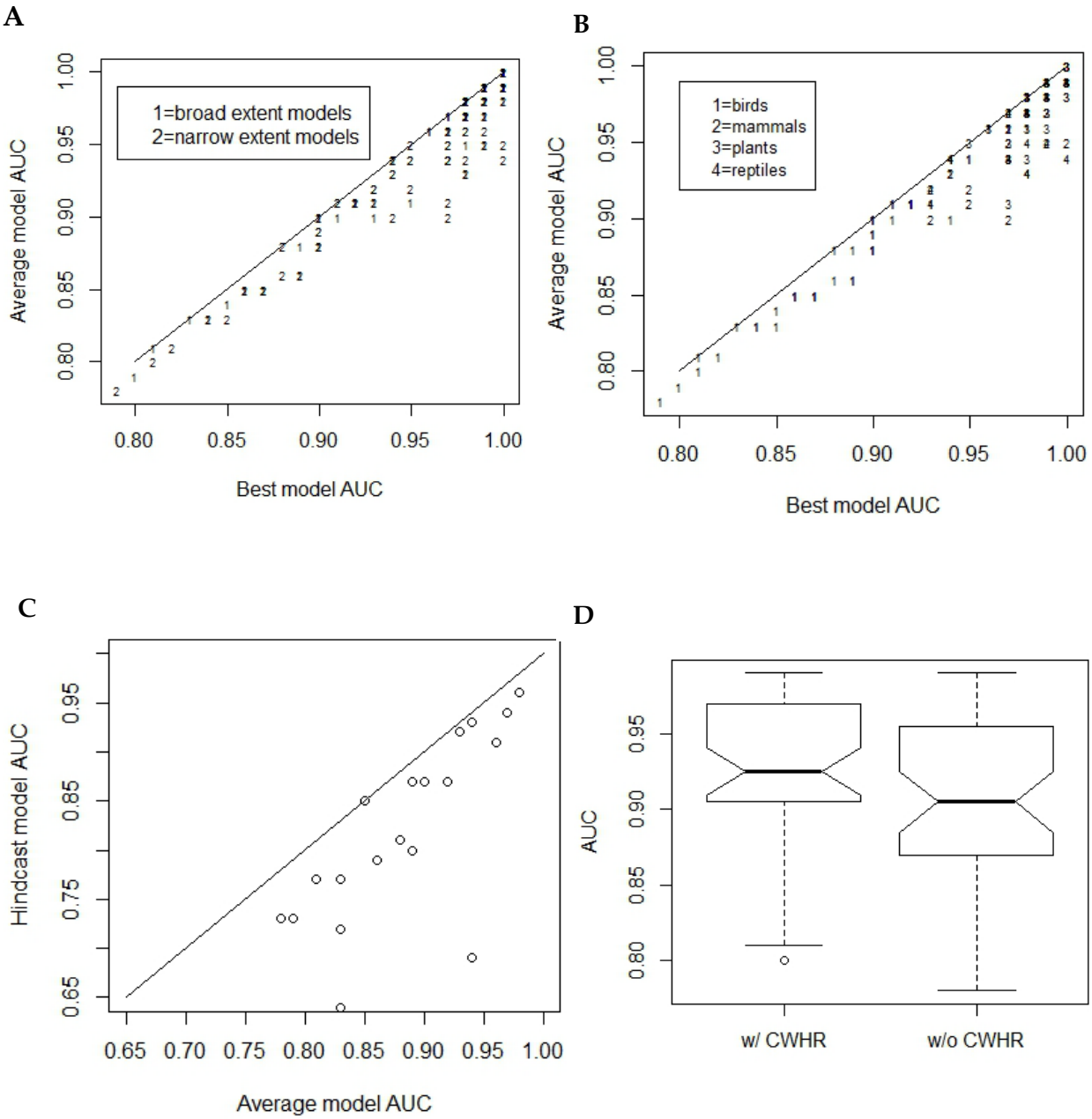
(Top left) and based on model hindcasting to the period 1951-1980 (top right). Points are observations from the period 1981-2010. The bottom panels shows the thresholded presence-absence models for the periods 1981-2010 (lower left) and 1951-1980 (lower right).

Table 7: Mean and maximum contribution of environmental variables to 65

Variable	Mean (%)	Max (%)	Species for maximum
Warm quarter precipitation	30.4	90.1	Spiny cliff-brake
CWHR habitat suitability	27.6	64.3	Ferruginous hawk
Temperature seasonality	17.2	59.5	Parry's spineflower
Minimum temperature	13.4	40.7	Harwood's milk-vetch
Relief	11.6	23.8	Desert tortoise
Aridity	8.2	38.2	White-margined beardtongue
Annual precipitation	8.2	40.8	Pallid San Diego pocket mouse
Growing degree days	7.3	32.6	Narrow-leaved psorothamnus
Soil thickness	7.2	51.1	American badger
Maximum temperature	6.8	38.9	Gila woodpecker
Soil pH	5.9	30.1	Tidestrom's milk-vetch
Perennial surface water	5.6	40.8	California black rail
Soil water holding capacity	4.8	25.7	Burrowing owl
Spring solar radiation	3.9	19.4	Ferruginous hawk
Soil coarse fraction	3.0	17.5	Robison's monardella
Water flow accumulation	2.9	18.0	Southwestern willow flycatcher
Soil porosity	1.6	13.4	Charlotte's phacelia
Playas	0.1	4.7	Emory's crucifixion-thorn
Dunes	0.1	1.2	White-margined beardtongue

Maxent species distribution models (broad extent models, 1981-2010 climate data). CWHR scores based on the CWHR habitat map were only included for wildlife species.

Figure 16: Summary of SDM model robustness (best vs. mean bootstrapped AUC)



(A) for broad vs. narrow extent distribution models, (B) as a function of taxonomic group, (C) based on hindcasting 1981-2010 models to 1951-1980 observations and climate grids for species with at least 20 observations, and (D) for vertebrate species with or without CWHR habitat type as a predictor variable.

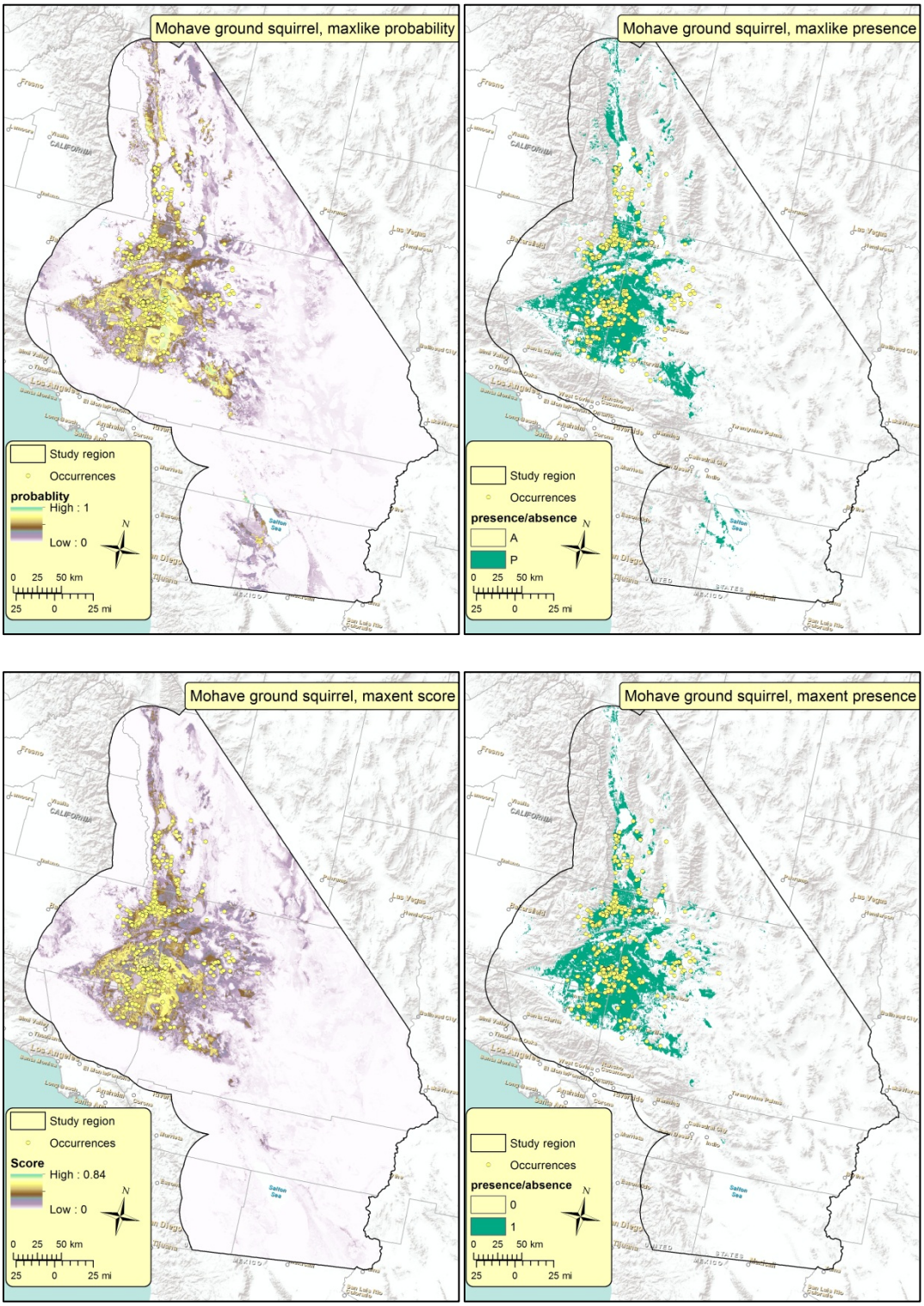
3.7.2 Maxlike models

Maximum likelihood models varied greatly in performance and in comparison to Maxent models, depending on the number of observations available for the species and the method used to estimate model parameters. Example model outputs are shown for Mohave ground squirrel (Figure 17) and Barstow woolly sunflower (Figure 18). For models based on a relatively

large number of observations, such as for the Mohave ground squirrel (n=481), Maxlike presence-absence models were broadly similar to Maxent models, regardless of which optimization method was used to estimate model parameters, but models varied considerably in their details, as illustrated by models for the Barstow woolly sunflower (Figure 18). Despite the relatively large number of observations for this species (n=322), Maxlike models were sensitive to the optimization method and showed only moderate agreement with Maxent models.

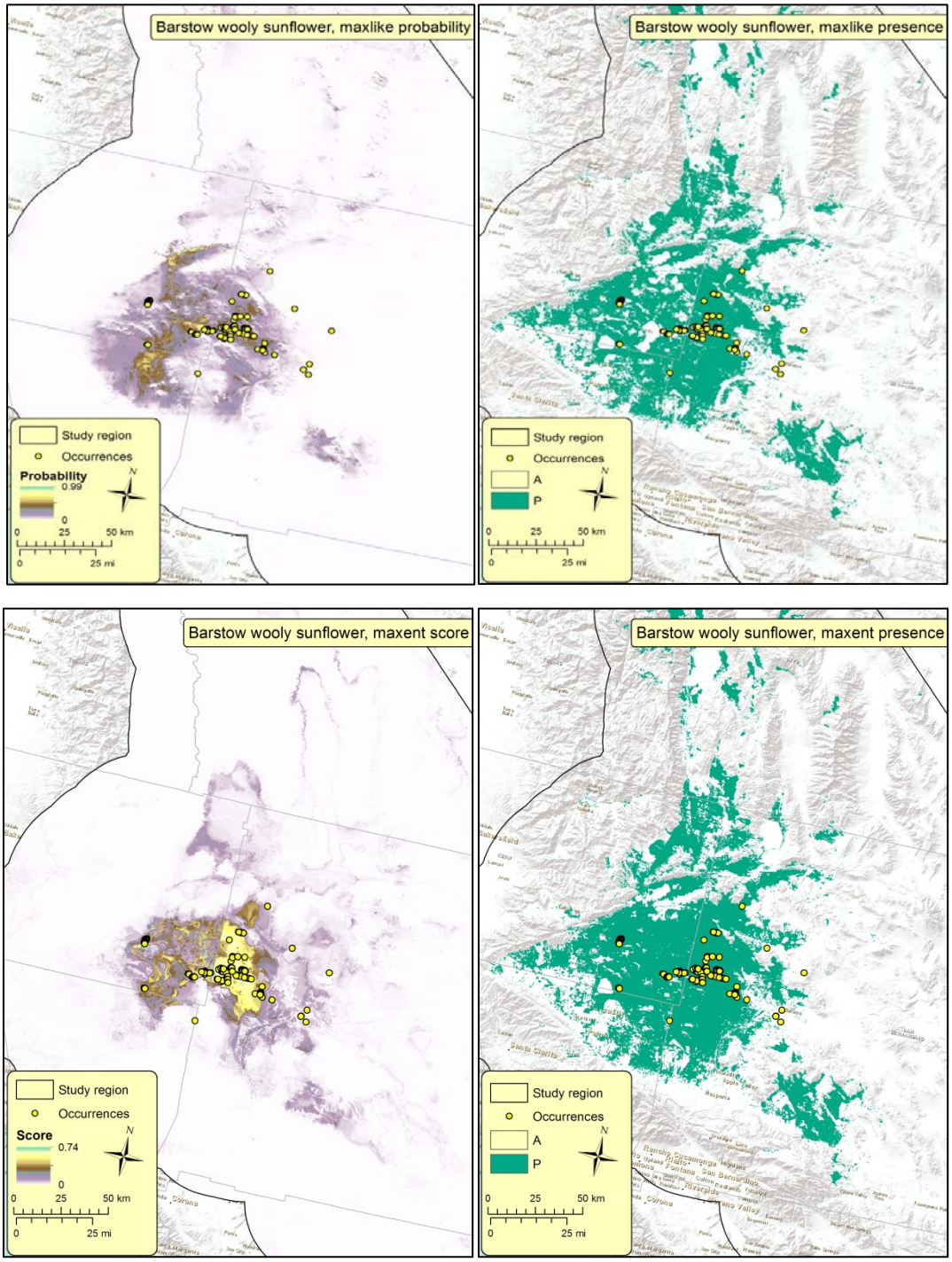
The Maxlike results serve to highlight the high sensitivity of species distribution models to the choice of algorithm. As described by Fitzpatrick et al. (2013), Maxlike models generally predicted much broader distributions than Maxent models. Based on comparisons of model outputs with the distribution of observations, Maxent models appeared to do a better job capturing important environmental associations and recovering the spatial pattern of the observation data. The greatest challenge in using Maxlike proved to be achieving convergence in the optimization algorithms used to parameterize the variables. This could be due in part to the relatively large number of candidate variables, which ranged up to six for some species. Based on results with the 10 test species, Maxent was used for offsets modeling and cumulative effects modeling. A fuller exploration would entail using multiple modeling approaches.

Figure 17: Maxlike vs. Maxent models for Mohave ground squirrel, including maxlike probabilities



(Upper left), maxlike presence/absence (upper right), maxent scores (lower left), and maxent presence/absence (lower right). Species observations are indicated by yellow dots.

Figure 18: Maxlike vs. Maxent models for Barstow woolly sunflower, including Maxlike probabilities



(Upper left), Maxlike presence/absence (upper right), Maxent scores (lower left), and Maxent presence/absence (lower right).

3.8 Model Limitations and Caveats

Species distribution models provide important and useful information to conservation planners, so long as they are used with an appreciation for their limitations. These limitations have been discussed in detail by many authors, for example Wiens (2009), Austin (2002), Syphard and Franklin (2009), and Dawson et al. (2011). Major uncertainties include basic knowledge of species biology and ecology, the quality of the observation data (e.g., reliability, locational accuracy, and spatial and temporal sampling bias), choice of predictor variables (e.g., resolution and accuracy), model domain, and choice of statistical method.

Like other SDMs, the models developed for this study are based on where the species has been observed and thus reflect the "realized niche" of the species, which is controlled not only by environmental factors but also by factors that are not accounted for in the models such as biological interactions and dispersal. Known occurrences of a species may exist outside of modeled climatic suitability or new populations outside of modeled range may be discovered in site assessments or field surveys. The team's models are impacted to an unknown degree by spatial and temporal sampling bias in the observation data sets. As has been illustrated, the predicted distributions also vary depending on the modeling technique.

Species distribution modeling is especially challenging for rare species and for poorly surveyed species. In this study, model skill as measured by AUC, bootstrapped AUC, and hindcasting varies considerably among the the study species and is generally weakest for wide-ranging bird species. *The models will be especially useful when combined with field surveys to inform management decisions, as has been done for some high-profile species like the desert tortoise.* At a minimum, the Maxent models developed for this project should be vetted with experts on each species to help assure their appropriate application to planning and decision processes.

Finally, it is important to understand that the SDMs presented in this chapter do not account for habitat condition. The distribution models are combined with maps of habitat condition (Chapter 2) as part of the process for modeling offsets (Chapter 5) and cumulative effects (Chapter 6).

CHAPTER 4:
Mid-century Projections of Species Distributions

4.1 Climate Change Futures for the California Desert

Global climate models agree on warming for most parts of the planet. These same models (General Circulation Models – GCM) however, show strong disagreement on precipitation change in many regions. California is among the regions for which GCM projections on precipitation change were in strong disagreement until recently. Projections for the California desert followed this pattern, with GCMs projecting warming, but some GCMs showing precipitation increase for the Mojave, and others showing drying trends. These disagreeing results were common up until and including the fourth assessment of the Intergovernmental Panel on Climate Change (IPCC).

Recent GCM runs for the fifth assessment of the IPCC show more agreement about precipitation change in California (Neelin et al. 2013). These models suggest that California may become marginally wetter, with very few models showing decrease in precipitation.

Regional climate models provide a higher resolution picture of climate change in the Mojave. Models run with last-generation GCMs (IPCC AR4) showed an increase in temperature of between 1.8 and 2.4˚C (3.2-4.4˚F) by mid-century (Stralberg et al. 2009). Diurnal temperature range was projected to increase slightly (0.2˚C). Simulated precipitation change varied from an increase of 3 percent to a decrease of 45 percent.

Regional climate model results based on model outputs from the fifth assessment are not yet available for the entire California desert region using latest-generation (CMIP5) GCMs, but results for the western Mojave and Sonoran deserts indicate the potential for significant warming by mid-century (Hall et al. 2012).

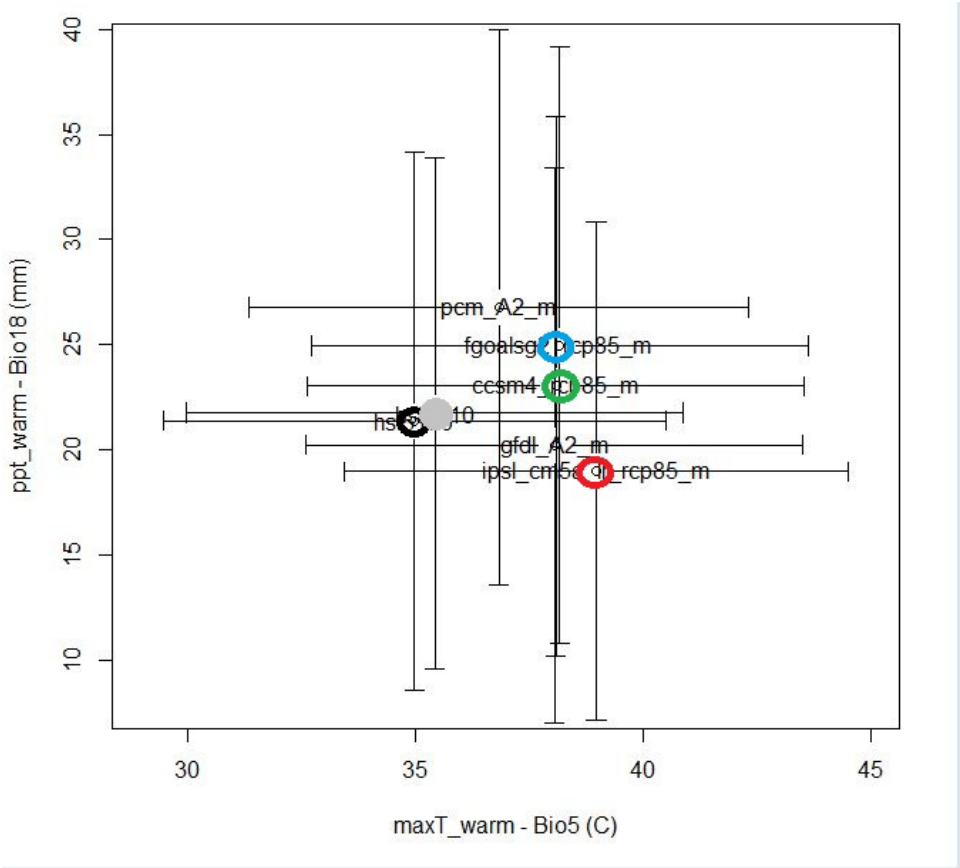
Although this project was not strictly motivated by concerns about climate change impacts, foreseeable climate change was considered an important consideration in assessing cumulative impacts. As part of this project, CMIP5 model outputs were statistically downscaled to 270m resolution for the project study area using the methods described in Chapter 3. The same key bioclimatic variables were produced for the middle 21st Century (2040-2069) as for the two historical periods (1951-1980 and 1981-2010) (see Table 3.3). For mid-century climate projections, 5 alternative climate models were applied using "business as usual" emission factors:

1) Community Climate System Model (CCSM) 4 – Representative concentration pathway (RCP) 8.5;
2) Flexible Global Ocean-Atmosphere-Land System (FGOALS) model G2 – RCP 8.5;
3) Institut Pierre-Simon Laplace (IPSL) CM5 model – RCP 8.5;
4) Parallel Climate Model (PCM) – A2 emissions scenario (used in prior State assessments and run here for comparative purposes);
5) Goddard Fluid Dynamics Laboratory (GFDL) – A2 emissions scenario (used in prior State assessments and run here for comparative purposes).

The three CMIP5 models were selected because they capture much of the variation in climate projections produced by 18 different CMIP5 models. The IPSL model is relatively hotter and drier, the FGOALS model predicts less warming and slightly wetter conditions, and the CCSM model is intermediate to the other two.

Regional overviews of change in temperature, precipitation, growing degree days and aridity (potential evapotranspiration/precipitation) are displayed in Figures 19-21. The large standard deviations around regional means reflect high spatial variation in the local climates in the study region, which spans subalpine to warm desert conditions.

Figure 19: Historical and projected mid-century precipitation for the warmest quarter and maximum daily temperatures for the warmest month.

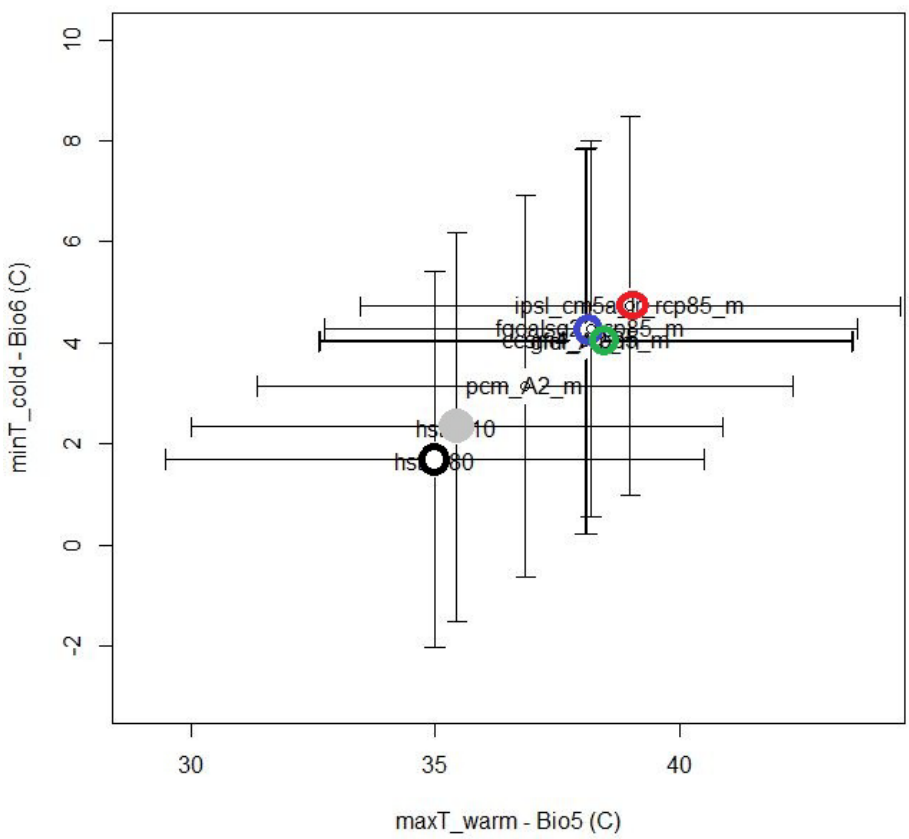


Historical means are illustrated by the circles (open black: 1951-1980, filled grey: 1981-2010).

Projections for mid-century (2040-2069) are illustrated by the cross-hairs labeled with GCM names (GFDL, PCM, etc). Models used for SDM forecasts are identified using open colored circles including FGOALS (blue), CCSM4 (green), and IPSL (red). The length of the whiskers on each cross-hair represents one standard deviation in combined spatial and annual variation. GCMs labeled 'A2' are from the older AR4 series of GCMs, while those labeled 'RCP' are from the newer CMIP5 series of GCM simulations. GCM outputs are based on "business-as-usual" (A2 for AR4 models, RCP 8.5 for CMIP5 simulations) scenarios.

Under business-as-usual scenarios, all GCMs project increases in summer daily maximum temperatures. Summer precipitation is projected to increase in most GCMs, though gfdl_A2 and ipsl_cm5a_rcp8.5 project future summer precipitation similar to or slightly less than the historical reference periods (Figure 19). Maximum temperatures (warmest quarter) and minimum temperatures (coldest quarter) are projected to increase approximately proportionately (Figure 20). Most GCMs project an increase in maximum temperatures of about 2.5-3.5 ˚C, which is similar in magnitude to their projections for increase in minimum temperature. The GCM that projects the least increase in maximum temperature also projects the least increase in minimum temperature (PCM_A2).

Figure 20: Modeled summer (JJA) maximum daily temperatures (maxT_warm-Bio5) and minimum daily winter (DJF) temperatures for two historical periods

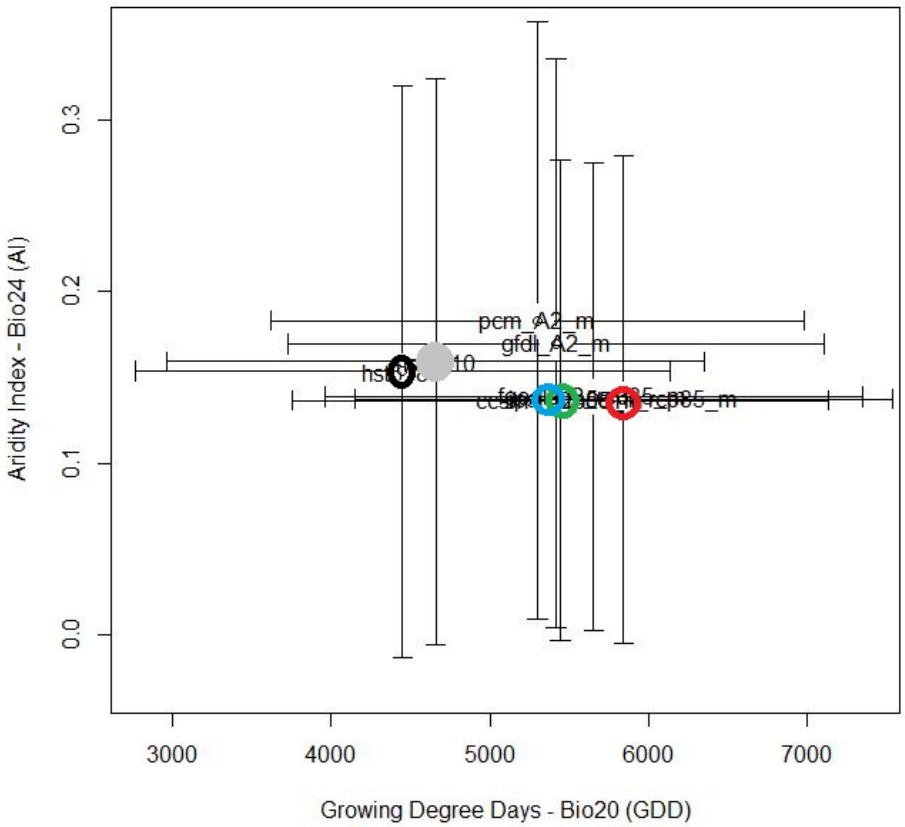


(1951-1980 (hst51080) and 1981-2010 (hst8110)) and based on five different GCMs with business-as-usual emissions scenarios for 2040-2069.

Changes in biologically relevant variables follow from these changes in temperature and precipitation (Figure 21). Aridity (Aridity Index - AI) increases with increasing temperature, but decreases with increasing precipitation. These opposing forces largely balance one another, resulting in little change in AI. Conversely, Growing Degree Days (GDD) increase with rising

temperature and are unaffected by precipitation change, so substantial increase in growing degree days is seen. This may have significant implications for the phenology of desert plants.

Figure 21: Mid-century (2040-2069) projections for Growing Degree days



(5°C threshold, Bio20) and Aridity (Bio24) for the study region compared to two historical periods (1951-1980, 1981-2010). The aridity index, precipitation/potential evapotranspiration, decreases under drier conditions.

See the text and legends for Figure 18 for an explanation of the models and plotting symbols.

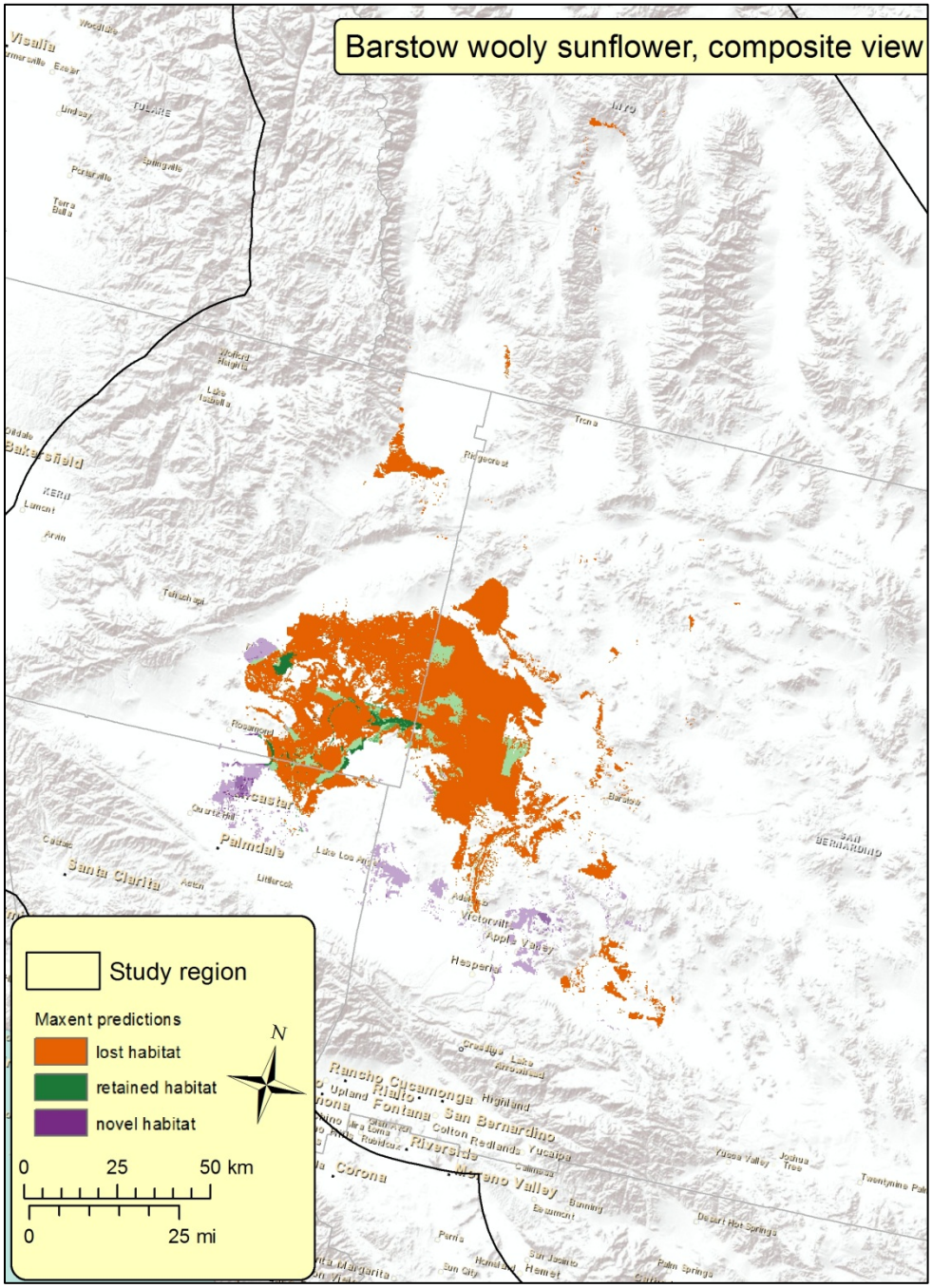
4.2 Projected Changes in Species Distributions

Each species has unique climatic tolerances that will limit its distribution as climate changes. This results in a shift in range as the species responds to climate change. Extensive evidence from paleo-ecology, such as the transition from the last glacial period, indicates that these range shifts are the primary mechanism species have used to survive rapid climate change in the past. Similarly in the future, species will likely undergo shifts in local and regional distribution as climate changes.

Mid-century projections of Maxent models fitted to 1981-2010 climate data display significant changes in species bioclimatic habitats for most plant and animal species, as illustrated in Figure

22 and Figure 23 for Barstow woolly sunflower, Mohave ground squirrel, Alkali mariposa lily, Desert cymopterus, and the Flat-tailed horned lizard.

Figure 22: Composited view of current and projected future habitat distribution for Barstow woolly sunflower



Future distribution is based on 3 climate models (CCSM4, FGOALS, and IPSL), and the level of model agreement is show by the density of the color. Orange areas are current habitat predicted by all 3 models to be lost by mid-century. Lightest purple areas are new suitable habitat according to only 1 climate model, and darkest purple areas are new suitable habitat based on all 3 climate models.

To help visualize projected changes in species distributions, mid-century Maxent scores were converted to presence/absence maps and combined to indicate the level of model agreement. The result is illustrated for Barstow woolly sunflower in Figure 22. Figure 23 shows the same display for four other species. The amount of projected change in habitat is striking given that these projections are centered on a period only 37 years into the future and include other factors besides climate such as soil factors, hydrography and solar radiation that were unchanged between the two time periods.

Figure 24 summarizes the frequency distribution of the proportion of species' ranges projected to remain suitable habitat ("stable range") by mid-century for each of the 5 different GCMs. The proportion stable range varies from near 0 to almost 1 across the 65 study species, but is close to 0.5 for most species. For CMIP5 projections, the median proportion stable range varies from 0.32 for IPSL to 0.48 for CCSM4 and 0.54 for FGOALS models. Put another way, half of the species are projected to lose at least 68 percent of current suitable range based on the IPSL-RCP8.5 model projection, and half are projected to lose at least 46 percent of current suitable range based on FGOALS-RCP8.5. These numbers are surprisingly high and indicative of the relatively specialized combination of bioclimatic and soil conditions associated with most of the study species.

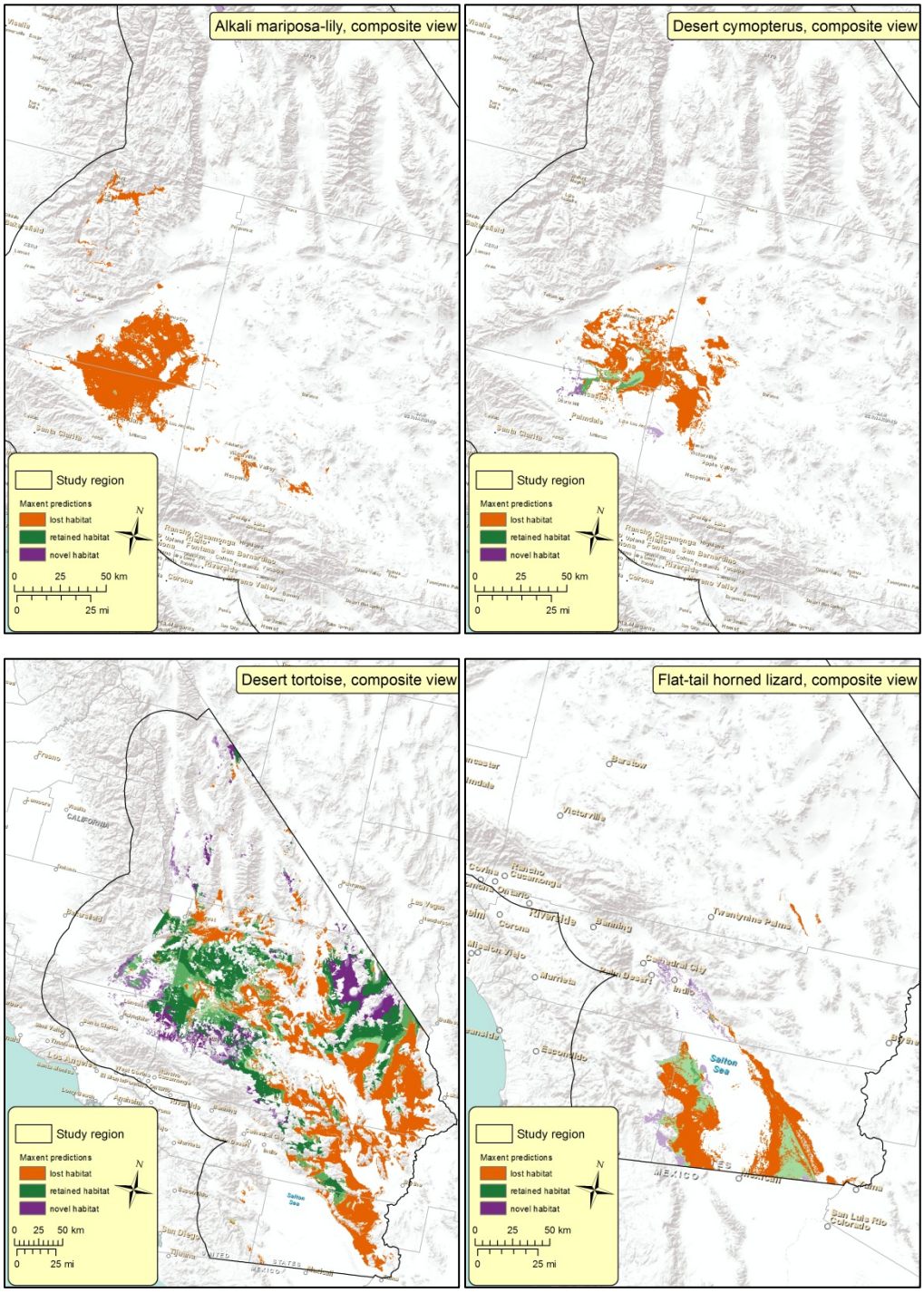
Maxent projections vary from large decreases to large increases in the total area of suitable habitat. Expressed as the ratio of (future suitable area)/ (current suitable area), the "range ratio" indicates that suitable habit area increases for roughly half of species (Figure 25). For example, based on FGOALS-RCP8.5, half of the study species are projected to experience an increase in range size (ratio > 1.04). Based on IPSL-8.5, half of species are projected to undergo at least an 8 percent reduction in total range size (median ratio = 0.92).

Changes in species habitats under climate change are relatively consistent across the five GCM models, with the PCM projection from AR4 generating the smallest – but still significant – changes in projected distributions and the IPSL project from the most recent CMIP5 assessment generating the largest changes in habitat distributions. For most species, the majority of area mapped as suitable today is projected to be unsuitable by mid-century, and the majority of the area modeled as suitable in mid-century is currently mapped as unsuitable. This implies the need to consider connectivity between current and future habitats in evaluating cumulative impacts of habitat loss or restoration efforts associated with renewable energy development.

It is important to emphasize that the projected changes in habitat distribution based on Maxent SDMs do not take into account current or future habitat condition related to roads, land use or edge effects. Habitat condition is modeled separately for current and future periods and is combined with the habitat suitability models as part of modeling offsets and cumulative effects.

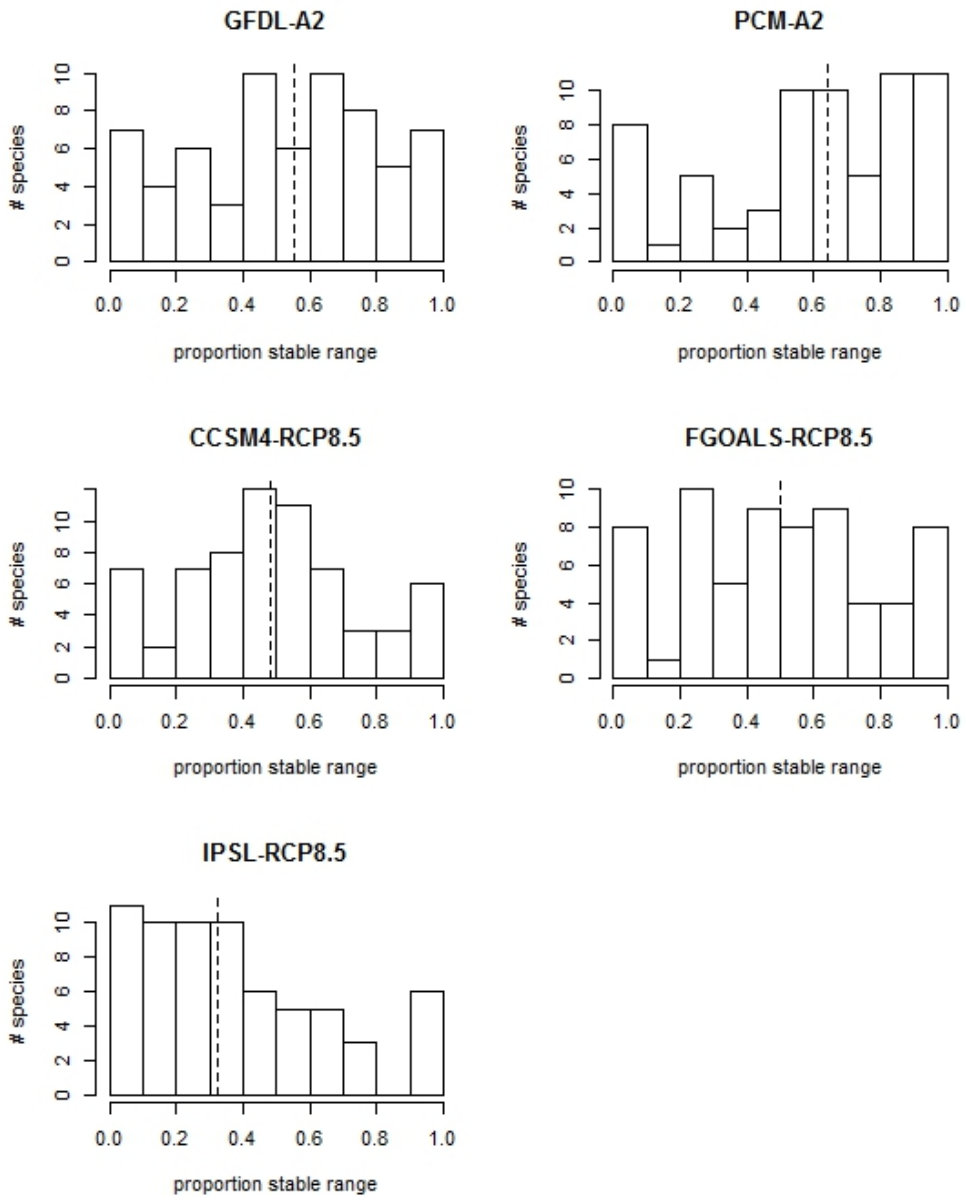
The projected species distributions are subjected to multiple assumptions and sources of uncertainty, and results from model hindcasting recommend caution in applying the Maxent models to forecast future habitats. Nevertheless, attempts to offset habitat losses from energy development need to at least consider climate-driven changes in the distribution of suitable habitats as areas are identified for conservation, as discussed in Chapter 6).

Figure 23: Representative examples of current vs. mid-century habitat areas for four study species



Showing current suitable habitat (orange and green areas), area of current habitat projected to be unsuitable by mid-century (orange), future suitable habitat (green and purple), and currently unsuitable areas projected to become suitable by mid-century (purple). The species are alkali mariposa lily, desert cymopterus, desert, and flat-tailed horned lizard, Models do not account for changes in land use or habitat condition, which are incorporated in a separate step.

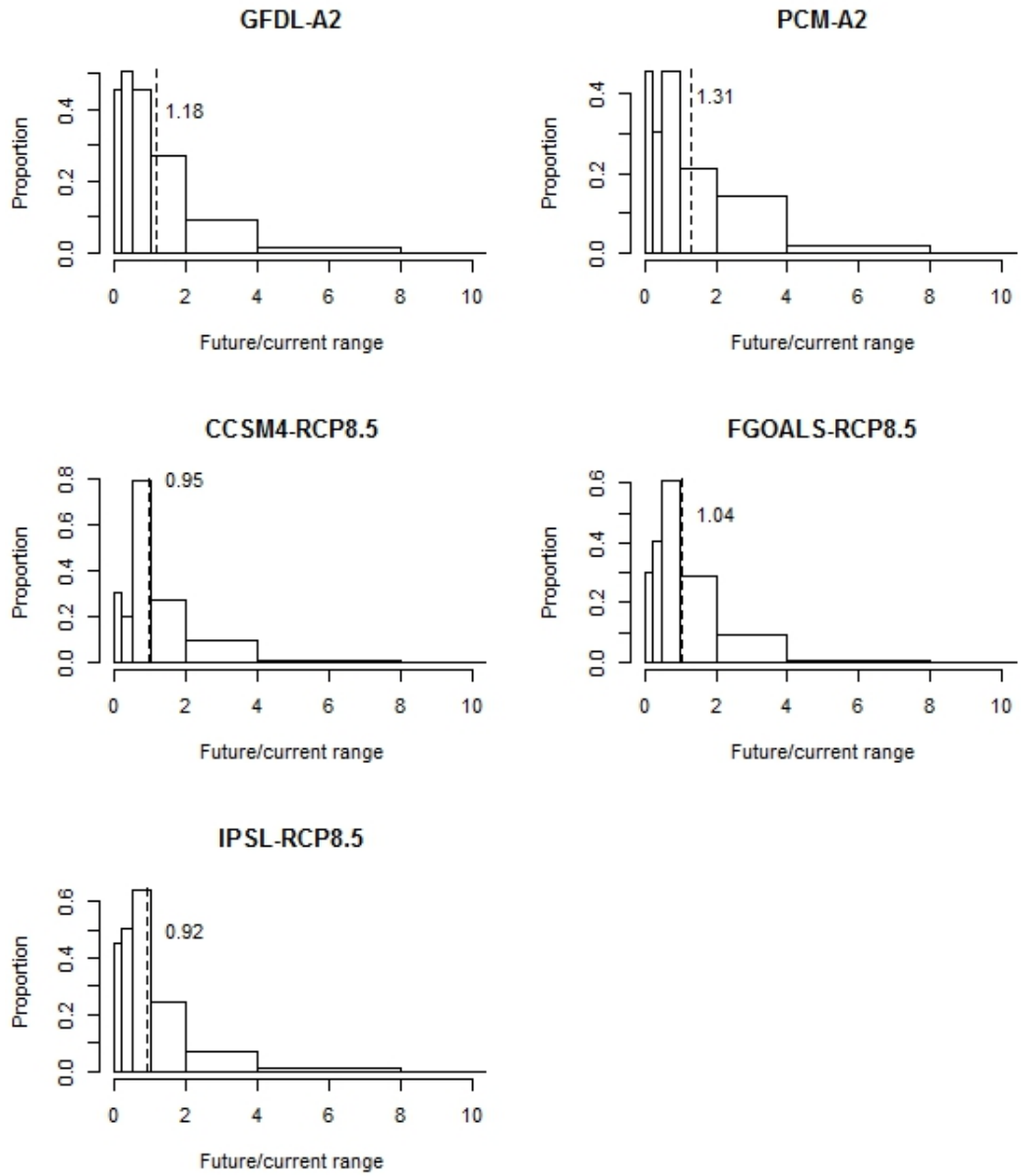
Figure 24: Frequency distributions of proportion stable range for 65 study species



Based on Maxent models using 5 different downscaled GCMs.

Proportion stable range is the fraction of currently suitable habitat projected to remain suitable by mid-century. The vertical dashed lines indicate the median value. Models do not incorporate changes in land use or habitat condition, which are incorporated in a separate step.

Figure 25: Frequency distribution of the ratio of future to current suitable habitat area within the study region.



Y axis is the proportion of species in each frequency bin

The vertical lines show the median range ratio for the set of 65 species based on each model. The numbers next to the line provide the actual median value of the range ratio. For example, based on the IPSL model, half of the species are projected to have total habitat area that is less than or equal to 92 percent of the current range area. Models do not incorporate changes in land use or habitat condition, which are incorporated in a separate step.

CHAPTER 5:
A Planning Support Tool for Offsetting the Impacts of Energy Development

5.1 Background

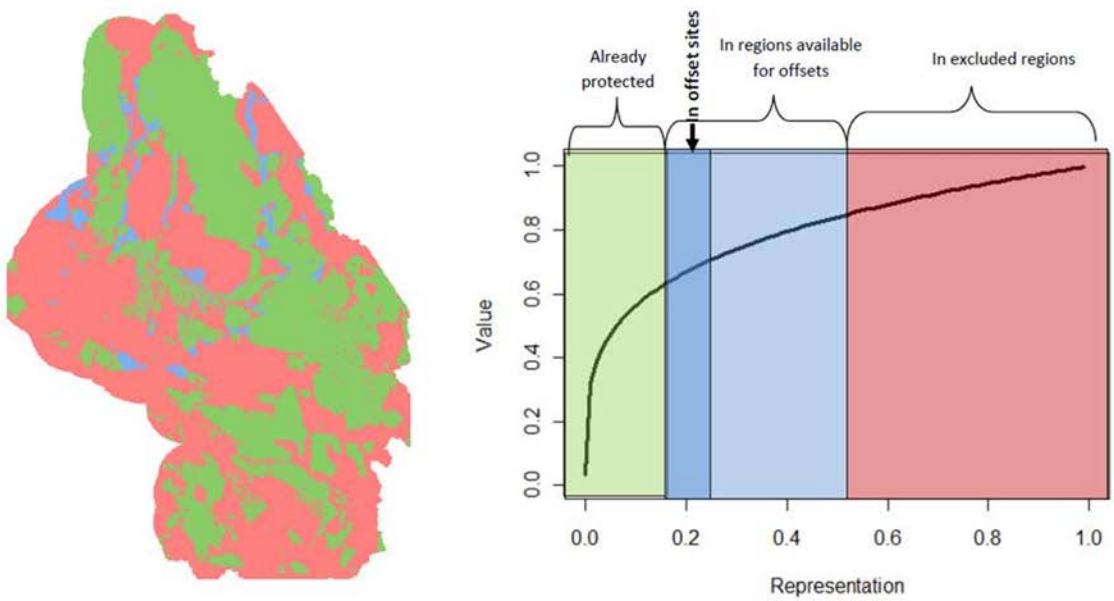
The mitigation hierarchy defined in the U.S. National Environmental Policy Act specifies four levels of dealing with environmental impacts in decreasing order of preference—avoid, minimize, restore, offset. Offsets are a valuable tool to protect and enhance habitat for species or communities when impacts cannot be avoided, minimized, or restored (Ten Kate et al. 2004). The goal of offsets is to achieve a net neutral or positive outcome for biodiversity (Gibbons and Lindenmayer 2007; Kiesecker et al. 2009). One challenge in selecting offset sites is to match them as closely as possible to the impact sites, which often dictates that offset and impact sites are relatively close together. Another challenge is to satisfy the mitigation requirements that sites are superior in terms of their condition, connectivity to other sites, and cost-effectiveness.

Recently Kiesecker et al. (2009) described a multi-species framework for selecting offset sites that uses available spatial data and employs Marxan site selection software (Wilson et al. 2009) to find an optimal collection of offset sites. Their 5-step process involves forming a working group, identifying biological targets, gathering spatial data on those targets, setting impact goals for each target, and then using the Marxan algorithm over increasing spatial extents to identify a portfolio of offset sites. In their case study of selecting mitigation offsets for oil and gas development in western Wyoming, sites with high oil and gas potential were excluded from the set of candidate offset sites. Site "integrity" or condition was used as a proxy for restoration cost for each candidate site, and a set of sites was selected that met the offset target for each species while minimizing the total cost of the offset portfolio.

The offset model developed for this study is similar in many ways to that of Kiesecker et al. (2009) in that it requires a set of biological targets (species or ecological systems, which will be referred to below as "features" to avoid confusion with other uses of the term "target" in the conservation literature), uses spatial data about those features as well as habitat condition, and identifies high priority areas for offsets. The team's approach differs in that it considers multiple projects, accounts for projected climate and land use change, and ranks all areas in the region for their potential value for conservation offsets as opposed to identifying a least-cost set of sites to achieve the conservation goals. The offsets model makes use of the spatial products described in Chapters 2, 3 and 4 of this report and the public Zonation conservation software package (Moilanen 2007; Moilanen et al. 2009). The model attempts to explicitly address the following questions: which sites(s) could most cost-effectively offset any unavoidable impacts of solar energy development? Where offsets should be sited if they are required to remain within a specified geographic region (e.g., DRECP region or sub-region)? How do selected sites compare to sites selected to maximize conservation gain for the full set of conservation targets, as opposed to those directly affected by the projects?

Zonation uses the concept of conservation utility functions. Utility functions are routinely used in economic cost-effectiveness analysis and seek to represent the relationship between the amount of a particular social service or good and its total social value. Figure 26 provides an example of a utility curve in which total value increases non-linearly with the degree of protection (representation) of a conservation target, such that the marginal utility of additional protection or restoration for a particular biological target diminishes as total protection of that target across the planning region increases. Zonation allows the user to establish separate utility curves for each conservation target and employs an iterative removal algorithm to remove units (grid cells) from the conservation solution in an order that produces the smallest loss of total conservation value at each step (Moilanen 2007). The order of removal determines the relative value of each cell and identifies a hierarchy of conservation priorities through the landscape. This hierarchy is helpful not only in determining the most valuable locations, but also in identifying the least valuable choices that can be given up.

Figure 26: Map illustrating the use of the utility curve in Zonation.



The colors on both map and chart correspond to regions of protected lands (green), area available for offsets (blue), selected offset sites (darker blue), and areas excluded for offset site consideration (red). Map is for illustrative purposes and does not accurately reflect current availability status.

Zonation may be better suited to the offset design problem than Marxan or other "set covering" approaches for a number of reasons. The iterative removal algorithm and resulting rank ordering of conservation priorities is helpful not only in highlighting the most valuable locations to retain for multiple species or ecological resources, but also the least valuable sites that can be lost, or made available for energy development. Second, Zonation uses benefit functions such as the example in Figure 26 to derive a cell's marginal value. The benefit function approach more closely approximates the way society values ecological resources, and the way species respond to changes in habitat area. Finally, projections of future impacts of proposed

projects are highly uncertain, and any offset design framework that tries to include such projections should be adaptable and continually updated to reflect current conditions.

For this project, functions for the public R statistics library (R Core Team 2012) were written that process geospatial data, take user inputs, and run the Zonation software to prioritize sites to be considered for offsets. Collectively, this set of modeling tools is labeled Mojavset. Mojavset generates the required Zonation input files via a series of user responses to text prompts. Along with the standard Zonation output, Mojavset generates ASCII grids that delineate potential offset sites and corresponding site reports with information on land management and biodiversity representation specific to the offset sites.

5.2 MOJAVSET – A Planning Support Tool for Offsetting the Impacts of Solar Energy Development in the California Deserts

Mojavset is a spatial planning support tool that evaluates the potential impacts to biodiversity from any given solar development site in the Desert Renewable Energy Conservation Plan area, and identifies potential biodiversity offset sites for conservation action. Mojavset provides decision support for the four steps (avoid, minimize, restore, offset) of the mitigation hierarchy. The tool is for the spatial prioritization of offset sites; to avoid and minimize steps are implemented as a way to cancel an offset analysis if sites are in direct conflict with land management status or sites of known high conservation priority.

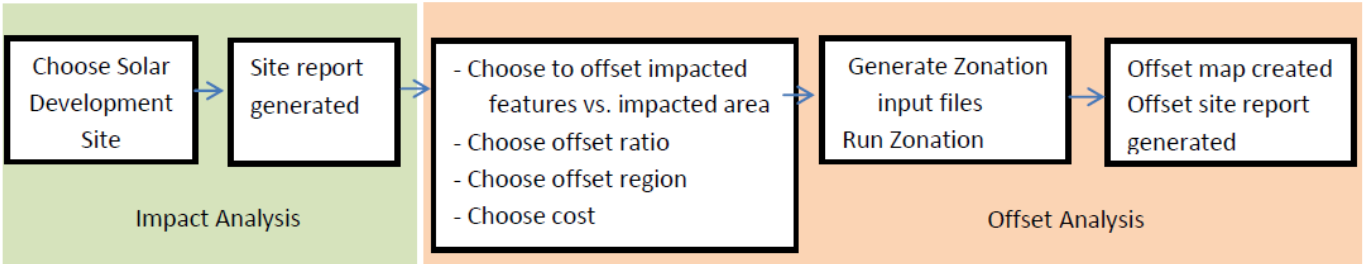
Avoid: Mojavset uses overlays of spatial data to provide site reports that describe potential impacts to biodiversity from development at a site. The program warns the user of potential conflicts if a development site occurs in an area that is already identified as an important area for conservation. This information allows the user to avoid the selection of development sites with the greatest impact to biodiversity and/or the greatest potential conflict with conservation objectives. Through comparison of site reports at several potential sites, the user can select development sites that will likely have less relative impact and/or conflict.

Minimize: Once a site is chosen for development, the user can consider ways to minimize the footprint at the development site. For large scale projects, the user can upload detailed shapefiles of the potential site footprint into Mojavset to compare the changes in potential impacts from alternative development plans.

Restore: The third step in the mitigation hierarchy, restore, is not considered in Mojavset due to the slow rate of recovery for delicate desert systems. In other systems, including some desert wetland systems, the restore option could be used in the project team's decision support tool if ecologically appropriate.

Offset: The main function of Mojavset is the ranking of offset sites through the spatial conservation prioritization of area required to meet stated conservation goals. Mojavset provides maps of potential offset sites and corresponding site reports for a development site, or sets of sites, to be mitigated. A thorough treatment of each decision point, Zonation option, dataset, and type of offset analysis is included in the Mojavset user manual (Appendix C); an abbreviated explanation is provided below.

Figure 27: General workflow of the Mojaveset.



Offset analysis begins with choosing direct offsets or offsetting to maximize conservation gains (Figure 27). In the case of direct offsets, only conservation features that will be impacted by potential solar sites are used for offset prioritization. For example, if 8 species and 3 ecological systems will be impacted, then only these 11 features out of the entire suite of species and ecological systems will be considered when prioritizing sites for offsets. The distributions of all other conservation features will be ignored and will not add value to a network of sites for offsets. Area or occurrence goals will be set for impacted features as a user-defined multiple (i.e. offset ratio) of the quantity of impacted occurrences.

To prioritize offsets with maximum biodiversity conservation gains, any mapped conservation feature is considered available for offset prioritization. The user has the option to use all of the features or to select the specific features to be used in Zonation for offset prioritization by varying the weight of each feature. A weighting of 0 will remove the feature from the analysis. Higher weightings give the feature more value. Zonation is then run two times. First, offset sites are prioritized around the core areas of each feature (core area zonation). Second, offset sites are prioritized based on feature richness (additive benefit function). Mojavset will produce a combined output layer highlighting the offset sites that are identified in both planning methods and the areas that are unique to each method. More detail on benefit functions and their use in Mojavset is available in the user manual (Appendix C).

The impact of energy development on conservation features for either direct offsets or maximum biodiversity gains can be evaluated based on species distributions, ecological systems, or both. The use of future species distributions is considered in the cumulative impact analysis approach described in Chapter 6.

The user must supply feature-specific offset ratios, where the offset ratio measures units of offset per unit of impact. Units of impact can refer to the actual impacted area of the development site or to the quantity of impacted feature occurrences within the development site. The offset ratios are applied differently depending on the user's choice to offset directly-impacted features or to offset based on maximum biodiversity conservation gains.

Zonation ranks grid cells as priorities for conservation objectives by iterative, sequential cell removal. However, cells can be aggregated into planning units and then groups of cells can be evaluated and removed together. The user has the option to use planning units for offset

prioritization rather than individual grid cells, in cases where planning units more closely represent actual implementation of conservation actions.

Costs can be used in Mojavset in multiple ways to affect the prioritization, whether using planning units or a grid surface of potential offset sites. A unit acquisition cost layer for offset sites can be included such that the algorithm incorporates heterogeneity in land value to find cost effective offset solutions according to the objectives of the analysis. Similarly, an ecological condition can be included as a cost layer to influence site value from an ecological perspective. In Mojavset, a low ecological condition will be more expensive for the algorithm to prioritize compared to a site with high ecological condition. In this manner sites with fewer disturbances, and presumably a more intact ecological community, will be prioritized over degraded sites.

Cell rankings that are based solely on cell value and offset sites corresponding to these rankings may be dispersed across the region of potential offset sites. The region can be constrained by the user to specify acceptable areas for siting offsets through the use of a mask (below). The user can also aggregate solutions through the implementation of a boundary length penalty which discourages cell removal if the removal of that cell increases the perimeter to area ratio of the network of offset areas.

Mojavset allows the user to force areas in or out of the solution to restrict the offset analysis to specific areas or land use/land cover types. Mojavset automatically excludes the following from the offset analysis: 1) the user-specified solar development site and 2) protected areas with GAP status 1 or 2. The user also has the option to further specify acceptable regions for potential offset locations and, conversely, regions in which to avoid siting offsets using a mask. A mask can be uploaded that specifies sites to be included as acceptable regions for offsets or can be created by making decisions within the Mojavset program.

Mask layers are implemented differently depending on the type of prioritization selected for offset siting. For direct offsetting of impacted features, a mask is used to clip the analysis region for inputs and outputs. For identifying offsets that maximize conservation gains, the mask specifies zones which impact the order of cell-removal. All cells are included in cell-removal and prioritization. Only the zone for potential offsets will be used to site offsets.

Regardless of the method for mask implementation, offset sites are chosen within the user-specified region. Other details regarding the use of masks are relegated to Appendix C.

Once user inputs are entered Mojavset generates the text and batch files for the Zonation runs.

5.3 Western Mojave Worked Example to Illustrate the Use of Mojavset for Mitigation Offsets.

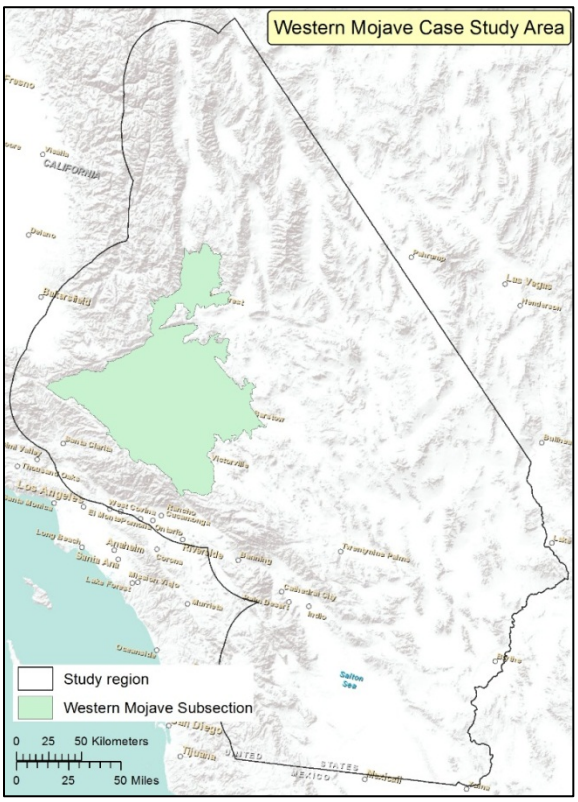
5.3.1 Location, offset decisions, data, and species covered

To demonstrate Mojavset, the proposed solar projects in the Western Mojave region, as defined by Goudey and Smith (1994) were evaluated (Figure 28). This test case is purely a demonstration; future offset planning and analyses should be vetted through the appropriate processes and channels, with official data and offset requirements. It was beyond the scope of this project to undertake field evaluations of the potential impact of the candidate solar sites

used in this analysis. The project team simply estimated their location and footprint from point data.

The Western Mojave ecological subsection is a 1.27 million hectare region in the western region of the DRECP boundary (Figure 28). The region is a relatively densely populated area within the DRECP planning region containing the cities of Lancaster, Palmdale, and Barstow, among others. Local land use authority is divided among three county planning agencies, multiple urban incorporated areas, and state and federal agencies. The region has undergone large-scale land cover transformation, and a high proportion of the area is within this report's "highly degraded condition" class (Figure 11, Figure 12). However, the area still contains a high level of native biodiversity, and the juxtaposition of a high concentration of proposed solar projects and numerous conservation features of interest makes this a particularly interesting study area to test the Mojavset offset siting tool.

Figure 28: Location map of the Western Mojave study area



(California Ecological Subsection 322Ag: High Desert Plains and Hills (Goudey and Smith 1994).

5.3.2 Proposed utility scale solar projects

The California Energy Commission (Energy Commission) maintains information detailing the location and size of existing and proposed utility scale solar facilities (http://www.energy.ca.gov/33by2020/). The project team queried this database to determine the locations of facilities for the offset analysis and demonstration. Proposed projects are still in the

planning and permitting phases, and actual parcel boundaries were not available at the time of this study. To approximate their footprint, circular impact sites with area equal to the reported area were created, centered on the reported coordinates. This approximation likely captures the scale of impacts from the proposed projects, but will not represent the final impacts with the accuracy required for mitigation.

5.3.3 Conservation Features

For this test case, 64 species were considered. These species differ somewhat from the list of species in Tables 4 and 5 and were chosen early in the project based on guidance at the time from the Independent Science Advisers Report (Spencer 2010). Note that the Desert tortoise is not included in the list. The absence of desert tortoise and inclusion of several species that are peripheral to the study region underscore the hypothetical nature of this case study (Table 8).

5.3.4 Mojavset parameters for the test case

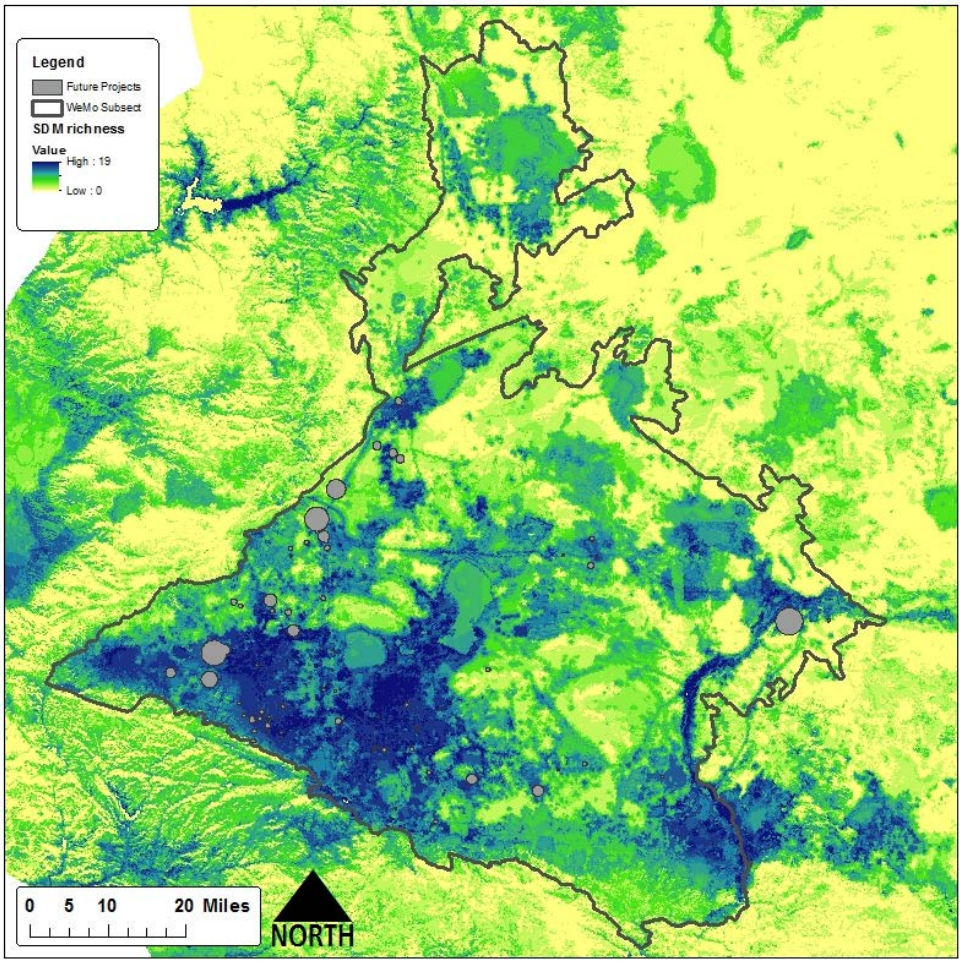
Two offset scenarios were assessed in this case study, illustrating the two types of offset analyses in Mojavset: direct offsets for the impacted features and offsets sited to maximize biodiversity conservation for both impacted and non-impacted features. A 2:1 offset ratio was specified, and ecological condition (Chapter 2) was as used as a proxy for site cost (the lower the ecological condition the higher the offset site cost). Locations of proposed utility scale solar facilities provided the set of hypothetical impact sites, and the Western Mojave subsection was used as an analysis mask to specify the planning region.

5.3.5 Projected impacts and offset scenarios

The hypothetical impact sites of the Western Mojave are distributed primarily in the western portion of the subsection, and cover 15,330 hectares (Figure 29). These projects occur almost exclusively on private land with minimal overlap with priority areas of the BLM and TNC (Table 9). However, the sites do tend to occur in areas of greater species richness based on the modeled species distributions (Figure 29), and intersect with the ranges of 33 species of potential conservation concern. The amount of impacted distribution by species and the species' total modeled distribution is shown in Table 8, and varies from no impact to 14,296 ha, or nearly 93 percent of the impact area falling with the distribution of the American badger. The alkali mariposa lily is impacted the greatest as a proportion of its range, at 3.3 percent.

Sites selected to offset impacts to species affected directly by the proposed projects are clustered in species-rich areas in the center of the study region that are in good ecological condition, in areas at the western margin of the study region that support intact habitats for a few species especially associated with that portion of the study area, and in the easternmost and northern portions of the study region where sites provide the most cost-effective opportunities for some riparian species and narrowly endemic plant species (Figure 30, Table 9). The important result is that the value of these sites is readily apparent in terms of their composition, condition, land ownership and land management. Sites selected to maximize biodiversity are more concentrated in species-rich areas in the center of the study region (Figure 31). While not unexpected, this result serves to emphasize how sensitive the location of offsets can be to one or a few individual species.

Figure 29: Western Mojave ecological subsection with species richness and proposed utility scale solar development locations.



Species richness is based on SDMs described in Chapter 3 and does not account for current land use and habitat condition. These are incorporated as part of the offset model.

Table 8: Species list, summary of modeled solar development impact, and offsets achieved for each species based on Direct Offset vs. Maximum Biodiversity objectives.

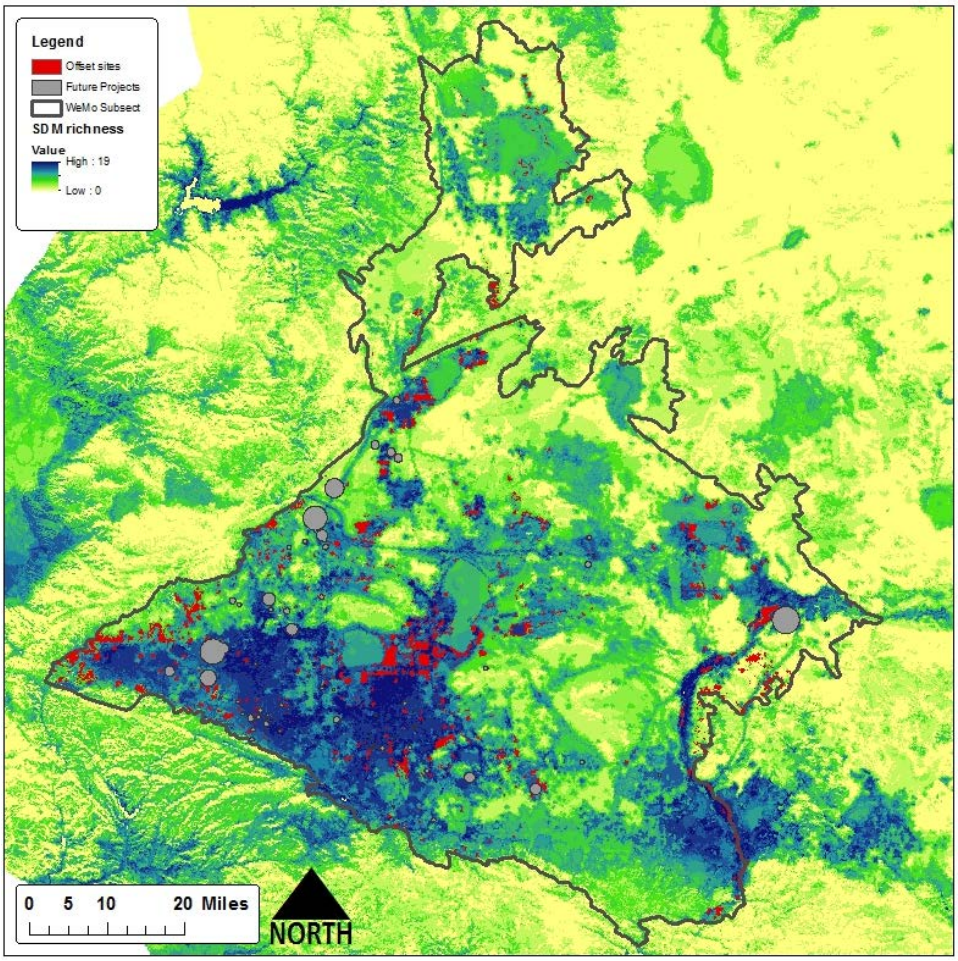
Species	Impact	SDM	Target	Max Gains	Direct	Achieved
	Site (ha)	Total (ha)	Goal (ha)	Offsets (ha)	Offsets (ha)	%
Abronia_villosa_var_aurita	117	36,282	233	-	-	0.0
Acmispon_argyraeus_var_multicaulis	36	35,305	73	-	-	0.0
Agelaius_tricolor	9,426	715,339	18,852	2,165	18,852	100.0
Allium_nevadense	-	92,014	-	-	-	NA
Androstephium_breviflorum	66	100,522	131	-	7	5.6
Arctomecon_merriamii	124	168,516	248	-	-	0.0
Asclepias_nyctaginifolia	-	46,117	-	-	-	NA
Asio_otus	10,345	2,640,803	20,689	19,610	25,646	124.0
Astragalus_cimae_var_cimae	-	31,296	-	-	-	NA
Astragalus_insularis_var_harwoodii	-	74,890	-	-	-	NA
Astragalus_tidestromii	-	61,367	-	-	-	NA
Astrolepis_cochisensis_ssp_cochisen	-	62,701	-	-	-	NA
Athene_cunicularia	11,540	1,249,900	23,080	6,248	23,087	100.0
Boechera_shockleyi	-	52,393	-	-	-	NA
Buteo_regalis	9,630	2,289,541	19,260	15,273	25,741	133.6
Buteo_swainsoni	9,739	2,246,494	19,479	10,155	23,255	119.4
Calochortus_striatus	2,610	78,280	5,220	13,479	7,137	136.7
Castela_emoryi	7	115,087	15	7	22	150.0
Chaetodipus_fallax_pallidus	139	351,130	277	-	-	0.0
Charina_trivirgata	-	679,246	-	160	518	Inf
Chorizanthe_parryi_var_parryi	-	24,815	-	-	-	NA
Cordylanthus_parviflorus	-	30,122	-	-	-	NA
Coryphantha_alversonii	-	104,794	-	-	-	NA
Coryphantha_chlorantha	-	67,141	-	-	-	NA
Crotalus_ruber	-	199,826	-	-	-	NA
Cymopterus_deserticola	467	59,202	933	15,090	5,402	578.9
Cymopterus_gilmanii	-	97,132	-	-	-	NA
Cymopterus_multinervatus	109	100,434	219	-	7	3.3
Delphinium_recurvatum	15	962	29	722	153	525.0
Empidonax_traillii_extimus	131	129,135	262	168	372	141.7
Enneapogon_desvauxii	-	47,378	-	-	-	NA
Eriastrum_harwoodii	-	149,321	-	-	-	NA
Erioneuron_pilosum	-	73,571	-	-	-	NA
Eriophyllum_mohavense	642	75,677	1,283	3,047	2,909	226.7
Eschscholzia_minutiflora_ssp_twisse	131	65,202	262	4,075	1,939	738.9
Falco_columbarius	7,990	2,607,888	15,980	11,613	20,259	126.8
Falco_mexicanus	12,502	3,070,235	25,005	22,001	34,802	139.2
Lanius_ludovicianus	11,737	4,304,045	23,474	24,006	35,058	149.3
Laterallus_jamaicensis_coturniculus	-	58,291	-	-	-	NA
Layia_heterotricha	-	12,772	-	678	80	Inf
Melanerpes_uropygialis	-	169,194	-	-	-	NA
Mimulus_mohavensis	1,290	71,398	2,581	204	2,595	100.6
Monardella_robisonii	-	65,479	-	-	-	NA
Muhlenbergia_appressa	-	173,487	-	-	-	NA
Opuntia_basilaris_var_treleasei	277	48,756	554	787	583	105.3
Pellaea_truncata	-	47,750	-	-	-	NA
Penstemon_albomarginatus	-	25,938	-	-	-	NA
Penstemon_stephensii	-	38,003	-	-	-	NA
Penstemon_utahensis	-	36,771	-	-	-	NA
Phacelia_nashiana	219	129,806	437	3,842	2,675	611.7
Phrynosoma_blainvillii	926	596,183	1,852	160	3,025	163.4
Phrynosoma_mcallii	-	256,265	-	-	-	NA
Psorothamnus_fremontii_var_attenua	-	47,903	-	-	-	NA
Sanvitalia_abertii	-	64,961	-	-	-	NA
Senna_covesii	-	42,326	-	-	-	NA
Sphaeralcea_rusbyi_var_eremicola	-	54,653	-	-	-	NA
Stipa_arida	7	323,333	15	-	-	0.0
Symphyotrichum_defoliatum	-	30,552	-	-	-	NA
Taxidea_taxus	14,296	3,787,170	28,591	26,251	33,979	118.8
Toxostoma_bendirei	7,523	571,383	15,047	153	306	2.0
Toxostoma_lecontei	9,696	2,756,611	19,391	27,403	29,160	150.4
Uma_scoparia	87	144,685	175	102	401	229.2
Vireo_bellii_pusillus	139	134,092	277	109	459	165.8
Xerospermophilus_mohavensis	9,083	645,916	18,167	21,586	18,174	100.0
Yucca_brevifolia	386	1,025,353	773	1,137	5,190	671.7

Table 9: Impact site and offset site reports

Impact Site	Amount
Site Area (hectares)	15,330.9
Ownership (max FED area)	DOD
Percent Fed	1.9
GAP STATUS - area majority	4.0
GAP STATUS - min status	3.0
% Priority Overlap - TNC	8.9
% Priority Overlap - ACEC	0.2
# of targeted species	33.0
% of targeted species	50.8
max % of range for a target species	3.3
# of ecological systems	14.0
% of ecological systems	15.2
max % of range of an ecological system	1.0
mean slope (%)	1.8
mean DNI	7.9
min distance to Road (meters)	-

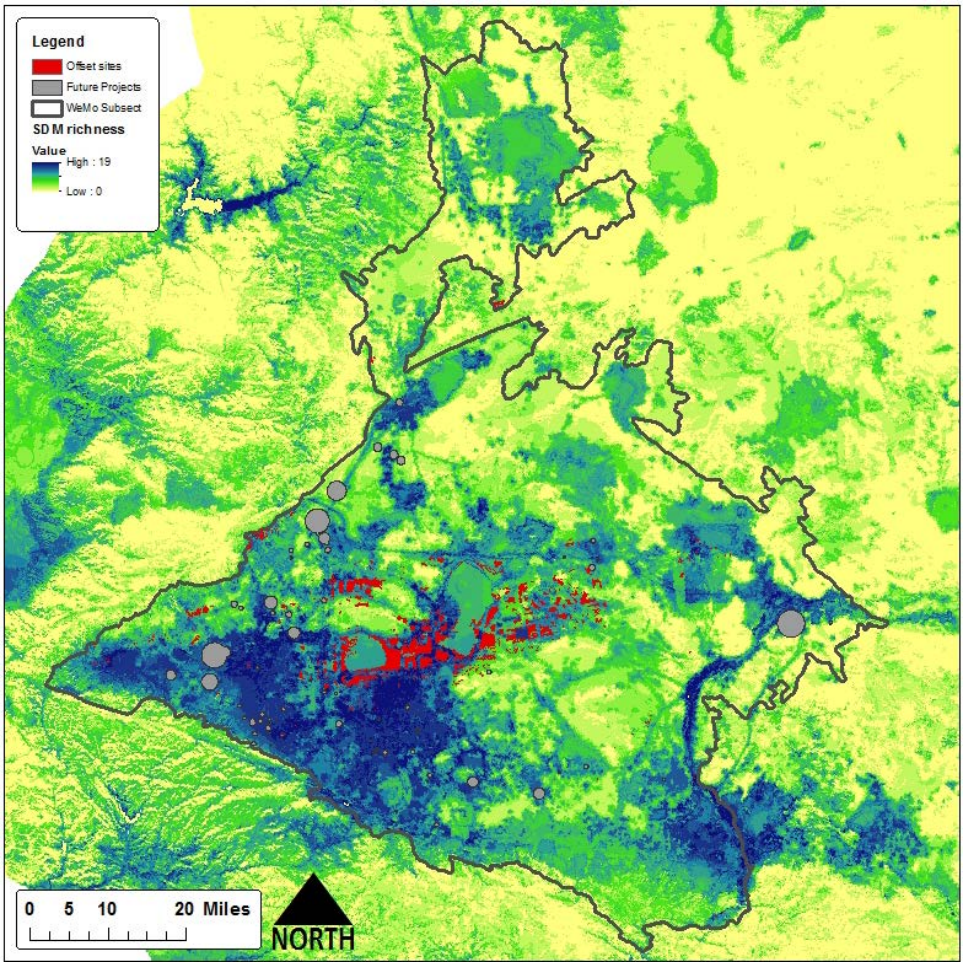
Status	Area	Max Cons	Direct
Total	(ha)	30,662	39,220
federal	(ha)	24,966	13,730
DOD	(ha)	22,404	10,233
BOR	(ha)	-	-
OTHER	(ha)	-	-
BIA	(ha)	-	-
BLM	(ha)	2,533	3,399
FS	(ha)	29	99
NPS	(ha)	-	-
FWS	(ha)	-	-
GAP 1	(ha)	-	-
GAP 2	(ha)	94	162
GAP 3	(ha)	3,003	3,132
TNC	(ha)	19,748	22,419
ACEC	(ha)	720	2,428

Figure 30: Direct offset sites (red) for hypothetical solar energy projects (gray) using a 2:1 offset ratio



Compared to modeled richness of conservation features (see Table 8).

Figure 31: Maximum conservation gains offset solution (red) using a 2:1 offset ratio for a hypothetical set of solar energy projects (gray).



5.4 Discussion

Conservation planning tools like **Mojavset** are designed to identify efficient solutions to problems with a large number of choices. When considering the collective impacts of multiple projects on multiple species, more efficient solutions will likely arise compared to implementing offsets one species at a time on a project-by-project basis. The degree of efficiency will depend on the extent to which modeled species habitats coincide. Determining a priori the area required to mitigate impacts of multiple projects on many conservation features could potentially assist both energy developers and permit granters to modify potential site locations to reduce both the potential impact and the cost that could be required to offset those impacts.

In this worked example, solutions for direct offsets differed significantly from those to maximize biodiversity in the location and extent of priority sites. As an analytical planning strategy, one could solve for direct offsets to determine how much area would be required to mitigate direct impacts. Subsequently, the maximize biodiversity conservation offset

formulation would be executed, but instead of using the same 2:1 offset multiplier, the offset ratio could be adjusted so that the area selected for offsets equaled that of the direct offset scenario, (a ratio of 2.56:1 in this case). Comparing these mitigation strategies, the maximize biodiversity conservation strategy could potentially yield improved prioritization of offset sites compared to direct offsets, particularly if the goal were to take a more DRECP-wide approach to mitigation offsets. The **Zonation** algorithm treats each species separately for purposes of determining current conservation status (representation) and in determining marginal cell values through the benefit function. In the worked example, the representation of each species was calculated for the entire DRECP. As a result, impacts on species from a proposed set of projects were evaluated relative to the species distribution and conservation status across the DRECP planning region.

The direct offsets scenario could not reach the specified goals for 7 of 33 species. Such shortfalls can occur when there is a limited extent of available habitat either because the habitat is exceedingly rare, most of the species' modeled habitat occurs outside the planning sub-region, or existing habitat is already protected and therefore not available for offsets. Lands in GAP status 1 and 2, for example, are already protected and therefore cannot be counted as offsets. **Mojavset** alerts the user before running if targets cannot be met through offsets given the input parameters and actual on the ground limitations.

Climate change may pose a significant challenge to providing durable mitigation offsets. As discussed below and in Chapter 6, one approach is to give preference to areas that appear to be more stable in the face of climate change (e.g., climate refugia) and to habitats such as washes and riparian areas that could play an important role in buffering climate change impacts. **Zonation** can be operated with consideration of both current and future habitats (Carroll et al. 2010), as will be demonstrated in Chapter 6.

One overarching issue with offsetting as a mitigation tool is ensuring the actions taken are actually additional to what would have occurred without conservation intervention (Maron et al. 2012; Moilanen 2012). If mitigation funds go towards offset areas that are not apparently threatened, do the offset actions provide a net positive ecological impact? Estimating potential additionality from offsets could be modeled through the differences among land use change scenarios by locating offsets in zones where biodiversity is threatened in the absence of conservation actions.

Sources of uncertainty in this test case arise from a number of causes, for example, the resolution and quality of data used to model ecological condition and species habitats, simplifying assumptions in the species distribution models, and crudely specified impacts of solar development within the project footprints.

Offsetting the impacts of renewable energy, and development in general, is a likely to increase as a mechanism to mitigate the impacts from development and economic growth (Madsen et al. 2010**). Mojavset** has been designed to support joint planning for solar energy and biodiversity conservation. Based on the worked example described here, the approach is promising as a tool

for planners seeking to balance renewable energy development and biodiversity conservation in the DRECP planning region.

5.4.1 Climate change and mitigation offsets

Species habitat offsets need to be effective in the long-term to avoid net loss of habitat and increased extinction risk. The literature on design of offsets for climate change is young and emerging, but suggests that offsets may be an effective conservation strategy in response to energy development, when species needs in multiple life history stages and across their full range are properly considered (Bull et al. 2013). The literature on protected areas planning for climate change, adaptation to climate change, and assessment of species response to climate change all offer insights that are transportable to offset design (Hannah et al. 2005; Kiesecker et al. 2009).

Higher mitigation offset ratios are commonly used to cope with uncertainty and to ensure future durability of offsets, and are a highly relevant tool for incorporating climate change concerns into offset planning (Bull et al. 2013; Overton et al. 2013). However, without specific climate change assessment, very large ratios may be needed because of the considerable uncertainty (both between present and future and between future scenarios) associated with climate change. Specifically assessing and planning for climate change can potentially reduce area requirements associated with offset ratios.

The challenge in siting offsets is to capture habitat that is currently suitable for the species as well as habitat that will be suitable in the future. The simplest way to do this is to select offset areas that are currently suitable for the species and remain suitable as climate changes (sometimes referred to as "stable range"). An alternative is to conserve portions of the present range of the species, portions of its future range and all intervening connecting suitable habitat to allow the species to move from its present range to future suitable conditions. This latter option presents a much more complex planning problem (even for a single species) and always carries much higher uncertainty.

CHAPTER 6:
Modeling Cumulative Effects of Solar Energy Development

6.1 Background

As presented in Chapter 1, The Council for Environmental Quality defines cumulative effects as "... the impact on the environment which results from the incremental impact of the action when added to other past, present, and reasonably foreseeable future actions regardless of what agency (Federal or non-Federal) or person undertakes such actions" (40 CFR 1508.7). Cumulative effect assessment (CEA) is not a new concept and many approaches have been developed ranging from conceptual and qualitative approaches to heavily quantitative and analytical approaches. In addition, various entities have attempted to provide guidance on how to go about doing CEA, each attempting to tailor the approach to the resource of concern and the constituency for which that resource affects and how that constituency, in turn, affects it.

Numerous federal environmental laws, specifically the National Environmental Policy Act (NEPA) require cumulative impacts assessment; however, a consistent and well-defined approach is typically lacking. The federal judicial system has generally focused on whether federal agencies have met the requirements of the law, not on the technical validity of the CE analyses (Sample 1991; Thatcher 1990).

6.1.1 CEA for Renewable Energy Development in Arid Environments

The effects of utility-scale solar energy development fall into two temporal categories, effects associated with construction and decommissioning activities and those that result from long term operation of these facilities. The former include direct mortality of wildlife, impacts of fugitive dust and dust suppressants, destruction and modification of habitat, including the impacts of roads and offsite material acquisition, processing, and transport (Lovich and Ennen 2011). The operational effects associated with this type of development include habitat fragmentation and barriers to gene flow, increased noise, electromagnetic field generation, microclimate alteration, pollution, water consumption, and fire (Lovich and Ennen 2011). Such effects have received only limited study in the deserts of the Southwest. For example, there have been very few studies on the population genetic consequences of habitat fragmentation related to utility-scale solar energy development. The project team is only beginning to understand the implications of large scale solar energy installations on animal behavior and mortality risk. Major unanswered questions remain about cumulative effects of such development, for example the relative environmental effects of concentrated or dispersed facilities.

Some work has begun considering utility-scale solar project effects into CEA for sensitive desert species. A conceptual model has been developed that assesses the risks to the desert tortoise using expert assessment and a population matrix model (Darst et al. 2013; Doak et al. 1994). In addition, an open source software tool called the Conceptual Model Manager was developed as a graphical display that shows direct and indirect threats, population effects and recovery

actions, and allows users to determine weights that prioritize recovery actions based on threats (Darst et al. 2013).

Invasive species invasions are a potential threat in arid climates and have the potential to have far-reaching cumulative effects. In principle, CEA approaches should account for the cumulative effects of disturbance associated with numerous energy developments and its ability to facilitate colonization and re-colonization of invasive species (Evangelista et al. 2011). Invasive species invasions can be difficult if not impossible to contain once they have commenced, thus minimizing development in landscapes prioritized for conservation is the most effective way to prevent potential new invasions (Mack et al. 2000).

Cumulative effects on sensitive birds may be substantial but difficult to predict. Bird mortality results from tall human-built infrastructure associated with energy development such as power poles and power lines. Also, support infrastructure such as cell towers to facilitate communication in remote areas of the Mojave Desert could produce a direct or indirect cumulative impact on desert bird populations, whether they be resident or migratory (Boyce and Naugle 2011). Recent observations suggest even migratory waterfowl may be at risk, perhaps mistaking large solar panel fields for open water.

The greatest challenge in analyzing cumulative effects is understanding and predicting the effects of numerous interactions of system elements and their indirect effects (Dixon and Montz 1995). For instance, energy development may increase the number of raptor perches causing increased predation rates on breeding and nesting sage grouse (Aldridge and Boyce 2007; Fletcher et al. 2003). Coyote populations may increasing because altered landscapes support higher populations of small mammals , causing increased predation on species of conservation concern such as kit foxes (Haight et al. 2002). Indirect effects may also manifest themselves as harmful avoidance behavior such as avoidance of roads or well sites, notably for ungulates such as Desert bighorn sheep.

6.2 Overview of the Cumulative Effects Assessment Framework Developed for this Project

Our approach to cumulative effects assessment is a compromise between the need to reflect current knowledge and understanding of the ecology of desert species at appropriate spatial and temporal scales and the need for a relatively simple and repeatable, spatially explicit process that can be applied to multiple species across a large planning region using available data. Essentially, the team's approach is to evaluate energy development in terms of its onsite and offsite impacts on species' habitat extent, location and condition, integrate species-specific effects across multiple species of concern, and place those impacts in the context of projected climate and land use change.

Table: 8 positions the project's approach to the typology proposed by Spaling (1994). Key elements of this approach are:

- Consideration of renewable energy impacts in the context of projected climate and land use change

- GIS-based mapping of expected impacts based on the ecological condition model described in Chapter 2, species distribution models described in Chapters 3 and 4, and development offsets model described in Chapter 5
- Ability to evaluate and directly compare scenarios based on alternative climate forecasts, land use change, and siting of renewable energy projects
- Static rather than dynamic modeling of environmental condition (Chapter 2)
- Static analysis of species' distributions based on statistical association of species occurrence and environmental conditions (SDM), rather than via dynamic modeling of population processes such as birth, death and dispersal.

Table 10: Typology of cumulative effects: sources, pathways, and effects

Attribute	Sub-Attributes	This study
Sources		
Temporal		
Scale	Short-term, Long-term	Long- term (Present-2050)
Frequency	Discontinuous, Continuous	Discontinuous. Sequencing of change between present and mid-century not considered.
Spatial		
Scale	Local, Regional, Global	Regional domain, fine grain (270m)
Density	Clustered, Dispersed	Clustered and dispersed (Clustered development impacts, dispersed climate impacts)
Configuration	Point, Linear, Areal	Areal. All impacts are represented at 270m model scale.
Perturbation		
Type	Similar, Different	Impact on wild species from climate change, urban development and renewable energy development.
Quantity	Single, Multiple	Multiple areas affected, multiple energy projects
Pathways	Additive, interactive	Additive climate change, solar development and land use change effects on species habitat suitability. Species modeled separately with no species interactions.
Effects		
Structural	Spatial- space crowding, cross-boundary movement, fragmentation	Habitat degradation and fragmentation. Both local and offsite effects considered.
Temporal	Time-crowding, time lags	No time lags

Our cumulative effects framework integrates all project components discussed up to this point into a coherent modeling framework that combines modeling of current and future environmental condition, current and future species distributions, and evaluation of the relative conservation importance of every part of the planning region with respect to conservation features of interest. Through the condition index, the model incorporates both direct onsite effects of development as well as offsite effects such as new transmission corridors and edge effects. The effects of multiple energy projects are measured as the change in landscape conservation value for individual species as well as multiple species based on changes in land

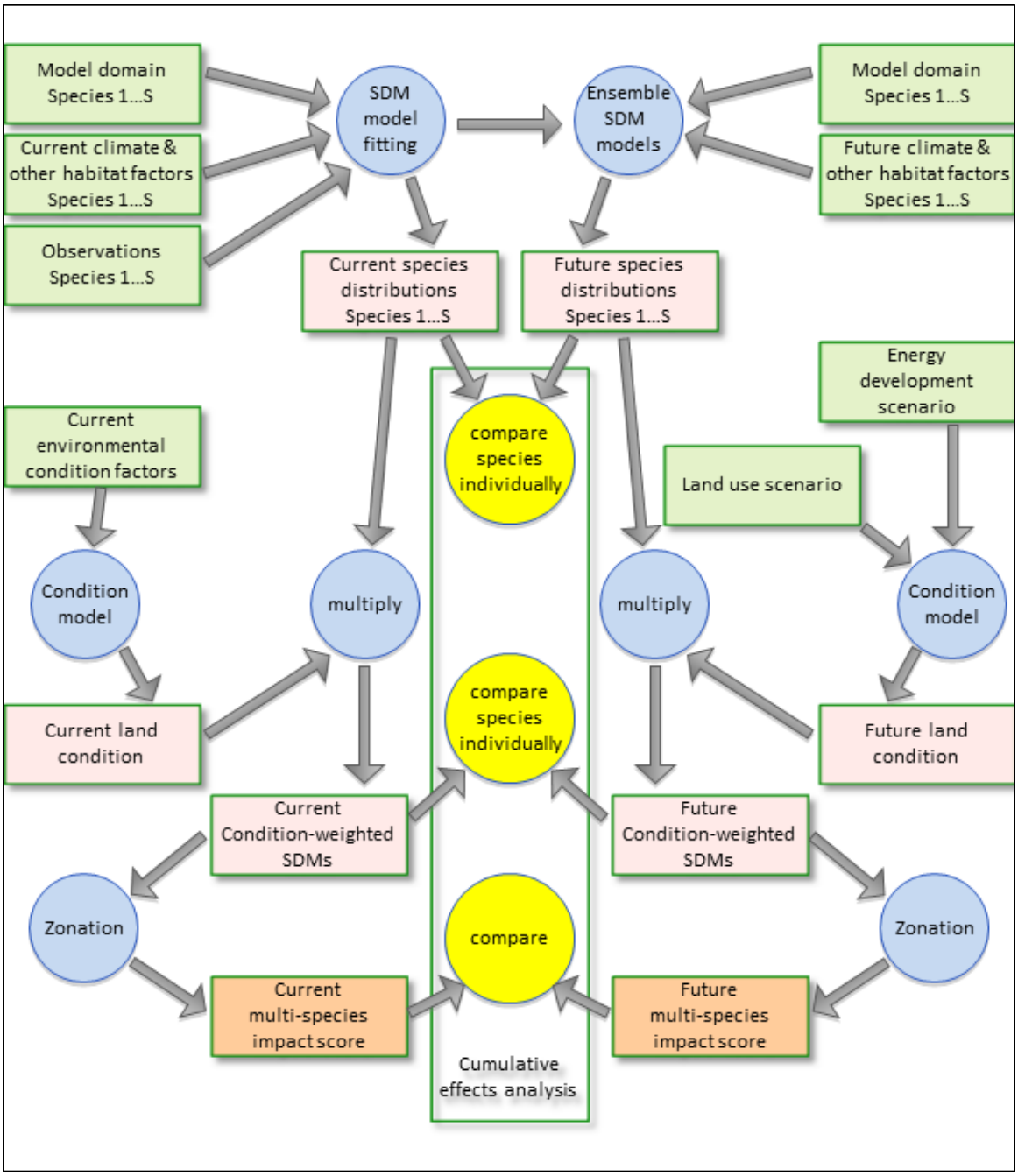
condition, amount and quality of species habitat, and ultimately in the distribution and extent of important conservation lands as revealed through Zonation analysis.

There are many processing steps required to develop the multi-species cumulative effects analysis. At a minimum, the approach uses three public-domain software libraries or tools: the **R** Statistics Library, **Maxent**, and **Zonation**. The commercial ArcGIS software is also valuable for spatial data management and visualization.

Model processing flow is graphically depicted in Figure 26. Initial inputs reflect a series of important choices. These include the delineation of the planning area (model domain and spatial resolution) and selection of focal species. As discussed in Chapter 3, constructing species distribution models for each species requires a number of decisions such as choice of observation data and treatment of potential sampling bias, choice of predictor variables, scale of spatial filtering for evaluating habitat suitability, choice of SDM modeling algorithm (e.g., Maxent vs Maxlike) and choice of threshold criterion for converting probability of occurrence to binary presence-absence maps. Spatially explicit scenarios of climate change, land use change, and renewable energy development must also be selected.

There is no attempt to model the population dynamics of the species or to explicitly model dispersal-mediated habitat connectivity. Approaches such as metapopulation models (e.g., **Ramas GIS**) and individual based models (e.g., **Hexsim**) were considered however there is simply not enough biological information to parameterize such models for most of the species. Similarly, there is not enough information on dispersal behavior for most of the species to construct connectivity models using **Circuitscape** (McRae 2006) or least cost path approaches (Beier et al. 2011). Other researchers have applied these more complex modeling approaches to a few high profile species such as desert tortoise and desert bighorn sheep. The project team's cumulative effects framework is complimentary to those more biologically detailed single-species models.

Figure32: Processing flow for cumulative effects analysis.



Green boxes represent model inputs, blue circles represent modeling operations, pink boxes represent intermediate products of modeling steps, and orange and yellow boxes and circles represent final steps and products of the analysis.

6.3 Worked Example for the Western Mojave Subregion

The project team demonstrated the cumulative effects approach for the Western Mojave subregion described in Chapter 5 (Figure 27). Their purpose is to illustrate the kinds of analyses that are possible with available tools and data from this project. *The example is hypothetical and resulting maps and statistical summaries should not be construed as an assessment of actual cumulative impacts or specific mitigation priorities.*

To simplify the analysis for interpretation and display purposes the team focused on 17 plant and animal species of high conservation concern (Table 9).

The cumulative impact analysis involved the construction of four models:

1) a **baseline model** that characterizes current (~2010) land use, bioclimate, ecological condition, modeled species distributions, and the spatial pattern of single species conservation value and multispecies conservation value across the planning region for the species of interest;
2) a **baseline + solar development** model that adds currently approved or proposed solar projects and adjusts current ecological conditions accordingly before modeling species distributions, single species conservation value and multispecies conservation value. These are the same solar project sites used in Chapter 5 (Figure 27);
3) A **future without solar development** model that incorporates a projected business-as-usual (using current county general plans) land use scenario for 2050 as well as Species Distribution Models based on projected bioclimate conditions for the period 2040-2069. Land use change scenarios were provided by Jim Thorne (Thorne et al. 2012). Future land development was constrained to areas that are not designated public lands and other protected areas (Figure 33).
4) A **future with solar development** model that incorporates the projected business-as-usual land use scenario for 2050 but also includes the same approved or proposes projects used in model 2, as well as Species Distribution Models based on projected bioclimate conditions for the period 2040-2069.

6.3.1 Models of current and future conditions

The study area is already degraded and in some areas highly impacted by urban and residential development, current and historical agriculture, roads, and other disturbances (Figure 28; see Chapter 2). Existing impacts such roads, urban and residential areas are especially extensive in the western and southern portions of the study area that include Lancaster, Palmdale and Victorville (Figure 28).

Most proposed and permitted solar projects are concentrated in areas that are already impacted; so that the team's scenario of solar development produces only modest changes in regional patterns of land condition (Figure 28).

The business-as-usual land use projection locates extensive new development near existing population centers and leaves little remaining natural habitat in the southern third of the study

region by 2050 (Figure 28). This extensive land transformation would overshadow currently proposed solar projects over most of the study region.

Combining species distribution models with current land condition indicates that many species have already experienced significant reductions in available habitat, especially those whose habitats are mainly in the western and southern portions of the region. Even species such as Mohave ground squirrel and desert tortoise, whose distributions extend to and beyond the eastern and northeastern parts of the region, are predicted to have experienced reductions of 30-40 percent in condition-weighted habitat area beyond what is captured by current wildlife habitat type maps (Table 11, Figure 29, and Figure 30). Permitted and proposed solar projects have little effect on remaining habitat: Species with significant habitat in the northwestern (tricolored blackbird, burrowing owl) and eastern (e.g., Mohave ground squirrel) parts of the region register the greatest impact of proposed developments but the portion of range effected is still only 2-4 percent of current condition-weighted habitat (Figure 30).

Mid-century climate projections indicate the potential for significant changes in the geographic distribution of suitable habitats for many species. *On average, the 17 case study species lose 81 percent of current suitable habitat in the Western Mojave to projected climate and land use change by the mid-century.* Habitats for some species such as Mohave ground squirrel are projected to contract (Figure 29, Figure 30) while others such as burrowing owl and Swainson's hawk are projected to expand as new areas become suitable (Figure 30). A few species with little or no baseline habitat are predicted to increase in the region under climate change, including California black rail, least Bell's vireo, and Mojave fringe-toed lizard.

The mid-century species distribution models show moderate-to-high concordance, as illustrated by the models for Mojave ground squirrel where at least 2/3 and frequently 3/3 models project similar range shifts. In addition to climate-driven changes, land use change also accounts for significant habitat loss in the southern portion of the study region (Figure 35).

6.3.2 Changes in biodiversity and areas of high conservation value

Areas that support multiple species of conservation concern, especially large habitat blocks supporting multiple species, are highlighted using maps of species richness and **Zonation** rank. Species richness maps are especially informative in showing how climate change and land use change shift could potentially shift patterns of biodiversity over the next several decades (Figure 31). These shifts reflect the loss of climatically suitable habitat for several species in the central portion of the study region, the loss of habitat due to land use conversion in the southern and southwestern portion of the study area, and an increase in suitable habitats for several species in the westernmost Antelope Valley and along the southern foot slopes of the Tehachipi Ranges (Figure 31).

Maps of **Zonation** rank are more difficult to interpret but provide somewhat different insights into modeled changes in site conservation value. A removal order was imposed based on land ownership such that unprotected private (undesignated) lands are removed first (Gap Status 4 lands), followed by Gap Status 3 public lands, followed by Gap Status 2 and finally Status 1

lands (Stoms 2000). This results in the large blocks of Designated Lands always having the highest rank conservation values (Figure 32).

Figure 33: Map of the case study area showing a hypothetical set of solar projects as well as designated protected lands that were treated differently in the Zonation model of land conservation value.

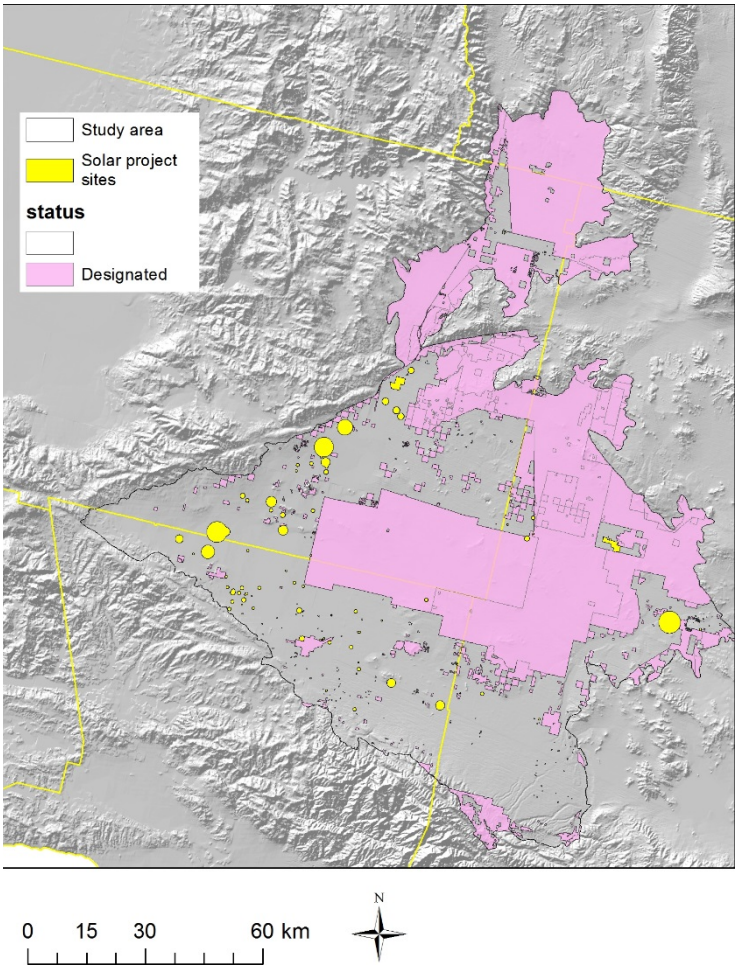
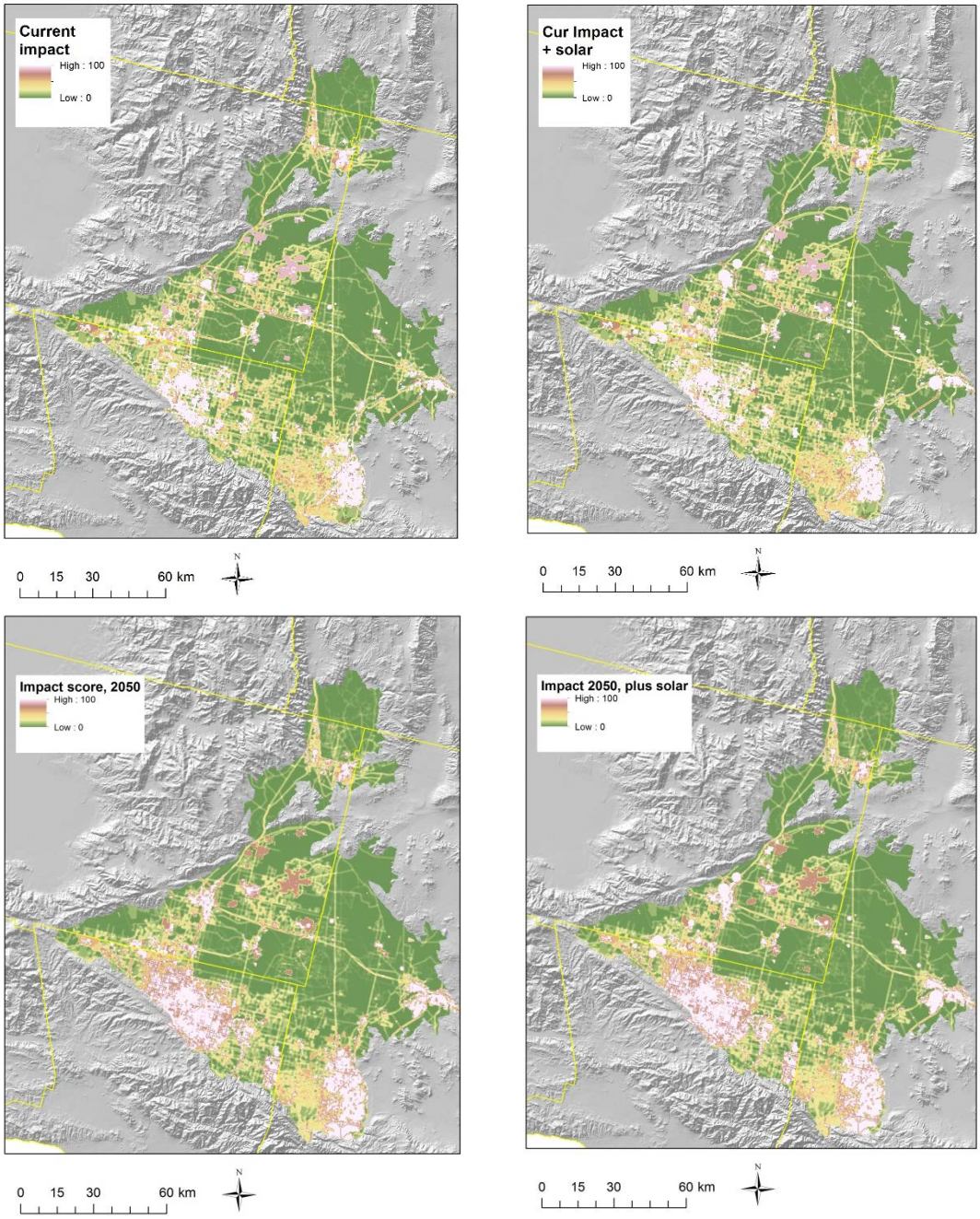


Table 11: List of species consider in the cumulative effects analysis.

Species	Name	Total habitat	Condition-weighted habitat	Mean habitat condition
Agelaius tricolor	Tricolored blackbird	21807	9475	0.434
Athene cunicularia	Burrowing owl	93374	51512	0.552
Buteo swainsoni	Swainson's hawk	93921	49587	0.528
Calochortus striatus	Alkali mariposa-lily	137	38	0.275
Cymopterus deserticola	Desert cymopterus	3513	1333	0.379
Empidonax traillii extimus	Southwestern willow flycatcher	10603	4932	0.465
Eriophyllum mohavense	Barstow woolly sunflower	6963	2497	0.359
Gopherus agassizii	Agassizii's desert tortoise	70308	48266	0.687
Laterallus jamaicensis coturniculus	California black rail	179	55	0.307
Melanerpes uropygialis	Gila woodpecker	20	7	0.325
Mimulus mohavensis	Mojave monkeyflower	5612	1515	0.270
Opuntia basilaris var treleasei	Bakersfield cactus	16218	9079	0.560
Penstemon albomarginatus	White-margined beardtongue	21	9	0.413
Toxostoma bendirei	Bendire's thrasher	13564	7905	0.583
Uma scoparia	Mojave fringe-toed lizard	1933	503	0.260
Vireo bellii pusillus	Least Bell's vireo	39346	20607	0.524
Xerospermophilus mohavensis	Mohave ground squirrel	85772	61619	0.718

Total habitat area (ha) is based on the thresholded (presence-absence) Maxent species distribution models (Chapter 3). Condition weighted habitat area is the weighted sum of cell habitat value (0,1) times the mean habitat condition (see Chapter 2). The same condition layer was applied to all species.

Figure 34: Ecological condition as represented in four models

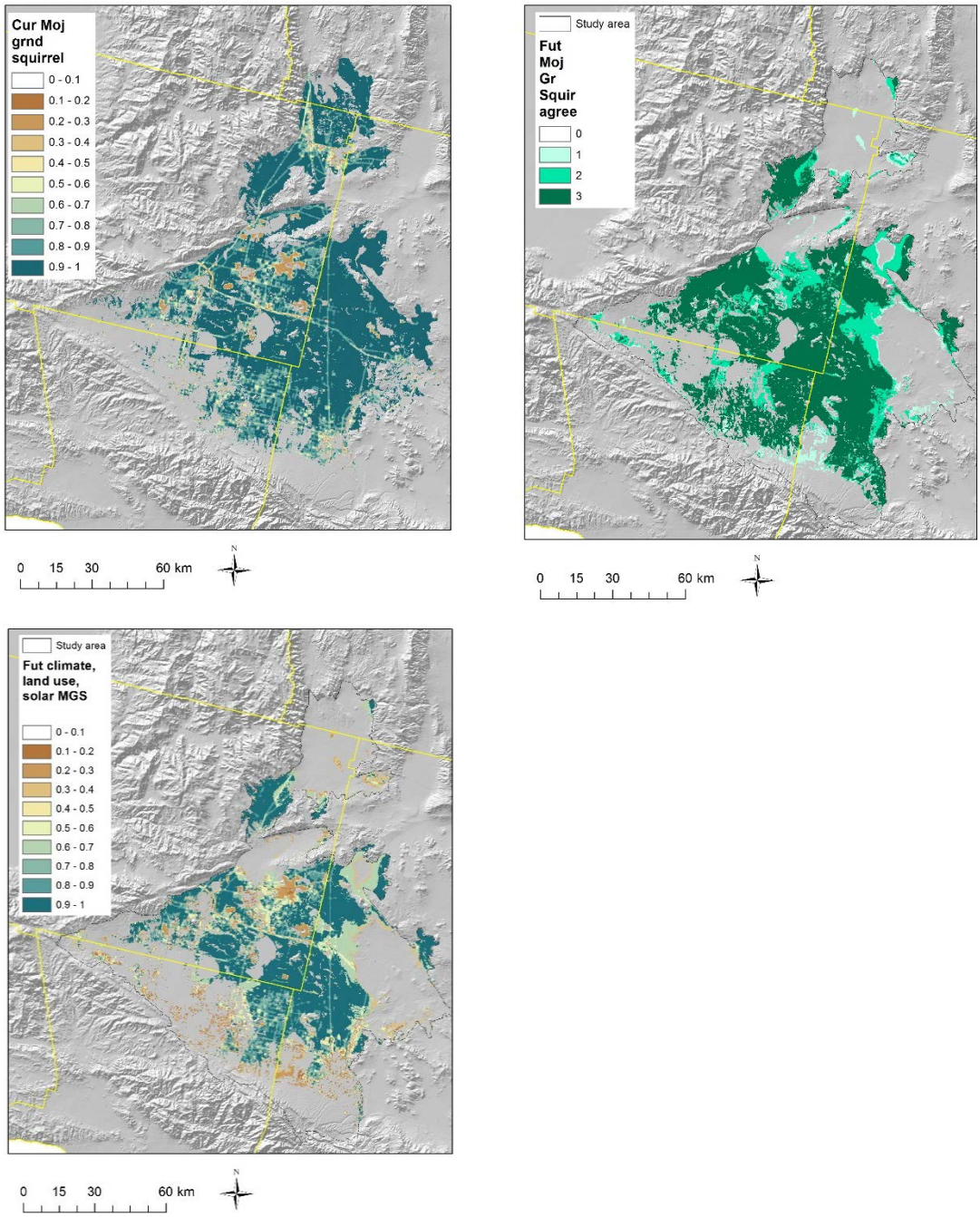


1) baseline conditions (upper left), 2) baseline plus approved or proposed solar projects (upper right), 3) mid-century based on projected land use change without solar projects (lower left), and 4) mid-century based on projected land use change plus approved or proposed solar projects.

The score, which ranges from 0-100, is identical to the "suitability for solar development" score described in Chapter 2 but is renamed here to highlight its use as a measure of level of impact on ecological condition. Extensive highly impacted areas are associated with Lancaster,

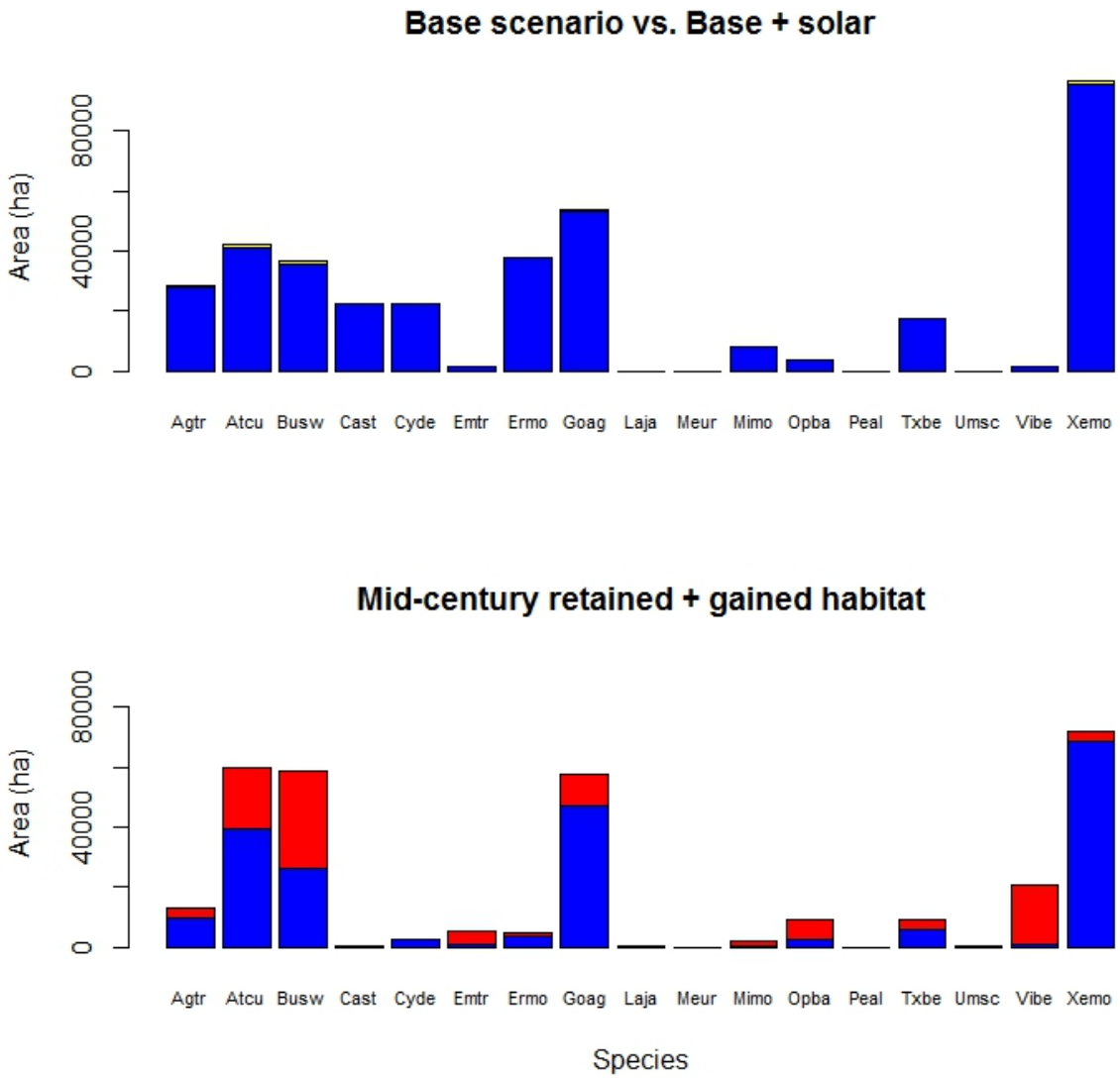
Palmdale, and Victorville in the southern and southeastern margins of the region. County boundaries are superposed as yellow lines.

Figure 35: Species distribution models for the Mojave ground squirrel



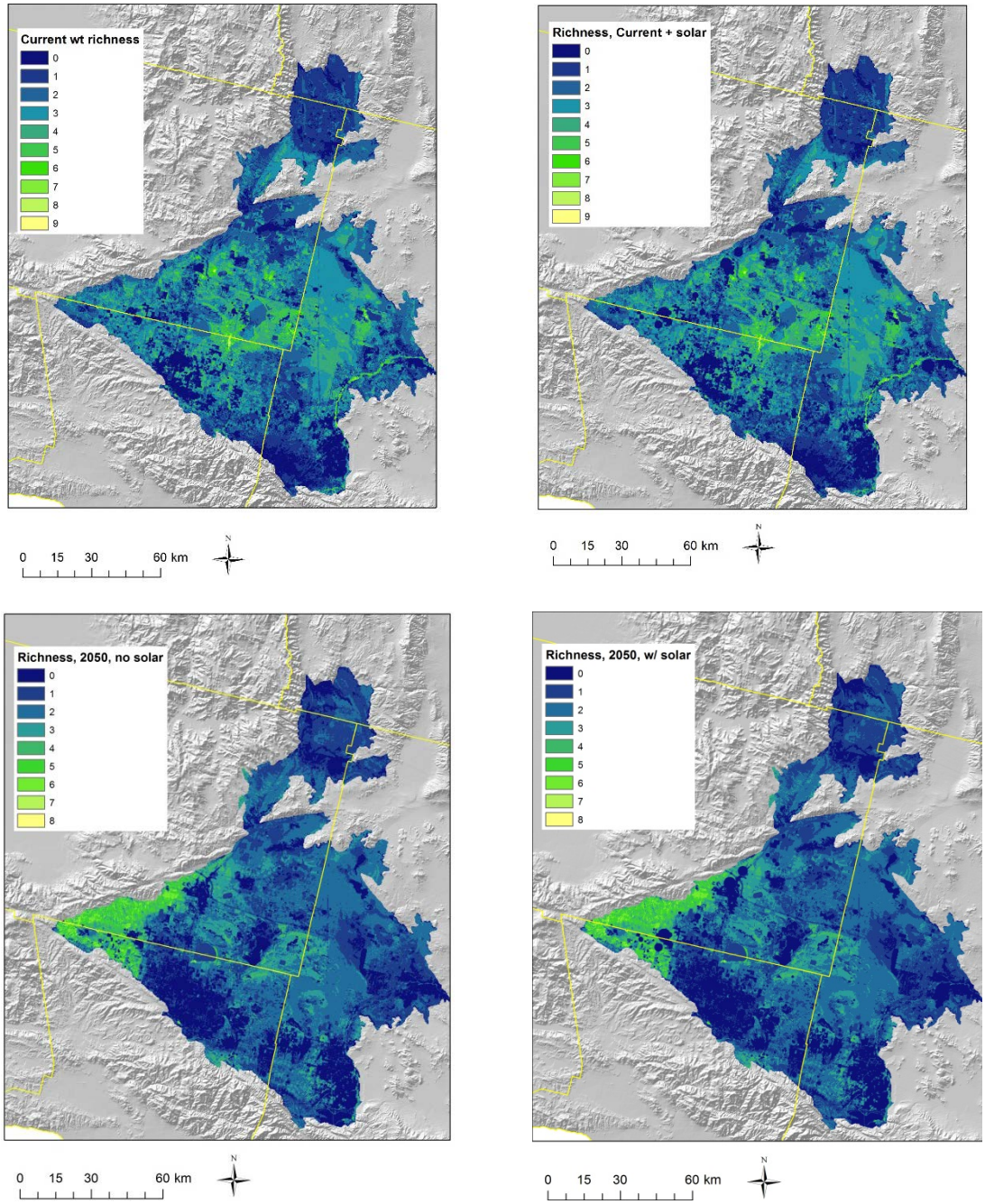
(Xerospermophilus mohavensis) based on presence-absence Maxent models (see Chapter 3) and condition models for the baseline model (upper left) and the mid-century projections.

Figure 36: Barplots summarizing changes in modeled species distributions as a result of proposed solar development and projected climate and land use change.



Species abbreviations are the first two letters of the genus and species names in Table 11. For example, Agtr is Agelaius *tricolor* (Tricolored blackbird). The upper plot shows the baseline, condition-weighted area (total bar height) and the amount that would be lost based on the solar projects shown in Figure 33 (yellow). The lower plot shows the projected mid-century condition- and concordance-weighted habitat area for each species including retained baseline habitat (blue) and projected new habitat (red).

Figure 37: Species richness patterns produced by summing condition-weighted



Maxent species distribution models for baseline conditions (upper left), baseline plus permitted and proposed solar projects (upper right), mid-Century projections of species distributions without solar projects (lower left) and with solar projects (lower right).

The most interesting areas in Figure 32 are those that are ranked low in the baseline scenario and show a significant increase in rank value in the mid-century projects, as well as those that show moderately high rank value in the baseline scenario and very low value in mid-century projections. One area that shows a significant increase is undeveloped lands between Lancaster and Victorville in the southeastern portion of the study region. This area is projected to provide new habitat for several species including willow flycatcher and least Bell's vireo (both riparian dependent species in an area with limited riparian habitat, so the emergence of improved habitat for these species is highly speculative). Another is the foothills of the Tehachipi Ranges southeast of the town of Tehachapi and west of the town of Mojave. This area is projected to provide stable or improved habitat for several species, for example Mohave ground squirrel (although much of the area is in wind farms).

Areas that show significant decrease in value include lands near existing urban centers such as Lancaster and Palmdale that are projected to experience significant new housing.

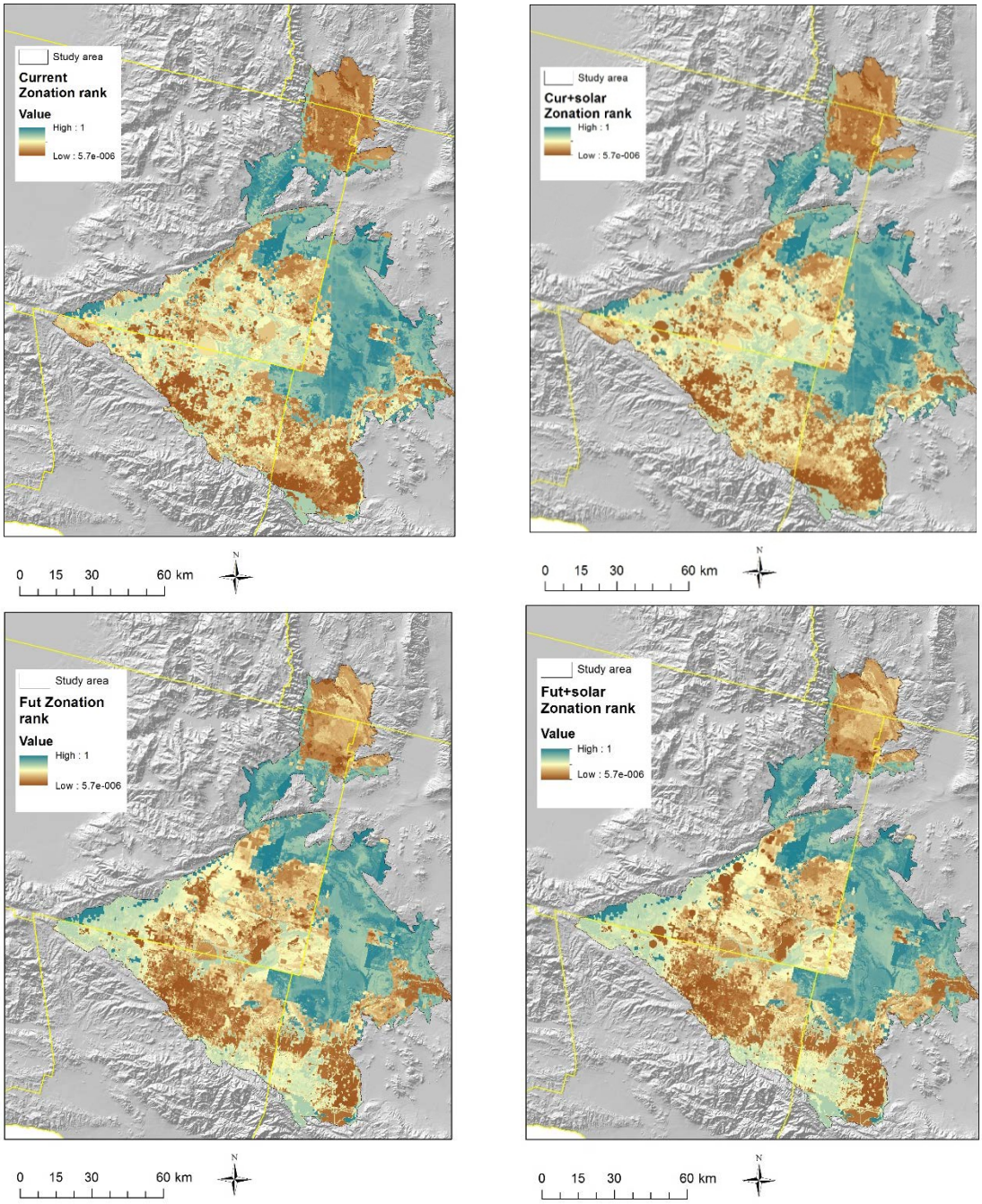
6.4 Discussion

In studying the intermediate and final products from the cumulative effects analysis a number of artifacts were discovered that were a result of idiosyncrasies of input environmental data or model rules, for example:

- Artifacts related to differences in the resolution and quality of soils data have already been discussed.
- The species-specific maps of WHR habitat suitability ratings were an important predictor variable in baseline Maxent models that were not used for mid-century distribution models because the project team did not project the mid-century distributions of those habitat types. This meant that for mid-century models the team had poor mapped representations of riparian and wetland environments that were based solely on hydrographic data and led to overly-generous predicted distributions for riparian and wetland species.
- The use of a generic condition layer is an over-simplication that also has undesirable consequences. For example, agriculture is assigned a low condition score. This produces unrealistically low scores in condition-weighted distribution models for species that use agricultural habitats, for example the Tricolored blackbird.
- Our mid-century land use projections are based on projected changes in housing density and thus do not capture associated changes in the landscape such higher road densities or changes in road type that in principle should also influence condition scores.

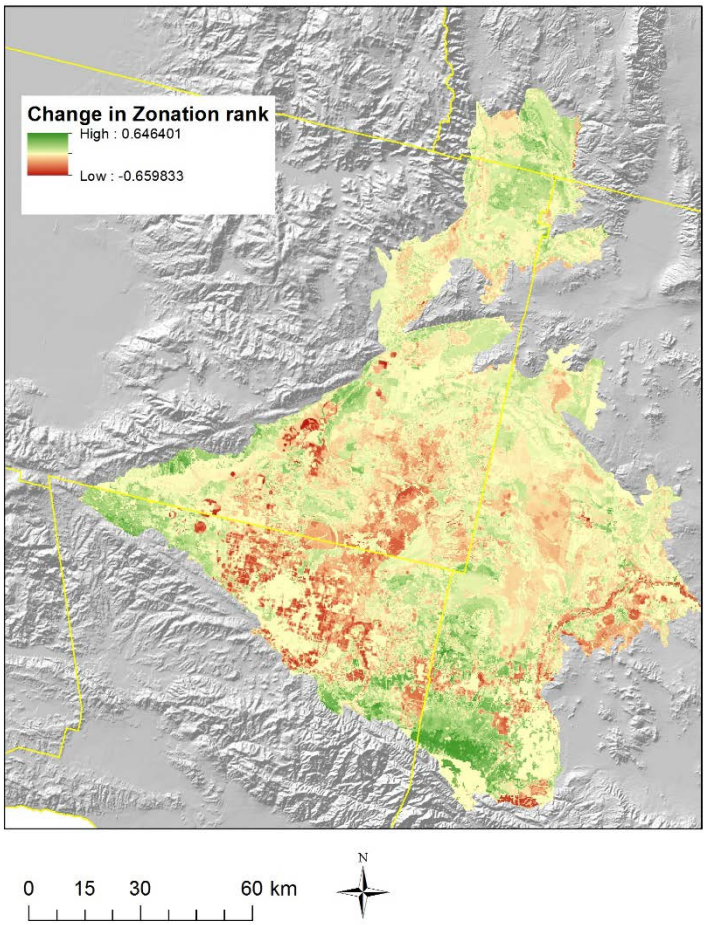
Despite these and other limitations, the cumulative effects analysis has produced several interesting results. *First, currently approved and proposed solar projects in the Western Mojave study area appear to have a relatively small impact on the study species or overall biodiversity patterns.*

Figure 38: Distribution of conservation value based on 17 focal species.



A hypothetical set of solar energy projects, a business-as-usual projection of urban and suburban land use change, and three downscaled global climate models. Four models include current ("baseline") conditions (upper left), baseline conditions plus proposed and approved solar energy projects (upper right), mid-century projections of land use and climate change (lower left), and mid-century projections of land use and climate change plus currently proposed and approved solar energy projects (lower right).

Figure 39: Change in Zonation removal rank based on comparison of the baseline model to mid-century model



Incorporating projected climate change, projected land use change, and currently proposed and permitted solar energy projects in the Western Mojave.

Dark green areas are areas with currently low conservation rank that are projected to increase greatly in value by mid-century. Red areas are areas that currently have relatively high conservation value and are projected to experience a significant loss in value due mainly to projected land use change and climate-driven changes in habitat suitability for multiple species of interest.

This is because most projects are located in areas mapped as low condition sites. *Also, model transmission corridors for these projects were not modeled.* Most projects are located near roads so the modeled offsite impacts associated with new transmission corridors were assumed to be modest.

The impact of projected land use change associated with residential development is much greater than solar development in this region. The business-as-usual development scenario reflects current county general plans and is thus likely to change. The development impact does highlight, however, the need to consider solar development in the broader context of ongoing land use change in the region, especially in siting mitigation offsets.

6.4.1 Climate change and cumulative effects analysis

Projected mid-century climate is significantly different from today's climate and the difference produces large changes in modeled distributions of the study species. This in turn leads to changes in apparent biodiversity conservation value over large landscapes in the study region. *Given the relatively small overlap between modeled species' habitats today vs. mid-century, maintaining regional habitat connectivity is an important consideration in evaluating cumulative impacts*. Slightly higher undeveloped lands around the margins of the Western Mojave also take on increased importance as future habitat for some species, as do lands at the northern end of the study region.

The cumulative effects analysis described here illustrates one approach to incorporating climate change for multiple species. As has been discussed at multiple points in this report, the input data and resulting indicators of cumulative impact on species habitats and site conservation value (e.g., Zonation rank) suffer from numerous sources of uncertainty that is compounded as the number of species increases. Expert opinion and examination of areas that appear to be important as stable range may help judge the actual conservation significance of these areas.

GLOSSARY

Term	Definition
AUC	Area under the receiver operating curve. AUC is a measure of model performance for a binary classifier, for example, a model that predicts species presence or absence. The Receiver Operating Characteristic (ROC) Curve is a plot of the rate of false positives versus the rate of true positives for different threshold values of the binary classifier. The area under the ROC curve evaluates to 1 for a perfect model and to 0.5 if the model is no better than chance.
CCSM4	Community Climate System Model 4
CMIP5	Coupled Model Inter-comparison Project. CMIP5 is a set of coordinated climate model experiments that supported the fifth assessment of the Intergovernmental Panel on Climate Change (IPCC). The set of climate model outputs resulting from this effort are often referred to as CMIP5 models.
CWHR	California Wildlife Habitat Relationship System
DRECP	Desert Renewable Energy Conservation Plan
FGOALS	Flexible Global Ocean-Atmosphere-Land System climate model
GFDL	Goddard Fluid Dynamics Laboratory climate model
IPSL CM5	Institut Pierre-Simon Laplace climate model
Maxent	Maximum Entropy (Maxent) model. Maxent uses methods from machine learning to analyze the co-variation between the distribution of species observations and predictor variables at those same locations relative to a set of "background samples" drawn at random from the study region.
Maxlike	A statistical method for estimating the probability of species' occurrence from presence-only data using a likelihood-based approach to model fitting.
PCM	Parallel Climate Model
RCP	Representative Concentration Pathway. One of four greenhouse gas concentration trajectories adopted by the Intergovernmental Panel on Climate Change for its fifth assessment.
SDM	Species distribution model
Zonation	Conservation planning software that uses an iterative removal algorithm to identify areas important for maintaining connectivity and habitat quality for multiple species in a planning region.

REFERENCES

Aldridge CL, Boyce MS (2007) Linking occurrence and fitness to persistence: habitat-based approach for endangered greater sage-grouse. Ecological Applications 17:508-526

Andreasen JK, O'Neill RV, Noss R, Slosser NC (2001) Considerations for the development of a terrestrial index of ecological integrity. Ecological indicators 1:21-35

Audubon California et al. (2009) Renewable Siting Criteria for California Desert Conservation Area

Austin MP (2002) Spatial prediction of species distribution: an interface between ecological theory and statistical modelling. Ecological Modelling 157:101-118

Beier P, Spencer W, Baldwin RF, McRae BH (2011) Toward Best Practices for Developing Regional Connectivity Maps. Conservation Biology 25:879-892. doi: 10.1111/j.1523-1739.2011.01716.x

Boyce MS, Naugle DE (2011) Energy development and wildlife conservation in western North America. Springer

Brooks ML, Matchett J (2006) Spatial and temporal patterns of wildfires in the Mojave Desert, 1980–2004. Journal of Arid Environments 67:148-164

Bull JW, Suttle KB, Singh NJ, Milner-Gulland E (2013) Conservation when nothing stands still: moving targets and biodiversity offsets. Frontiers in Ecology and the Environment 11:203-210

California Energy Commission (2012) Desert renewable energy conservation plan: renewable energy acreage calculator and the 2040 revised scenario's renewable portfolio, Sacramento, California

Cameron DR, Cohen BS, Morrison SA (2012) An Approach to Enhance the Conservation-Compatibility of Solar Energy Development. Plos One 7. doi: 10.1371/journal.pone.0038437

Carrión JA, Espín Estrella A, Aznar Dols F, Ridao AR (2008) The electricity production capacity of photovoltaic power plants and the selection of solar energy sites in Andalusia (Spain). Renewable Energy 33:545-552

Carroll C, Dunk JR, Moilanen A (2010) Optimizing resiliency of reserve networks to climate change: multispecies conservation planning in the Pacific Northwest, USA. Global Change Biology 16:891-904

Chandler R, Royle A, Chandler MR (2013) Package 'maxlike'.

Charabi Y, Gastli A (2011) PV site suitability analysis using GIS-based spatial fuzzy multi-criteria evaluation. Renewable Energy 36:2554-2561

Daly C et al. (2008) Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. International Journal of Climatology 28:2031-2064. doi: 10.1002/joc.1688

Darst CR et al. (2013) A Strategy for Prioritizing Threats and Recovery Actions for At-Risk Species. Environmental management 51:786-800

Dawson TP, Jackson ST, House JI, Prentice IC, Mace GM (2011) Beyond Predictions: Biodiversity Conservation in a Changing Climate. Science 332:53-58. doi: 10.1126/science.1200303

Dixon J, Montz BE (1995) From concept to practice: implementing cumulative impact assessment in New Zealand. Environmental management 19:445-456

Doak D, Kareiva P, Klepetka B (1994) Modeling population viability for the desert tortoise in the western Mojave Desert. Ecological Applications 4:446-460

Elith J et al. (2006) Novel methods improve prediction of species' distributions from occurrence data. ECOGRAPHY 29

Elith J, Phillips SJ, Hastie T, Dudík M, Chee YE, Yates CJ (2011) A statistical explanation of MaxEnt for ecologists. Diversity and Distributions 17:43-57

Ellison AM et al. (2005) Loss of foundation species: consequences for the structure and dynamics of forested ecosystems. Frontiers in Ecology and the Environment 3:479-486. doi: 10.1890/1540-9295(2005)003[0479:lofscf]2.0.co;2

Evangelista PH, Crall AW, Bergquist E (2011) Invasive plants and their response to energy development. Energy Development and Wildlife Conservation in Western North America. Springer, pp 115-129

Fielding AH, Bell JF (1997) A review of methods for the assessment of prediction errors in conservation presence/absence models. Environmental Conservation 24:38-49

Fitzpatrick MC, Gotelli NJ, Ellison AM (2013) MaxEnt versus MaxLike: empirical comparisons with ant species distributions. Ecosphere 4:art55

Fletcher QE, Dockrill CW, Saher DJ, Aldridge CL (2003) Northern harrier, Circus cyaneus, attacks on greater sage-grouse, Centerocercus urophasianus, in southern Alberta. The Canadian Field-Naturalist 117:479-480

Flint LE, Flint AL (2012) Downscaling future climate scenarios to fine scales for hydrologic and ecological modeling and analysis. Ecological Processes 1:1-15

Franklin J et al. (2013) Modeling plant species distributions under future climates: how fine scale do climate projections need to be? Global Change Biology 19:473-483. doi: 10.1111/gcb.12051

Franklin J, Miller JA (2009) Mapping species distributions: spatial inference and prediction. Cambridge University Press Cambridge

Gibbons P, Lindenmayer DB (2007) Offsets for land clearing: No net loss or the tail wagging the dog? Ecological Management & Restoration 8:26-31

Goudey CB, Smith DW (1994) Ecological units of California:subsections. USDA Forest Service, Pacific Southwest Region and Natural Resources Conservation Service, Washington, D.C.

Haight RG et al. (2002) Optimizing habitat protection using demographic models of population viability. Conservation Biology 16:1386-1397

Hall A et al. (2012) Mid-Century Warming in the Los Angeles Region-Part I of the "Climate Change in the Los Angeles Region" projec.

Hannah L, Midgley G, Hughes G, Bomhard B (2005) The view from the Cape: Extinction risk, protected areas, and climate change. BioScience 55:231-242

Hernandez R et al. (2014) Environmental impacts of utility-scale solar energy. Renewable and Sustainable Energy Reviews 29:766-779

Janke JR (2010) Multicriteria GIS modeling of wind and solar farms in Colorado. Renewable Energy 35:2228-2234

Kiesecker JM, Copeland H, Pocewicz A, McKenney B (2010) Development by design: blending landscape-level planning with the mitigation hierarchy. Frontiers in Ecology and the Environment 8:261-266. doi: 10.1890/090005

Kiesecker JM et al. (2009) A Framework for Implementing Biodiversity Offsets: Selecting Sites and Determining Scale. Bioscience 59:77-84. doi: 10.1525/bio.2009.59.1.11

Kiesecker JM et al. (2011) Win-win for wind and wildlife: a vision to facilitate sustainable development. PloS one 6:e17566

Leu M, Hanser SE, Knick ST (2008) The human footprint in the west: A large-scale analysis of anthropogenic impacts. Ecological Applications 18:1119-1139. doi: 10.1890/07-0480.1

Liu C, White M, Newell G (2013) Selecting thresholds for the prediction of species occurrence with presence - only data. Journal of Biogeography

Lobo JM, Jiménez - Valverde A, Real R (2008) AUC: a misleading measure of the performance of predictive distribution models. Global Ecology and Biogeography 17:145-151

Lovich JE, Ennen JR (2011) Wildlife conservation and solar energy development in the desert Southwest, United States. BioScience 61:982-992

MacDonald LH (2000) Evaluating and managing cumulative effects: process and constraints. Environmental management 26:299-315

Mack RN, Simberloff D, Mark Lonsdale W, Evans H, Clout M, Bazzaz FA (2000) Biotic invasions: causes, epidemiology, global consequences, and control. Ecological applications 10:689-710

Maron M et al. (2012) Faustian bargains? Restoration realities in the context of biodiversity offset policies. Biological Conservation 155:141-148

McRae BH (2006) Isolation by resistance. Evolution 60:1551-1561

Moilanen A (2007) Landscape Zonation, benefit functions and target-based planning: Unifying reserve selection strategies. Biological Conservation 134:571-579. doi: 10.1016/j.biocon.2006.09.008

Moilanen A (2012) Planning impact avoidance and biodiversity offsetting using software for spatial conservation prioritisation. Wildlife Research

Moilanen A, van Teeffelen AJA, Ben-Haim Y, Ferrier S (2009) How Much Compensation is Enough? A Framework for Incorporating Uncertainty and Time Discounting When Calculating Offset Ratios for Impacted Habitat. Restoration Ecology 17:470-478. doi: 10.1111/j.1526-100X.2008.00382.x

Neelin JD, Langenbrunner B, Meyerson JE, Hall A, Berg N (2013) California winter precipitation change under global warming in the Coupled Model Intercomparison Project 5 ensemble. Journal of Climate

Overton JM, Stephens RT, Ferrier S (2013) Net present biodiversity value and the design of biodiversity offsets. Ambio 42:100-110

Phillips SJ, Anderson RP, Schapire RE (2006) Maximum entropy modeling of species geographic distributions. Ecological modelling 190:231-259

Phillips SJ, Dudík M (2008) Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. Ecography 31:161-175

Phillips SJ et al. (2009) Sample selection bias and presence-only distribution models: implications for background and pseudo-absence data. Ecological Applications 19:181-197

R Core Team (2012) R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN: 3-900051-07-0

Royle JA, Chandler RB, Yackulic C, Nichols JD (2012) Likelihood analysis of species occurrence probability from presence-only data for modelling species distributions. Methods in Ecology and Evolution 3:545-554. doi: 10.1111/j.2041-210X.2011.00182.x

Sample VA (1991) Assessing cumulative environmental impacts: the case of National Forest planning. Envtl. L. 21:839

Scott JM (ed) (2002) Predicting species occurrences: issues of accuracy and scale. Island Press, Washington, D.C.

Scott JM et al. (1993) Gap analysis: A geographic approach to protection of biological diversity. Wildlife Monographs 123:1-41

Spaling H (1994) Cumulative effects assessment: concepts and principles. Impact Assessment 12:231-251

Spencer W et al. (2010) Recommendations of independent science advisors for the California desert renewable energy conservation plan (DRECP). Prepared for: Renewable Energy Action Team. Conservation Biology Institute, Corvallis, OR. Available at: http://www. energy. ca. gov/2010publications/DRECP-1000-2010-008/DRECP-1000-2010-008-F. PDF (accessed 29 October 2012)

Stoms DM (2000) GAP management status and regional indicators of threats to biodiversity. Landscape Ecology 15:21-33

Stralberg D et al. (2009) Re-shuffling of species with climate disruption: a no-analog future for California birds? PloS one 4:e6825

Syphard AD, Franklin J (2009) Differences in spatial predictions among species distribution modeling methods vary with species traits and environmental predictors. Ecography 32:907-918

Syphard AD, Franklin J (2010) Species traits affect the performance of species distribution models for plants in southern California. Journal of Vegetation Science 21:177-189

Ten Kate K, Bishop J, Bayon R (2004) Biodiversity offsets: Views, experience, and the business case. IUCN--The World Conservation Union

Thatcher TL (1990) Understanding interdependence in the natural environment: some thoughts on cumulative impact assessment under the National Environmental Policy Act. Envtl. L. 20:611

Thorne JH, Bjorkman J, Roth N, University of California D (2012) Urban Growth in California: Projecting Growth in California (2000-2050) Under Six Alternative Policy Scenarios and Assessing Impacts to Future Dispersal Corridors, Fire Threats and Climate-sensitive Agriculture. California Energy Commission

Webb RH, Belnap J, Thomas K (2009) Natural recovery from severe disturbance in the Mojave Desert. The Mojave Desert: Ecosystem Processes and Sustainability:343

Wiens JA, Stralberg D, Jongsomjit D, Howell CA, Snyder MA (2009) Niches, models, and climate change: Assessing the assumptions and uncertainties. Proceedings of the National Academy of Sciences of the United States of America 106:19729-19736. doi: 10.1073/pnas.0901639106

Wilson KA, Carwardine J, Possingham HP (2009) Setting Conservation Priorities. Year in Ecology and Conservation Biology 2009, vol 1162, pp 237-264

APPENDICES

Appendix A: Details of GIS Compatibility Modeling

Appendix B: Summary of Maxent Models

Appendix C: Mojavset Users Manual

These appendices are available as a separate volume, publication number CEC-500-2015-062-AP.