Mapping risk to minimize impacts from solar energy development in the California Deserts

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1.0 Purpose

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 has not been completed. Once conservation plans are completed, they will identify the sites of greatest ecological importance that should be off-limits to energy projects. In the interim, there is a great need to map sites that energy developers and conservation interests can agree have low potential conservation value and thus can avoid 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 a prescriptive binary map that declares where solar projects would not be allowed based on solely conservation value. They prefer to be informed of the decision risk and then make an informed business decision that considers all relevant factors.

The purpose of this document is to present an assessment method for modeling the relative degree of risk from new solar energy projects in the Mojave and Sonoran Deserts of southern California. We use the term "risk" as both the risk of loss of conservation values from solar energy development and as risk that solar developers may face stiff opposition from biodiversity conservation interests or high mitigation costs from siting projects. Although the two forms of risk are perceived from opposite directions, both share a similar measurement of the potential for conflict. For simplicity, we use "risk" for the remainder of this document.

This work, performed at the Biogeography Lab (http://www.biogeog.ucsb.edu/) at the University of California Santa Barbara (UCSB), was funded by the California Energy Commission PIER program. In developing the GIS tools to model risk, we incorporated the logic that highly degraded sites close to infrastructure would have the least potential value for biodiversity conservation (Audubon California et al. 2009, Kiesecker et al. 2011). Because of the large geographic scale, the analysis is dependent upon standardized, publicly available spatial data sets of land uses. Large-scale mapping of land uses will tend to miss some existing disturbances, such as off-road vehicle tracks through the desert. For the purposes of mapping risk, however, such errors of omission (ground conditions are more degraded than indicated by the model) 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). Therefore we have consciously taken a conservative approach 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, we have scaled scores by the following standard:

Higher score = lower risk = more likely suitable for solar development

The document 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:

1. The logic of how the criteria are assembled and combined
2. The spatial data—are there better sources? Are any key data missing?
3. Usefulness of the products—do they provide stakeholders with the right level of detail and accuracy?

The model and mapped outputs represent the final iteration following the validation and review processes.

1.1. What this model is not

Please note that this modeling only addresses potential conflict with biological resources based on ecological condition. It is not a complete assessment of suitability for solar energy development. However, this 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 comprehensive siting decisions.

The model is also not a comprehensive assessment of biological conservation value. No biological observations, species distribution models, or critical habitat designations 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. Our product is intended to complement the DRECP.

1.2. Disclaimer

The University of California makes no warranty, expressed or implied, as to the use or appropriateness of use of the data, nor are there warranties of merchantability or fitness for a particular purpose or use. No representation is made as to the currency, accuracy or completeness of the data set or of the data sources on which it is based. The University of California shall not be liable for any lost profits or consequential damages, or claims against the user by third parties.

2.0 Methods

2.1. Choice of study area, data type, and spatial resolution

Our study was charged with assessing the California Deserts and not 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 has not been mapped and was therefore excluded.

The relative ecological condition data layer generated from this analysis was also intended to be used in other phases of the overall study, including species distribution modeling, offset modeling, and cumulative impact assessment. To be most useful for these other tasks, 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 low-risk sites for solar energy projects, which typically require a minimum of 15 hectares, this resolution was considered adequate. The raster format is used in most species distribution modeling approaches. Furthermore the data must cover all lands in the study region, not just sites with good solar potential.

2.2. "Logic network"

In fragile ecosystems such as the California Deserts where the initial generation of utility-scale solar projects will be centered, 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 (Audubon California et al. 2009). Therefore the first level of our logic network for evaluating risk is to determine 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 1).

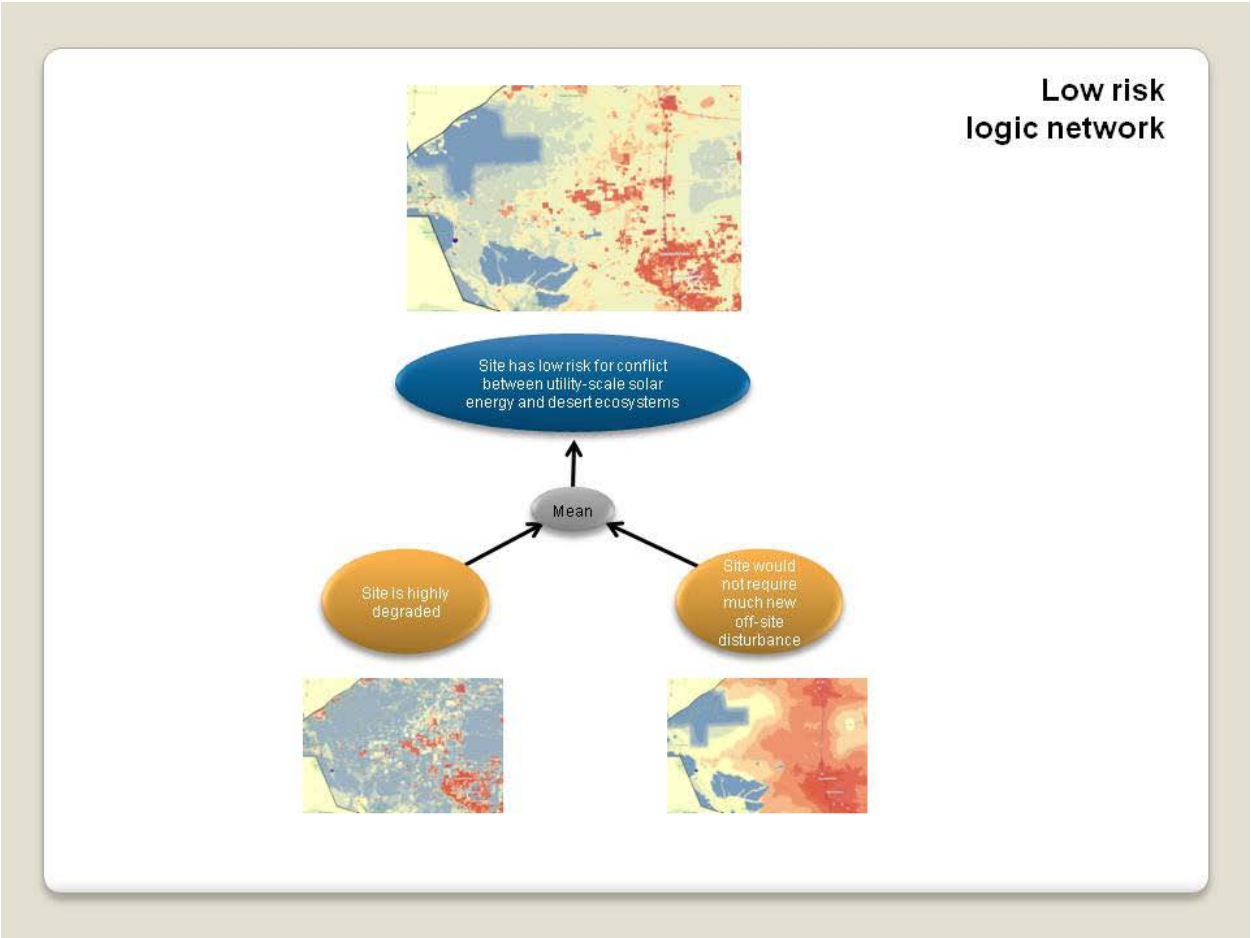

Figure 1. Top level of the logic network showing overall rating of biological risk based on-site degradation and off-site disturbance. In all map inserts, red indicates lowest potential risk to biological resources, and blue is the highest potential risk. Only the western Mojave Desert is shown to allow details to be seen.

2.2.1. 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 change in general ecological condition or landscape integrity. Specifically, degradation was modeled in terms of removal of vegetative cover (impacted native cover) and degree of habitat fragmentation (Figure 2). Scores were scaled such that the most degraded sites were rated highest, the best for solar development from the perspective of minimizing biological risk. 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.

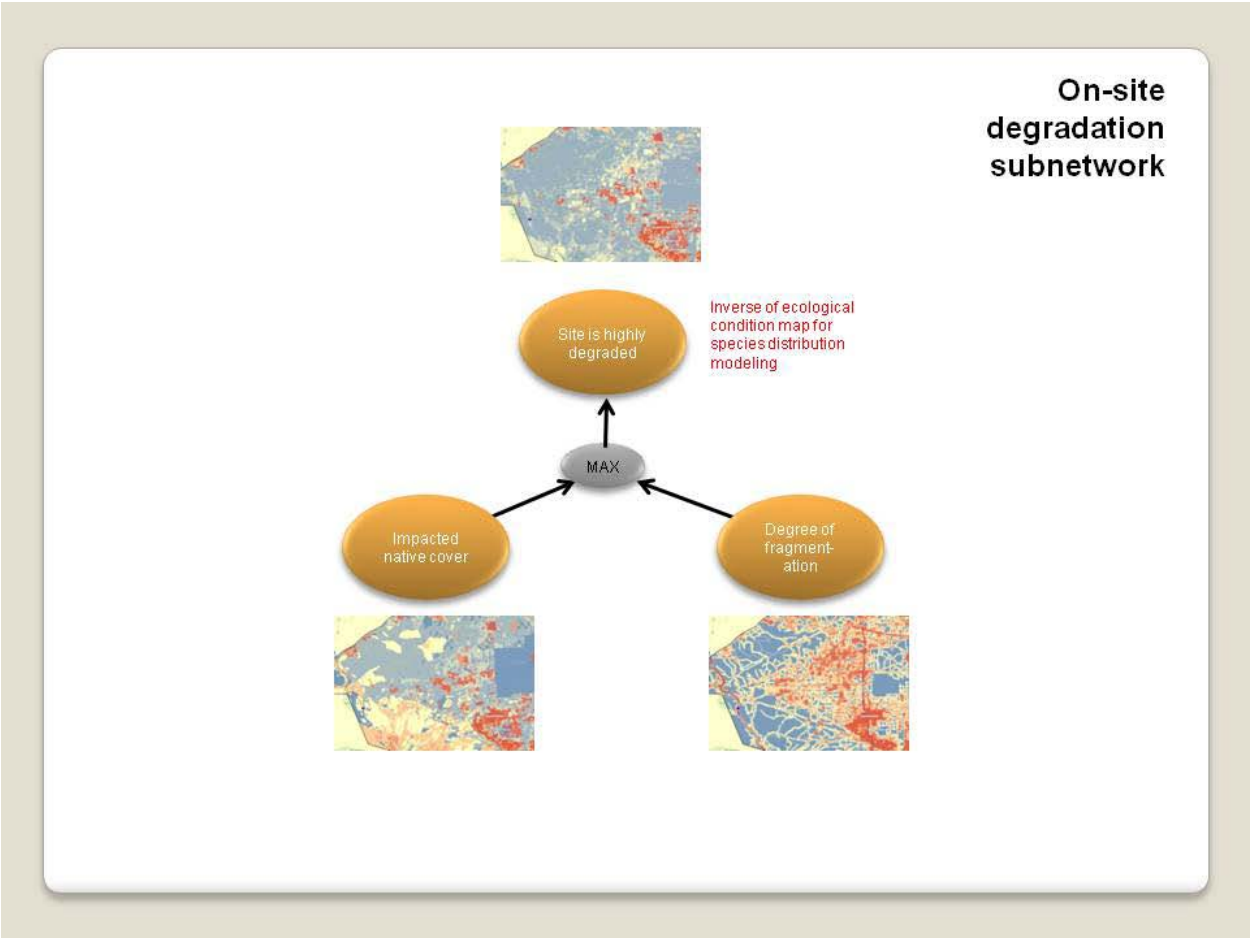

Figure 2. Logic for on-site degradation.

Loss or reduction of vegetative cover can either be considered essentially permanent where human activities have high investments such as urban development, contaminated sites, and utilities, or it may be recovering from past disturbance such as farming (Webb et al. 2009) (Figure 3). Although native vegetative cover may eventually recover from farming or fire, 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, T. Esque, personal communication). To model ecological condition in future time periods, such as for modeling cumulative impacts, urban growth scenarios and renewable energy projects (blue boxes) can be substituted for current land uses. Fragmentation is caused by linear features such as roads and railroads, transmission lines, and large canals or aqueducts (Figure 4). Future transmission lines (blue box) can be incorporated for modeling cumulative impacts.

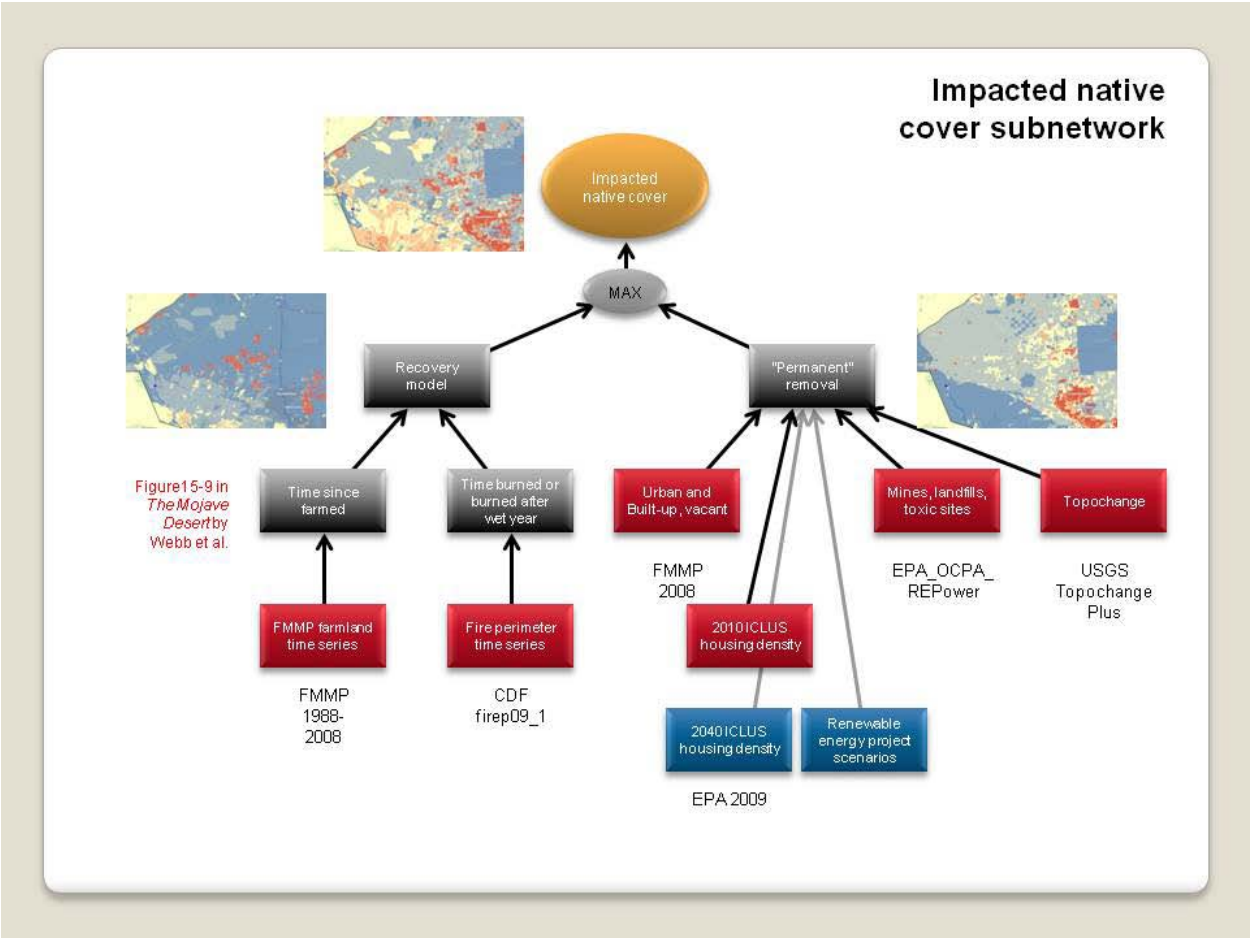

Figure 3. Logic for impacted native vegetative cover. Red boxes are data inputs. Gray boxes are intermediate outputs. Blue boxes with gray arrows represent future land use data to determine future ecological degradation in urban growth and energy scenarios.

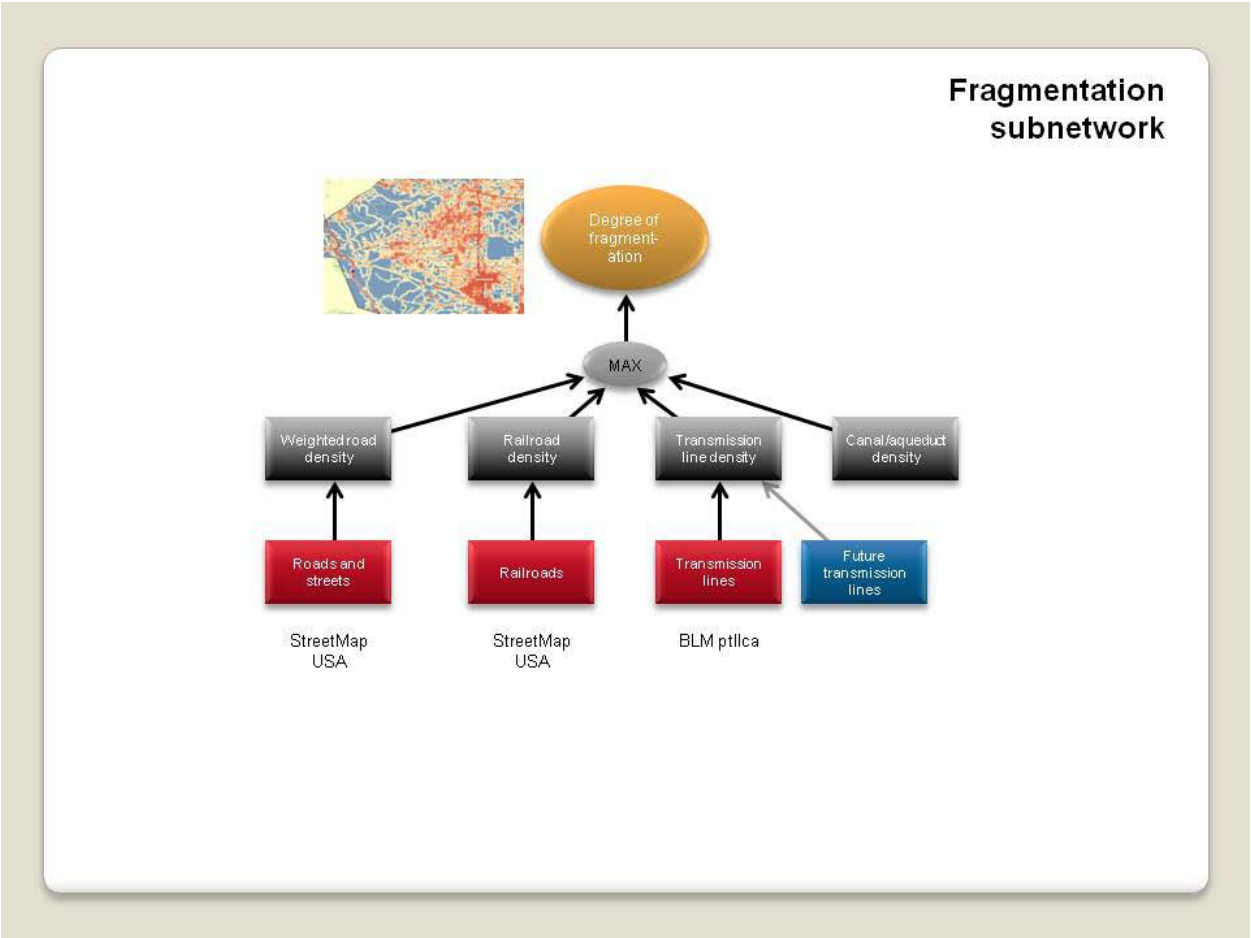

Figure 4. Logic for habitat fragmentation. Blue box with gray arrow represents future transmission lines to determine future habitat fragmentation in energy scenarios.

2.2.2. 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 (e.g., Carrión et al. 2008, Janke 2010, Charabi and Gastli 2011). From an ecological perspective, a greater distance to connect sites 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. Consequently the off-site impact was calculated as a "cost-distance" over a cost surface (inverse of condition layer) (Figure 5). 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. We therefore standardized condition scores by ecological subregions (ECOMAP subsections). Scores below the mean for the subregion were divided by two to make them higher risk than would otherwise be the case. This step has no effect on the sites modeled as lowest risk.

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), as barriers that were assigned very high costs. Designated critical habitat areas for listed species are not off-limits to infrastructure projects but are considered a risk to biodiversity; a high cost was assigned to them. In the case of off-site impacts, the lowest risk 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.

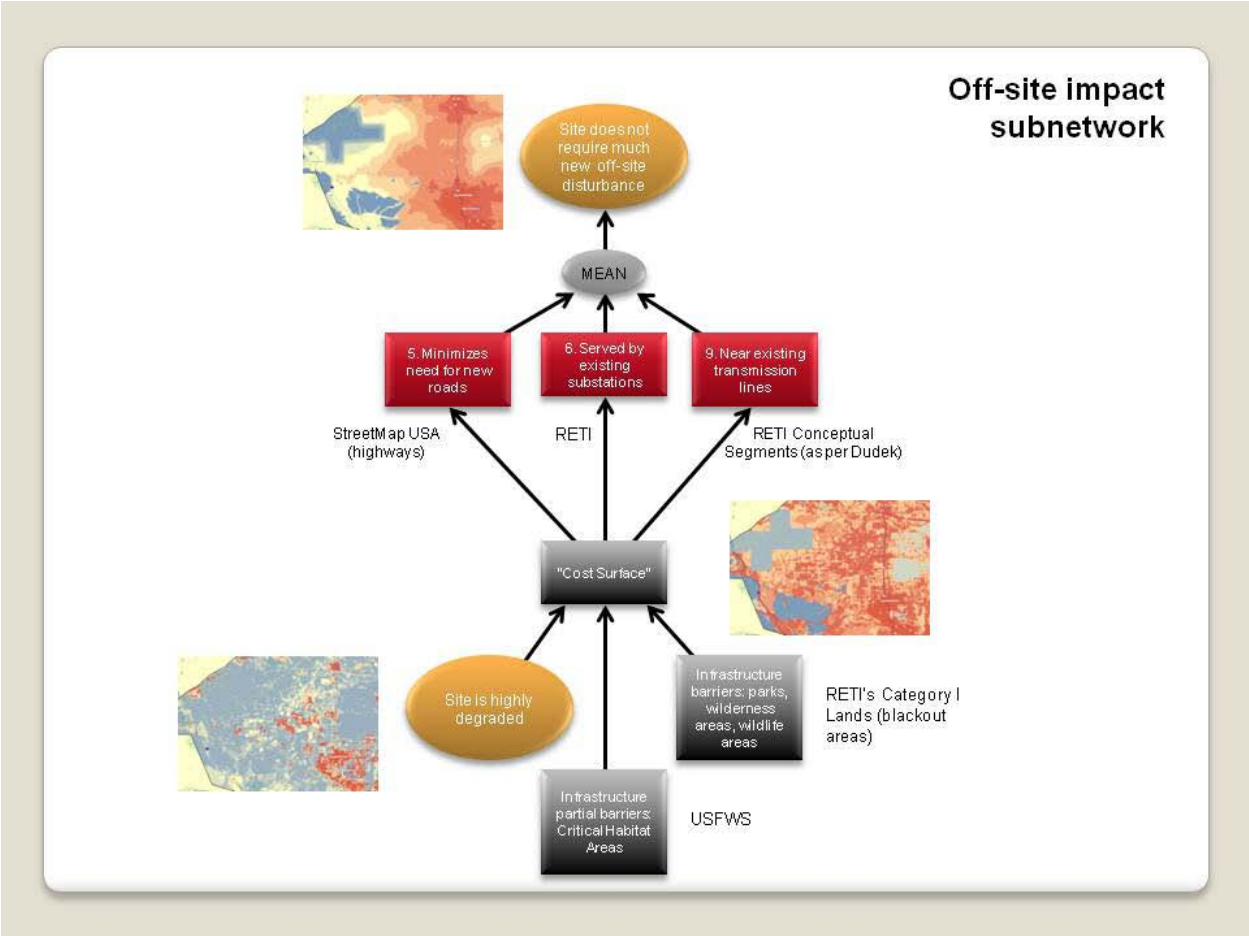

Figure 5. Logic for off-site impact. Cost-distance is calculated separately from highways, existing substations, and transmission lines.

2.3. Spatial modeling

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

For the modeling recovery of vegetative cover following agriculture, we adopted the natural log recovery function presented by Webb et al. (2009) (Figure 6).

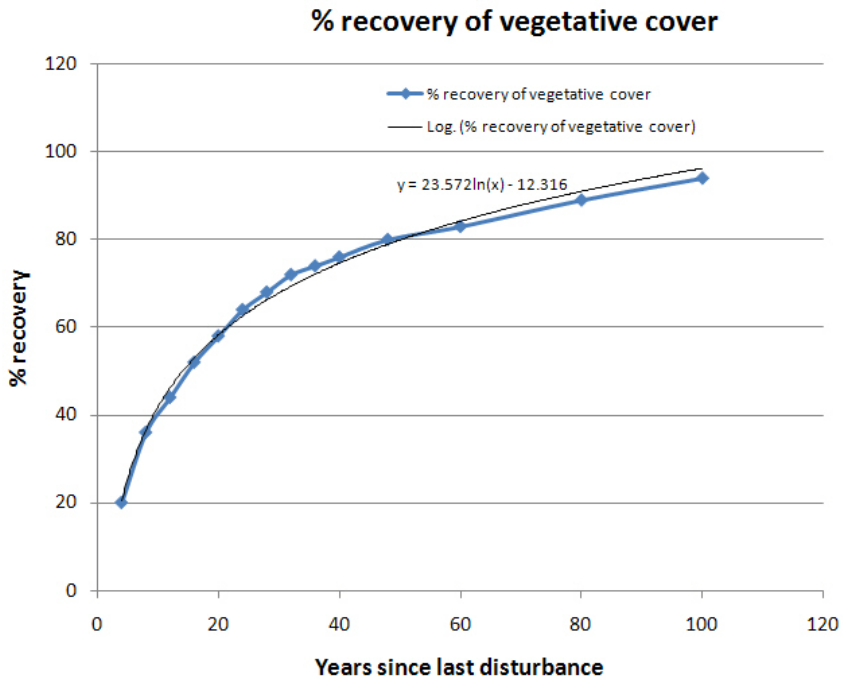

Figure 6. Recovery function for vegetative cover derived from Webb et al. (2009).

2.4. Validation and testing

Validation is challenging because the model outcome is not directly measureable in the field. Stakeholders can rightly be skeptical of the product if there is not some level of validation, however. The degradation/condition layer was evaluated against a set of 381 random points (Figure 7) that were photointerpreted from 2009-2010 NAIP natural color imagery with 1 m spatial resolution. Each random coordinate pair was used as the center point of a 90 m radius photo-plot. For each point, we recorded the overall level of disturbance of the land (none, slight, substantial, complete transformation). If land was disturbed, we recorded the land use associated with the disturbance, if discernable (see Appendix for details on coding). To test the modeled degree of fragmentation, we counted the number of highways, roads (paved and unpaved), transmission lines, and railways visible in the imagery and weighted each category similar to the modeled version. These points were then compared with the modeled predictions of On-site Degradation, Reduced Relative Cover, and Degree of Fragmentation. We looked for general patterns of agreement for the points identified to be located on land with some level of disturbance. Out of the 381 points, 284 showed no discernable land use disturbance.

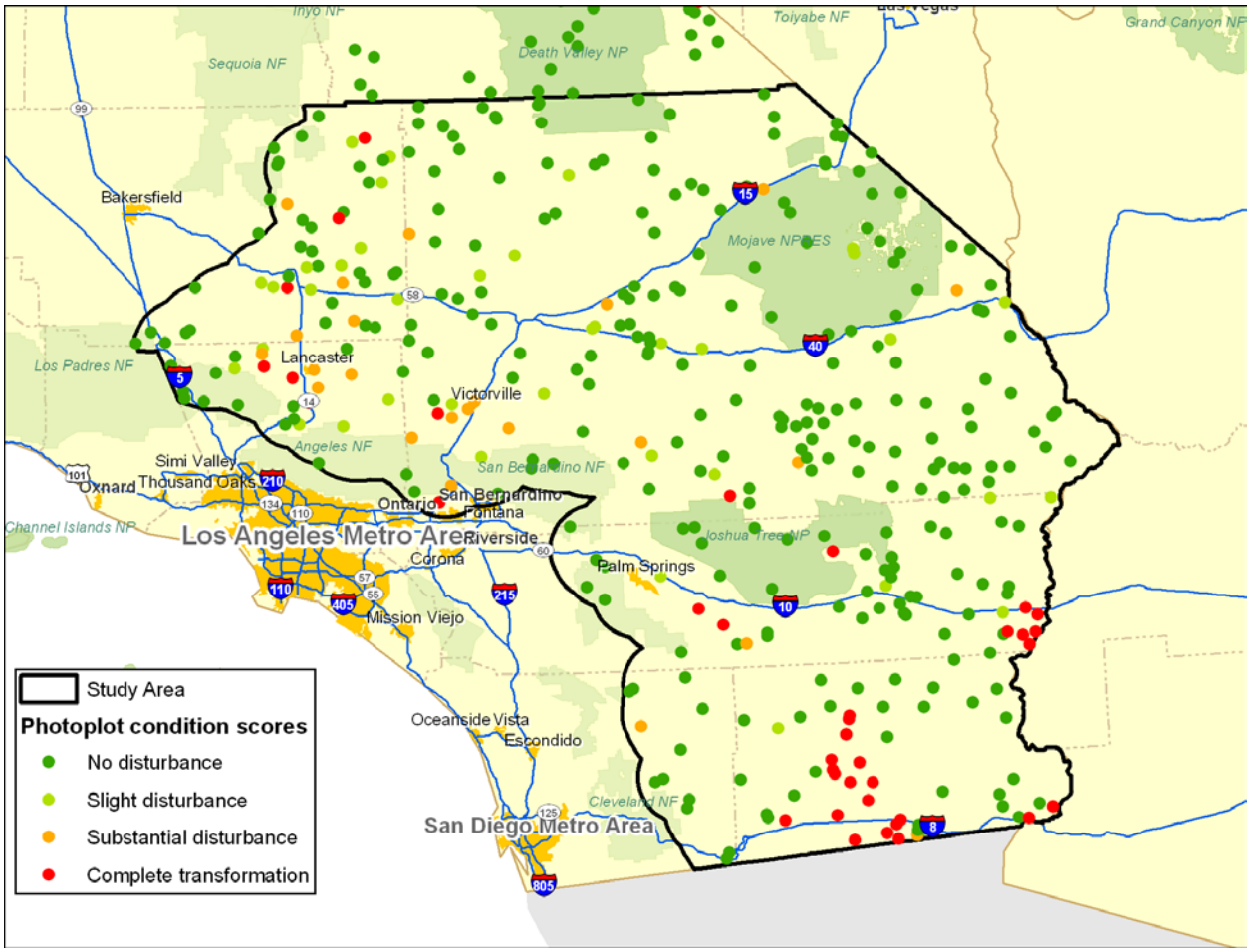

Figure 7. Locations of random points used for validation of risk modeling colored by coding for reduced relative cover.

2.5. Initial model modifications

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

- Farmland of Local Importance in FMMP mapping was removed from the Ag Disturbance model (Figure 3). In the desert counties, this class was generally used for agricultural soils that were not being irrigated or cultivated. Hence they were in better 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 3).
- Utility lines were dropped from the "Permanent" Removal model to avoid double-counting with fragmentation (Figure 3).

- 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 3).
- 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 4).

Overall, the on-site degradation model agrees strongly with the photoplot data in the no impact and high impact classes (Table 8 in Appendix). The model does best at not omitting identification of any 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 (Table 6 in Appendix). 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) (Table 7 in Appendix).

In the interest of finding the most parsimonious model, the correlations between some of the spatial data layers were calculated so that highly correlated criteria could be removed from the model. Specifically, the correlation between on-site degradation and off-site impact was only 0.36, indicating that they were not highly redundant. Sites closest to infrastructure may also tend to be the most degraded, although not all degraded sites would be located close to all forms of infrastructure. Cost-distance includes geographic distance so the former may be correlated with the latter. If so, using simple Euclidean distance makes fewer assumptions that stakeholders might dispute. However, the correlation between Euclidean distance and cost-distance was only 0.19.

2.6. Peer review of initial model and final revisions

We distributed the initial model results to a representative group of stakeholders on August 11, 2011. We emailed a package with 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. We asked reviewers for feedback on the process, the products, and how it could be applied in the DRECP process. On August 25, we hosted a web meeting for feedback from nine reviewers from environmental groups and consulting firms. A few others, including agency staff, submitted additional written or verbal comments. (List of reviewers and their affiliations are in Appendix 6.3). 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 risk 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 US Fish and Wildlife Service Critical Habitat designations in the cost surface; standardizing Degraded scores within subregions as part of the cost surface modeling; and rescaling the off-site disturbance values based on the cost-distance analysis.

2.7. 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. Therefore we also wanted to evaluate their scores with the photoplot data to determine if our modeling provided any systematic improvements. The first comparison is with the Human Footprint in the West (Leu et al. 2008). The Human Footprint (HF) initial scores had been binned equally into 10 classes, which we grouped into 4 larger groups roughly corresponding to our photointerpreted coding (Table 9 in Appendix). 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 low risk sites with high impact.

The Nature Conservancy (TNC) recently conducted their own GIS analysis of degradation and fragmentation (Dick Cameron, unpublished data). TNC's overall score was a combination of land use (0 undisturbed or 1 urban/agriculture, then smoothed using a focalmean function with an 810 m search radius) and fragmentation, weighted 4 to 1 respectively. Their study area was slightly different than ours so the number of points for comparison is different. 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 (Table 10 in Appendix). Overall agreement with the photoplot data was considerably higher than for the Human Footprint. Our method for calculating fragmentation as a weighted line density was very similar to TNC's. Like our results, TNC's fragmentation scores did best in the lowest fragmentation class, but had relatively poor agreement in more fragmented classes (Table 11 in Appendix). 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 our binning TNC fragmentation scores into classes may be suboptimal.

We also compared the spatial distribution of degraded land from our On-site Degradation model with that of both Human Footprint in the West (Figure 8) and TNC (Figure 9) to determine the geographic pattern of where they were consistent or inconsistent in identifying the most degraded class. First we classified all three maps into the same degradation classes used for the photoplots. The areas colored in tan symbolize areas where the least degraded classifications (0-2) agree across the two models being compared. The areas colored in light turquoise symbolize agreement in the most highly degraded areas. Dark green designates areas where our model has identified the area as less degraded (classes 0-2), yet the other model has classified it as highly degraded. Finally, brown designates areas classified as highly degraded by our model only.

In general, we found that the models tend to agree the most 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 our model, yet TNC picked up less degradation than ours. In comparison with the TNC model, there is some disagreement surrounding agricultural areas due to the fact that agriculture is dynamic and often shifts locations from year to year, in which case the publication year of input data would affect model results. It should be noted that, 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. Note that the HF and TNC models did not model Off-site Impact for connecting solar projects to the existing infrastructure, so they did not produce an output comparable to the Low Biological Risk map.

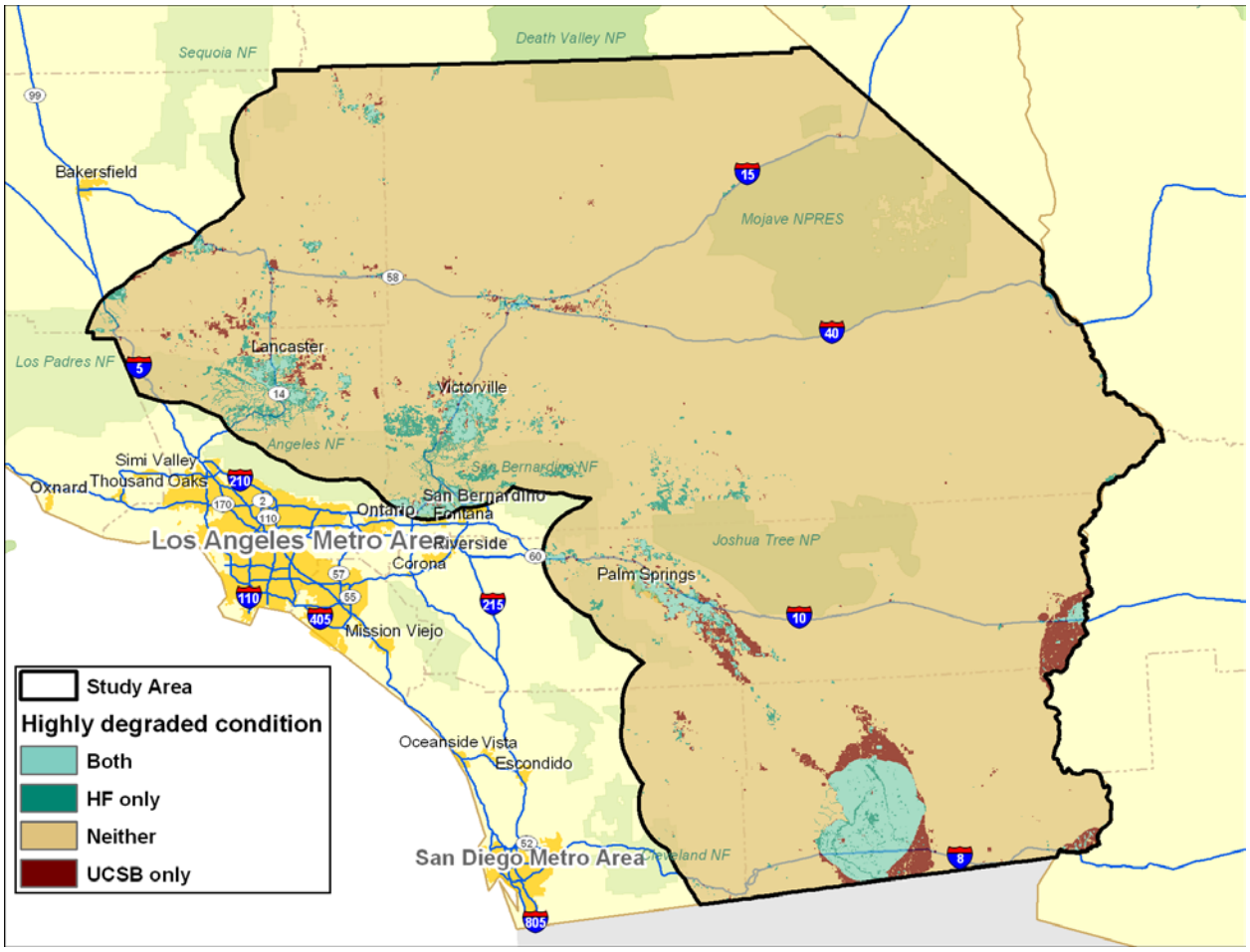

Figure 8. Comparison of degradation models by UCSB and the Human Footprint (Leu et al. 2008).

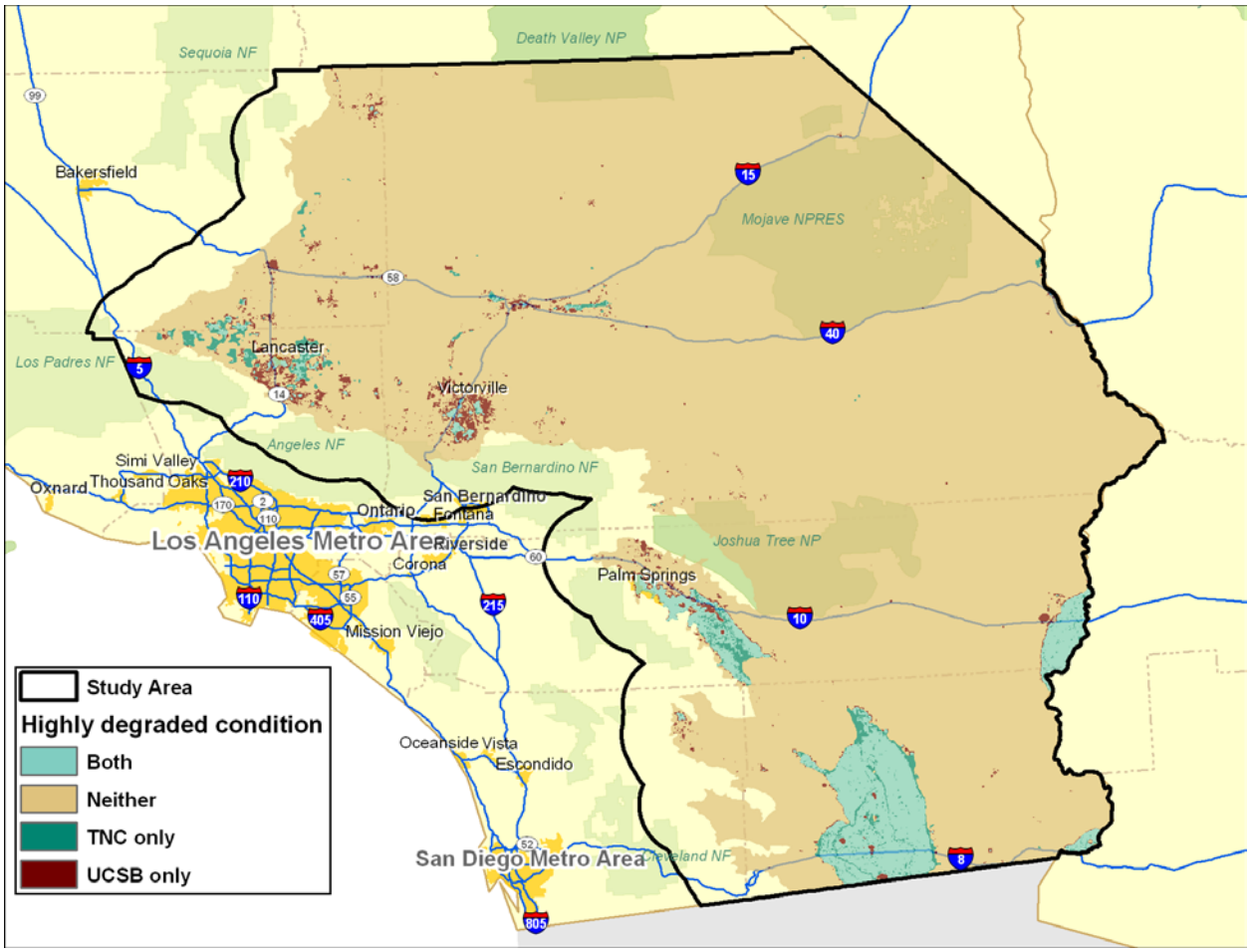

Figure 9. Comparison of degradation models by UCSB and TNC.

3.0 Results

3.1. Risk scores in urban areas

Because our purpose was to model risk to biological resources, and not suitability for solar energy projects, we included urban areas in the model and rated them as highly degraded and therefore as low risk. Urban areas, however, are generally agreed to be unsuitable for utility-scale solar energy. Therefore we summarized the low risk scores with and without urban areas to identify the area of low risk that is also potentially available for solar development. For an objective definition of urban land, we 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 overall low risk 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 low risk and available outside of urban areas. Because risk scores are relative, we used two threshold scores to define "low risk"—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% 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 CEC estimates that 60,000 hectares (± 40,000) of utility scale solar projects are required statewide to achieve GHG reduction goals (California Energy Commission 2011).

Table 2. Area of lowest risk land with and without urban lands.

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

3.2. Risk 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. We summarized the on-site degradation, off-site impact scores, and overall risk scores by major category of land owners or managers 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 bring up the low risk score compared to parks.

Table 3. Mean scores by land manager.

Land manager	Mean on-site degradation score	Mean off-site impact score	Mean overall low risk 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

3.3. 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 we would not expect SEZs to be relatively far from existing infrastructure nor on pristine land. We summarized our On-site Degradation Scores, Off-site Impacts Scores, and final Low Risk scores within the set of SEZs in the California Deserts (Table 12 and Table 13 in Appendix). Our results show that 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 impacts.

4.0 Acknowledgements

This project was funded by the California Energy Commission's Public Interest Energy Research (PIER) Program under Contract # 500-10-021. We thank the experts who reviewed a preliminary version of the modeling—they are listed by name and affiliation in Appendix 6.3.

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6.0 Appendices

6.1. Details of GIS risk modeling

Table 4. GIS input data sources.

GIS input data layer	Source
ECOMAP (USFS) EcoregionsCalifornia07_3	http://www.fs.fed.us/r5/rsl/clearinghouse/gis-download.shtml
Farmland Mapping and Monitoring Program (FMMP)	http://www.conservation.ca.gov/dlrp/fmmp/Pages/Index.aspx
Fire perimeters (FRAP) fire09_1.gdb	http://frap.cdf.ca.gov/data/frapgisdata/select.asp
Develop (extracted from FMMP 2008)	http://www.conservation.ca.gov/dlrp/fmmp/Pages/Index.aspx
Housing density (EPA) iclus2010b2	http://cfpub.epa.gov/ncea/cfm/recordisplay.cfm?deid=205305
Renewable Energy Generation Potential on EPA and State Tracked Sites, EPA_OCPA_Renewable_Energy_Shapefile	http://www.epa.gov/renewableenergyland/data.htm
Significant Topographic Changes (USGS) topochange	http://topochange.cr.usgs.gov/
Roads (ESRI) StreetMap USA\Streets\streets.sdc	ESRI
Railroads (ESRI) StreetMap USA\ stmap_plus\rail100k.sdc	ESRI
Transmission lines for condition (BLM) ptllca	http://www.blm.gov/ca/gis/
Canals and aqueducts (ESRI)	StreetMap USA\ mapdata\ md_riv.sdc
Category I Exclusion areas (RETI) CategoryI_Lands	http://www.energy.ca.gov/reti/documents/index.html
FWS Critical Habitat for Threatened & Endangered Species	http://criticalhabitat.fws.gov/docs/crithab/crithab_all/crithab_all_layers.zip, accessed 08/31/11
Highways (ESRI) StreetMap USA—Streets/highways.sdc	ESRI
Substations (RETI) Collector_Substations (select Existing only)	http://www.energy.ca.gov/reti/documents/index.html
Transmission lines for costdistance (RETI) RETI_Conceptual_Proposed_Transmission_Segments (as per Dudek Proposed Approach to the DRECP Effects Analysis, dated June 30, 2011)	http://www.energy.ca.gov/reti/documents/index.html
Census 2000 urbanized areas and urban clusters	http://www.census.gov/geo/www/ua/ua_2k.html

Study area delineation

Select by attributes from calecos94_4 (USFS ECOMAP) where Province = “322” or Subsection = “Salton”
BUFFER calecos94_4 by 20km FULL side type and ALL dissolve → ecomap322_buffer20km
FMMP shapefiles for Kern, San Bernardino, LA, Riverside, Imperial, and San Diego (Inyo not mapped)
CLIP fmmp2008 by ecomap322_buffer20km → fmmp_ecomap_clip

GIS pre-processing

Recovery model = CellStats Max (ag disturb score, fire disturb score) in Degradation ModelBuilder model

Recovery Model—Time since farmed

Run agconvert.py on yearlist.txt of FMMP<year> shapefiles from 1984 to 2008 where polygon_ty = P, S, U, I, N, CI, or sAC → grids with 0 if not farmed and <year> if farmed in that period
CELLSTATS Max on all grids 1988 to 2008 → Cellmax_fmmp
7/29/11 changed L (local importance) to 0 in AGCODE because in these counties it was usually used for P/S soils that were not irrigated or farmed and therefore not degraded habitat
Run Ag Disturbance ModelBuilder model
subtracts latest year farmed from 2009, takes natural log (Ln), then score = 100 - 13.14 * Ln_farm_age

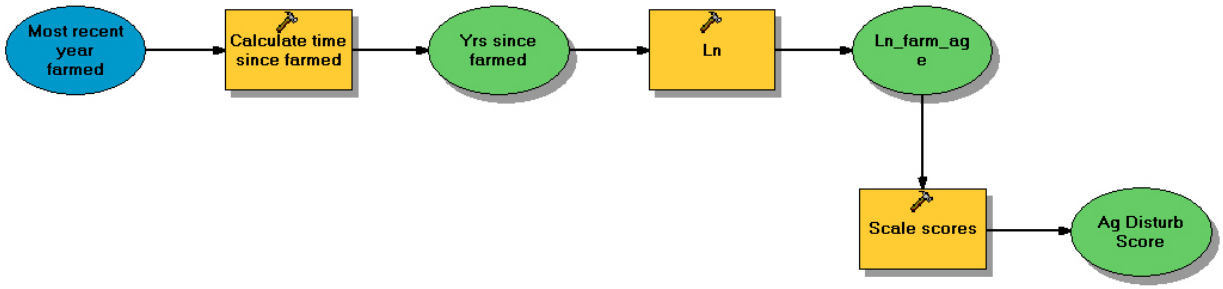

Figure 10. Ag Disturbance ModelBuilder model: "Time since farmed".

Recovery Model—Number of times burned—revised 09/29/11
Run firehistory2.py on fire09_1.gdb with startyear and endyear → timeburn grid with # of times burned and grids for each year burn<year>two with 0 if not burned and <year> if burned in that year
burnfreqscr = con([timeburn] > 3,40,[timeburn] * 10)
# max score = 40 if burned at least 4 times since 1895
# 1999, 2005, 2006 followed particularly wet years with a flush of non-native annual grasses so set those years to score of 30
burnwetyr = con([burn1999two] > 0 | [burn2005two] > 0 | [burn2006two] > 0,30,0)
firescore = max([burnfreqscr],[burnwetyr])

Permanent "Removal" Score = CellStats Max (develop, iclus2010b2, hazardsite3, and topochange) in Degradation ModelBuilder model
Permanent "Removal" Score—Urban and built-up land Score
JOIN FMMP.LUT to fmmp2008 attribute table by polygon_ty
FEATURE to RASTER fmmp2008 by Develop → develop, where D (urban or built-up) = 100, V (vacant or disturbed) = 70, R (rural residential) = 8 (as per housing density below), else 0
Vacant score reduced from 90 to 70 on 9/1/11 based on peer review

Permanent "Removal" Score—Housing Density Score
SA Reclass bhc2010b2 (ICLUS data) → EcoCondition/iclus2010b2 (ICLUS HD Score in Degradation Model), 1 (rural) = 1, 2 (exurban) = 8, 3 (suburban) = 57, 4 (urban) = 100, 99 (commercial/industrial) = 100, NODATA = 0 # with cell size 90 and extent/snap = cellmax_fmmp, and projected to dataframe coord system; based on Housing impacts factor in Legacy Ecological Condition Index (Davis et al. 2003) derived from Theobald and rescaled to 100 for urban class; note that public lands are considered undevelopable in ICLUS so
Convert fmmp2008 to raster → temp by polygon_ty

SA Reclass temp → EcoCondition\iclus2010b2, Rural Residential Land (0.25 – 1.25 housing units/ha approx = ICLUS Exurban class) = 8, Vacant or Disturbed Land = 90, Urban or Built up Land = 100, else 0
with cell size 90 and extent/snap = cellmax_fmmp, and projected to source coord system

Permanent "Removal" Score—EPA hazard sites
PROJECT CA-NV-AZ_GEODATA_Shapefile_Feb2011 → CA-NV-AZ_GEODATA_Shape_teale83 with NAD_1983_California_Teale_Albers coord system
need to project since original is in decimal degrees. Shapefile includes mines, landfills, and toxic sites that EPA tracks.

BUFFER CA-NV-AZ_GEODATA_Shape_teale83 → epasites_buf450 Field = Radius_m (450 meters)
Dissolve = NONE
Field Calculator Reg_ID = 100
but first select points in study area. roughly equivalent to 50 hectare circle; no size reported in EPA database of sites, which include AFS, TRI, LQG, ACRES (brownfields), RMP and others; often the point location is the entrance, but the position of the facility relative to the entrance is unknown.
SA Feature to Raster epasites_buf450 → epasites_buf2 by Reg_ID
Add Field to CA_EPA_OCPA_Renewable_Energy_Shapefile_subset Radius_m Float
subset excluded sites with no acreage given and sites in the Federal Superfund program that tended to have very large acreage like military bases
Field Calculator: Radius_m = Sqr(MapAcreage acres / 2.47 acres/ha / 3.1416 * 10000 m2/ha)

PROJECT CA_EPA_OCPA_Renewable_Energy_Shapefile_subset → CA_EPA_OCPA_Renewable_Energy_teale with NAD_1927_California_Teale_Albers coord system
need to project since original is in decimal degrees and radius needs to be in meters to create buffers.

BUFFER CA_EPA_OCPA_Renewable_Energy_teale → CA_EPA_OCPA_buffer Field = Radius_m and Dissolve = ALL
Field Calculator Ref = 100
SA Feature to Raster CA_EPA_OCPA_buffer → EPA_OCPA_buf by Ref
Raster Calc: hazardsite3 = con(IsNull([epasites_buf2]), con(IsNull([EPA_OCPA_buf]),0,100),100)
use if epasites_buf2 is null, and EPA_OCPA_buf is null, set background to zero, else set to 100

Permanent Score—Utility Score—dropped from model 07/29/11
SA Straightline Distance from ptllca → EcoCondition/utildist # includes pipelines, phone, and power transmission
SA Reclass utildist → utilscore, 0-90 = 50, 90-180 = 25, > 180 = 0

Permanent "Removal" Score—TopoChange Score (added 07/29/11)
Topochange layer from USGS at http://topochange.cr.usgs.gov/ as used in Kiesecker et al. (2011).
Delete polygons for road cuts or that do not appear to be real impacts (remote areas) → topo_change_CA_mines
PROJECT topo_change_CA_mines → topo_change_CA_mines_Teale83
Convert to raster → topochangerst
Raster Calc: topochangescr = con(IsNull([topochgrst]),0,100)

Degree of Fragmentation Model = CellStats Max (rd_score2, rr_score, tx_score, and can_score) in Degradation ModelBuilder model

Roads
Select Streets (Detailed) from the StreetMap USA\Streets\streets.sdc Feature Dataset in the Desert study area → my_streets in EcoCondition folder
Join streetclass_lut to my_streets by CLASS_RTE
weighting the class of road derived from TNC lu_rd_cost\metadata.xml: Limited Access (freeways, CLASS_RTE 0,1) = 9; Highway (2) = 6; Major Road (3) = 4; Local Road (4) = 3; Minor Road (5) = 1; Other Road (6) = 3; Ramp (7) = 9; Ferry (8) = 0; Pedestrian Way (9) = 1
Note that NPScape SOP weights interstate roads by a factor of 5 and remaining major roads (FCC: A20-A38) by a factor of 3, else weight = 1, and they summed weighted road length in 1 km^2 polygons, so approximately 500m search radius.

LINEDENSITY mystreets streetclass_lut.rd_weight 90m cell size 450m search radius, units in km/sq.km → street_linedn
Raster Calc: Ist_LineDn = int(street_linedn)
(original version) Raster Calc: rd_score2 = con(Ist_LineDn >= 25,100,Ist_LineDn * 4)
Raster Calc: rd_score2 = con(Ist_LineDn >= 50,100,Ist_LineDn * 2) # modified 08/31/11 to reduce influence of fragmentation
linear transform between 0 and 50, then plateaus at 100 above 50

Railroads
Select Railroads (Local) from the StreetMap USA\ stmap_plus\rail100k.sdc Feature Dataset in the Desert study area → my_railroads in EcoCondition folder
railroads between a Highway and Major Road so weight = 5 using the Weight field
LINEDENSITY my_railroads Weight 90m cell size 450m search radius, units in km/sq.km → rr_linedn
(original version) Raster Calc: rr_score = int(con(rr_LineDn >= 25,100,rr_LineDn * 4))
Raster Calc: rr_score = int(con(rr_LineDn >= 50,100,rr_LineDn * 2)) # modified 08/31/11 to reduce influence of fragmentation
linear transform between 0 and 50, then plateaus at 100 above 50

Transmission lines
Select FEATURE_TY = Power from the ptllca shapefile from BLM
PROJECT to Teale AD 1983 projection → ptllca_Tealeproj
Transmission lines associated with unpaved roads so weight = 1 (default)
LINEDENSITY ptllca_Tealeproj default 90m cell size 450m search radius, units in km/sq.km → itx_linedn
(original version) Raster Calc: tx_score2 = int(itx_LineDn * 4)
Raster Calc: tx_score2 = int(itx_LineDn * 2) # modified 08/31/11 to reduce influence of fragmentation
linear transform between 0 and 50, then plateaus at 100 above 50

Canals/aqueducts
Select Rivers (Detailed) from the StreetMap USA\ mapdata\ md_riv.sdc Feature Dataset in the Desert study area where CFCC = H21 → my_aqueducts_H21
Select only those LIKE '%California Aqueduct%' OR LIKE '%All-America%' OR = 'Coachella Canal'
Delete some branch canals by hand and then hand-digitize gaps in California Aqueduct → my_aqueducts3
PROJECT to Teale AD 1983 projection → my_aqueducts3_Teale83
canals/aqueducts vary from 8-25 meters across plus embankments so weight them between a Highway and Major Road = 5 using the Weight field

LINEDENSITY my_aqueducts3_Teale83 Weight 90m cell size 450m search radius, units in km/sq.km → canal_linedn
Raster Calc: Ican_LineDn = con(IsNull([canal_linedn]),0,int([canal_linedn])) # also replaces NoData
(original version) Raster Calc: can_score = con(Ican_LineDn >= 25,100,Ican_LineDn * 4)
Raster Calc: can_score = con(Ican_LineDn >= 50,100,Ican_LineDn * 2) # modified 08/31/11 to reduce influence of fragmentation
linear transform between 0 and 50, then plateaus at 100 above 50

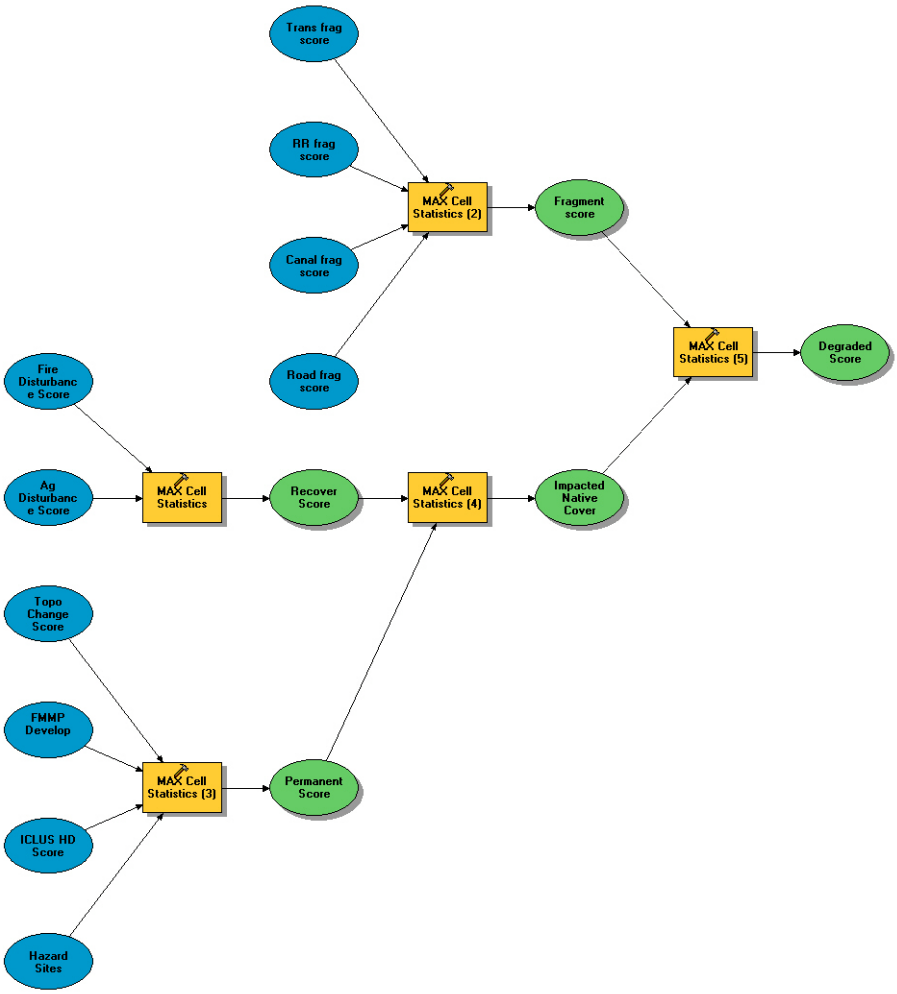

Figure 11. On-site Degradation ModelBuilder model. Tools use the Maximum option so that most degrading factor prevails.

Cost Surface

Add Field to RETI_CategoryI_Lands Cost Long integer
Field Calculator: Cost = 10000 # make artificially high cost to preclude costpath from crossing exclusion areas
CLIP RETI_CategoryI_Lands by selected counties → myCategoryI_Lands
PROJECT myCategoryI_Lands → myCategoryI_Lands_teale83 # to make raster conversion work right
SA Feature to Raster myRETI_CategoryI_Lands_teale83 → EcoCondition/cat1_cost by Cost

Repeat for Military_Lands → EcoCondition/dod_cost # deleted, 7/1/11 based on guidance from Dudek's Proposed Approach to DRECP Effects Analysis memo dated 6/30/11 that transmission lines could cross military bases

CLIP CRITHAB_POLY by study area → crithab/crithab_clip # added 9/1/11 based on peer review
Add Field to crithab_clip Cost Long integer
Field Calculator: Cost = 1000 # make artificially high cost to preclude costpath from crossing exclusion areas
PROJECT crithab_clip → mycrithab_clip_teale83 # to make raster conversion work right
SA Feature to Raster mycrithab_clip_teale83 → crithab_cost by Cost

Cost Distance Model, reverses Degraded Score, and replaces NULL with 1 in cat1_cost and crithab_cost, then finds Maximum CellStatistics for costsurface; computes costdistance across costsurface from highways, existing substations, and transmission lines.

Figure 12. Cost Distance ModelBuilder model: "Off-site Impacts" subnetwork.

The Risk model scales the Off-Site Disturbance raster by con(100 - 0.000025 * Off-Site Disturbance < 0, 0, 100 - 0.000025 * Off-Site Disturbance), which converts the costdistance measure into a 0-100 range. Subracting from 100 flips the scale so that lower off-site disturbance equals lower risk. The original off-site scaling was revised as suggested by the peer review, since the original version tended to indicate low risk even in remote areas. This value and the Degraded Score are then averaged.

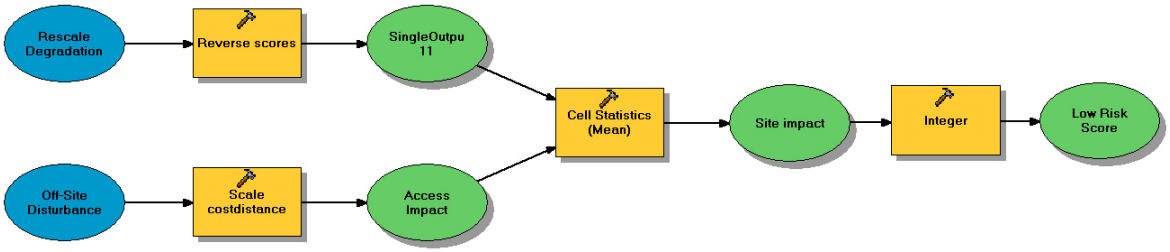

Figure 13. Low risk ModelBuilder model.

6.2. Details of photo interpretation of NAIP imagery

6.2.1. Data Sources

- National Agricultural Inventory Program (NAIP) 2009. Available for download from the State of California's Geospatial Library (http://atlas.ca.gov/download.html#/casil/imageryBaseMapsLandCover/imagery/naip/naip_2009/2009_NAIP_sid_county_compressions). Format: digital ortho quarter quads (DOQQs) compressed into a single mosaic (MrSID MG3).
- NAIP 2010. Imagery for the State of California was accessed through the USDA's Aerial Photography Field Office (APFO) ArcGIS server (adding http://gis.apfo.usda.gov/arcgis/services to the Add ArcGIS Server connection). Format: Digital Ortho Quarter Quad (DOQQs) in GeoTIFF format.
- BLM solar energy zones (SEZs) and solar energy development areas ((Solar Programmatic Environmental Impact Statement, PEIS): http://solareis.anl.gov/maps/gis/index.cfm.
- DRECP boundary (January 28, 2011): http://www.drecp.org/maps/DRECP_Boundary_Shape_Files/
- Western Mojave Ecoregion designation "322Ag: High Plains and Hills": http://www.fs.fed.us/r5/projects/ecoregions/322a.htm
- Solar Constraints Map, Bren Group Project: "The Future of Large-scale Solar Energy in California": http://fiesta.bren.ucsb.edu/~solar/documents.html.

6.2.2. Methodology

- Using the "Create Random Points" tool, a point shapefile of 500 random points was created with the minimum distance between points designated as 500 meters and the DRECP boundary assigned as the constraining feature class.
- Using the "Buffer" tool, a buffer with a radius of 90 meters was created for each of the points (Figure 14).
- Based on photointerpretation of the NAIP digital orthophotography within each 90 m buffer, the following attributes were assigned to each point:

Table 5. Attributes and coding for photoplots.

Attribute	code	description
checked	Y	point has been checked
	Blank	Not yet checked
condition		This is codified depending on the condition of the land and the type of land use. The first number is the level of disturbance (0-3) and the second number in the code is the type of land use causing the disturbance.
	Level of Disturbance	

	0	no apparent disturbance
	1	slight land cover disturbance
	2	substantial land cover disturbance
	3	complete transformation of land
	Land Use	
	1	fire
	2	farming
	3	urban (rural, residential, commercial)
	4	pipelines
	5	landfills
	6	mines
	7	road
	0	unclassified or unidentifiable
highways	0-n	Number of highways that intersects a 90 meter buffer around each point.
paved	0-n	Number of paved roads (other than major highways) that intersect a 90 meter buffer around each point.
unpaved	0-n	Number of unpaved roads (including OHV roads) that intersect a 90 meter buffer around each point.
trans	0-n	Number of transmission lines that intersect a 90 meter buffer around each point.
rail	0-n	Number of railroads that intersect a 90 meter buffer around each point.
notes		Notes on the area regarding information that is not otherwise codified in the other columns.

We recorded the attributes for 381 points within the study area boundary. Five hundred points were randomly created, 250 of these were photointerpreted using the coding in Table 5. With the remaining 250 points, we selectively chose points within the Western Mojave Desert Ecoregion, the BLM's Solar Energy Development Areas, and in the areas where solar development is feasible (outside of U.S. Department of Defense lands, urban areas, airports, National Parks, etc.)

Figure 14. Example of a photoplot point and 90 meter radius buffer. This point was scored with a condition value of 1, slight land cover disturbance.

6.2.3. Comparison of Photo Interpreted Plots with Model Results

The contingency tables below compare the classifications assigned to the set of photo interpreted points within each respective study area to the output scores of each model. The continuous scores were grouped based analysis of the distribution of scores for each model.

Table 6. Comparison of model scores to photo interpreted point scores for Impacted Native Cover. Model scores were binned to align with the definitions for each class.

		Model Impacted Native Cover Score				
		0-1 (0)	**>1 - 45 (1)**	**>45 - 90 (2)**	**>90 (3)**	**TOTAL**
Photo Interpretation Condition Score	**0**	**214**	70	0	0	**284**
	1	13	**22**	2	0	**37**
	2	7	11	**4**	1	**23**
	3	1	6	3	**27**	**37**
	TOTAL	**235**	**109**	**9**	**28**	**381**

Overall Agreement:	0.70
Kappa Statistic:	0.41
Model shows more degradation than aerial photography	0.19
Aerial photography shows more degradation than model	0.11

Table 7. Comparison of model scores to photo interpreted point scores for fragmentation.

		Model Fragmentation Score				
		0-1 (0)	**1 - 33 (1)**	**33 - 67 (2)**	**67 - 100 (3)**	**TOTAL**
Photo Interpretation Fragmentation Score	**0**	**162**	70	9	1	**242**
	1	19	**67**	24	7	**117**
	2	1	5	**6**	4	**16**
	3	0	0	1	**5**	**6**
	TOTAL	**182**	**142**	**40**	**17**	**381**

Overall Agreement:	0.63
Kappa Statistic:	0.36
Model shows more fragmentation than photoplots	0.30
Photoplots show more fragmentation than model	0.07

Table 8. Comparison of model scores to photo interpreted point scores for degradation.

		Model Degradation Score				
		0-1 (0)	**1 - 45 (1)**	**45 - 90 (2)**	**>90 (3)**	**TOTAL**
Photo Interpretation Overall Score	**0**	**128**	91	6	0	**225**
	1	15	**65**	8	3	**91**
	2	2	13	**9**	3	**27**
	3	0	4	4	**30**	**38**
	TOTAL	**145**	**173**	**27**	**36**	**381**

Overall Agreement: 0.61

Kappa Statistic: 0.40

Model shows more degradation than photoplots 0.29

Photoplots show more degradation than model 0.10

Table 9. Comparison of Human Footprint (HF) classes to photo interpreted point scores for degradation.

		HF classes				
		1 (0)	**2,3,4 (1)**	**5,6,7 (2)**	**8,9,10 (3)**	**TOTAL**
Photo Interpretation Degraded Score	**0**	**21**	190	49	1	**261**
	1	3	**34**	32	1	**70**
	2	0	13	**25**	2	**40**
	3	0	1	27	**25**	**53**
	TOTAL	**24**	**238**	**133**	**29**	**424**

Overall Agreement: 0.29

Kappa Statistic: 0.15

Model shows more degradation than photoplots: 0.65

Photoplots show more degradation than model: 0.10

Table 10. Comparison of TNC overall scores to photo interpreted point scores for degradation.

		TNC scores				
		0 (0)	**0-0.3 (1)**	**0.3-3 (2)**	**>3 (3)**	**TOTAL**
Photo Interpretation Overall Score	**0**	**145**	66	7	2	**220**
	1	13	**38**	6	0	**57**
	2	3	15	**15**	2	**35**
	3	1	8	14	**26**	**49**
	TOTAL	**162**	**127**	**42**	**30**	**361**

Overall Agreement: 0.62

Kappa Statistic: 0.41

Model shows more degradation than photoplots: 0.23

Photoplots show more degradation than model: 0.15

Table 11. Comparison of TNC roads to photo interpreted point scores for fragmentation.

		TNC roads score				
		0 (0)	**>0-0.02 (1)**	**>0.02-0.1 (2)**	**>0.1 (3)**	**TOTAL**
Photo Interpretation Frag Score	**0**	**144**	37	35	2	**218**
	1	16	**21**	47	19	**103**
	2	1	0	**0**	4	**5**
	3	0	0	1	**5**	**6**
	TOTAL	**161**	**58**	**83**	**30**	**332**

Overall Agreement: 0.47

Kappa Statistic: 0.15

Model shows more degradation than photoplots: 0.43

Photoplots show more degradation than model: 0.05

6.2.4. Model Results in Solar Energy Zones (SEZs)

Table 12. Mean scores within each SEZ designated by BLM.

		Mean on-site degradation score	**Mean off-site impact score**	**Mean overall low risk score**
BLM Solar Energy Zone (Solar PEIS)	**Imperial East**	15.70	96.22	48.02
	Iron Mountain	3.17	93.85	37.20
	Pisgah	17.42	96.58	49.75
	Riverside East	5.93	91.00	26.98

Table 13. Summary of Scores within BLM-designated SEZs.

		On-Site Degradation Score			
		Mean	**Min**	**Max**	**StdDev**
BLM Solar Energy Zone (Solar PEIS)	**Imperial East**	8.74	0.07	100	13.78
	Iron Mountain	1.62	0.07	57	3.68
	Pisgah	8.82	0.07	100	11.16
	Riverside East	3.06	0.07	100	6.09
		Off-site Impact Score			
		Mean	**Min**	**Max**	**StdDev**
BLM Solar Energy Zone (Solar PEIS)	**Imperial East**	96.22	96	97	0.41
	Iron Mountain	93.85	91	97	1.06
	Pisgah	96.58	94	99	0.95
	Riverside East	91.00	87	96	1.97
		Overall Low Risk Score			
		Mean	**Min**	**Max**	**StdDev**
BLM Solar Energy Zone (Solar PEIS)	**Imperial East**	48.02	40	90	6.89
	Iron Mountain	37.20	20	53	5.47
	Pisgah	49.75	34	98	6.77
	Riverside East	26.98	0	94	8.43

6.3. List of reviewers of initial model

Name	Affiliation
Dick Cameron, Brian Cohen, and John Randall	The Nature Conservancy
Ileene Anderson	Center for Biological Diversity
Jerre Ann Stallcup and Wayne Spencer	Conservation Biology Institute
Mike Howard	Dudek
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 Game
Ashley Conrad-Saydeh	Bureau of Land Management