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Siting solar energy development to minimize biological impacts

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ABSTRACT

After solar and other renewable energy developers select generally suitable sites for exploration, they frequently encounter conflict over biodiversity conservation values that were not factored into the initial suitability rating methods. This paper presents a spatial multicriteria analysis method for modeling risk of conflict with biological resources and applies the model in the California deserts where such conflicts are rapidly rising. The premise of the model is that the least conflict will occur on sites that are the most ecologically degraded with low conservation value and that would engender low off-site impacts when connecting to existing transmission infrastructure. Model results suggest sufficient compatible land exists in flat, non-urban areas to meet state solar energy targets of 8.7 GW of installed capacity in the California deserts for 2040. The model is a promising tool to fill the gap between site suitability analysis for renewable energy and regional biodiversity conservation planning to identify areas where rapid impact assessment and permitting will generate the least regrets.

1. Introduction

Areas of high solar energy potential are often in fragile ecosystems that are easily disturbed and hard to restore. The best way to minimize environmental impacts in accordance with the mitigation hierarchy of the US National Environmental Policy Act is to avoid sites where impacts are likely to be unacceptably high. Great interest in utility-scale solar energy development in the deserts of the southwestern U.S. has created an urgent need for regional conservation planning to map and protect areas of high conservation value [1–3]. However, this planning approach requires time-consuming collection, compilation and analysis of biological data. In the interim, it makes sense to quickly map sites that stakeholders can agree have low potential conservation value and thereby avoid unnecessary conflicts and delays in the review and permitting process.

Such mapping builds on the long tradition of land suitability analysis based on spatial multicriteria analysis. Its application for renewable energy is more recent, however [4–6]. Geographic information systems (GIS) have been used to model spatial patterns of suitability and constraints for development of solar [6–8], wind [6,9,10], and wave or tidal [11,12] resources. Two basic approaches have been used. Some studies used Boolean logic to exclude lands based on "hard constraints" where development is legally prohibited (e.g., parks) or operationally infeasible (e.g., greater than a threshold distance from roads and transmission lines) [4]. Other studies combined values of energy potential with those of technical and environmental factors to derive an overall suitability score [5,6,8,9]. Known biological constraints such as designated critical habitat for endangered species can be incorporated in this approach. Outside of these constrained areas, however, the potential for conflict with biological resources is highly uncertain, ranging from most compatible to most potential conflict. Energy developers, permitting agencies, and conservation interests would all benefit from information to reduce this uncertainty, particularly for identifying the most compatible or "no regrets" sites [3].

To help fill this need, this paper presents an alternative approach based on modeling the relative likelihood that a site will not incur substantial impacts on biological resources from renewable energy development. We refer to this metric as a *Compatibility Index*. Developing projects on low compatibility lands increases the risk of loss of conservation values and the risk that solar developers would face stiff opposition from conservation interests or high mitigation costs. Although the two forms of risk are perceived from opposite perspectives, both share a similar measurement of the potential for conflict [13]. We have chosen the term "compatibility" or the absence of conflict, to highlight the potential for meeting renewable energy objectives without unacceptable loss of biological resources.

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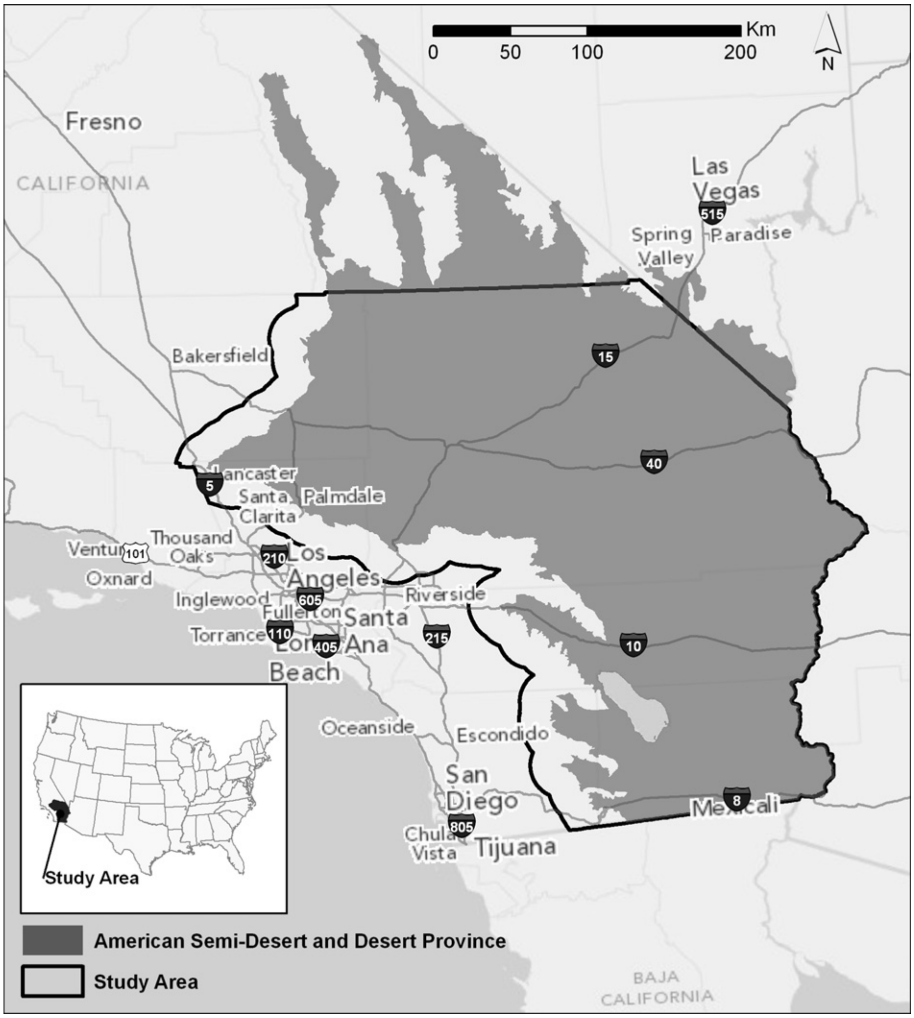

Fig. 1. Location map of American Semi-Desert and Desert Province and the study area in southeastern California.

The paper lays out the logic and assumptions of the model, and implements it for the California deserts. The model 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 and opportunities in order to make comprehensive siting decisions. The model is also not a comprehensive assessment of biological conservation value but provides a landscape level overview of areas that are unlikely to have high value. To illustrate the utility of the model, we answer two research questions: What areas in the region could be considered most compatible with conservation of biological resources? What is the total area of the most compatible sites relative to projected need?

2. Methods

2.1. Study area description

The American Semi-Desert and Desert province (#322; [14]) in the southwestern United States is endowed with excellent solar insolation, averaging 6.5 kWh m^{-2} day^{-1} (National Renewable Energy Laboratory, http://www.nrel.gov/gis/). The average for the conterminous 48 states is only 5.1 kWh m^{-2} day^{-1}. The topography includes extensive plains between rocky mountain ranges. The vegetation is very sparse, dominated by shrubs such as creosote bush (*Larrea tridentata*) and burrobush (*Ambrosia dumosa*). The region is relatively unencumbered by land uses that would preclude solar energy development.

State and federal laws and policies to increase low-carbon energy production have spurred a flurry of permit applications from solar energy developers in this region. The agencies charged with issuing permits have been hard-pressed to keep up with the workload [2]. At the federal level, the Bureau of Land Management (BLM) and the Department of Energy (DOE) are conducting a study to designate desirable “solar energy zones” (SEZ) for fast-tracking solar energy permitting on lands managed by BLM [2]. Agencies are also planning for transmission corridors to support the anticipated development [15].

The presence of many sensitive species, ecological processes and natural communities in this region, has made the siting of large-scale renewable energy development challenging. Within California, a group of stakeholders—agencies, energy companies, and conservation groups—are developing the Desert Renewable Energy Conservation Plan (DRECP) to protect areas of highest conservation value and to mitigate impacts from renewable energy development projects on species and habitats in areas designated for energy development [16]. 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 [17]. The Energy Commission assumed that 42% of this capacity would be for solar thermal

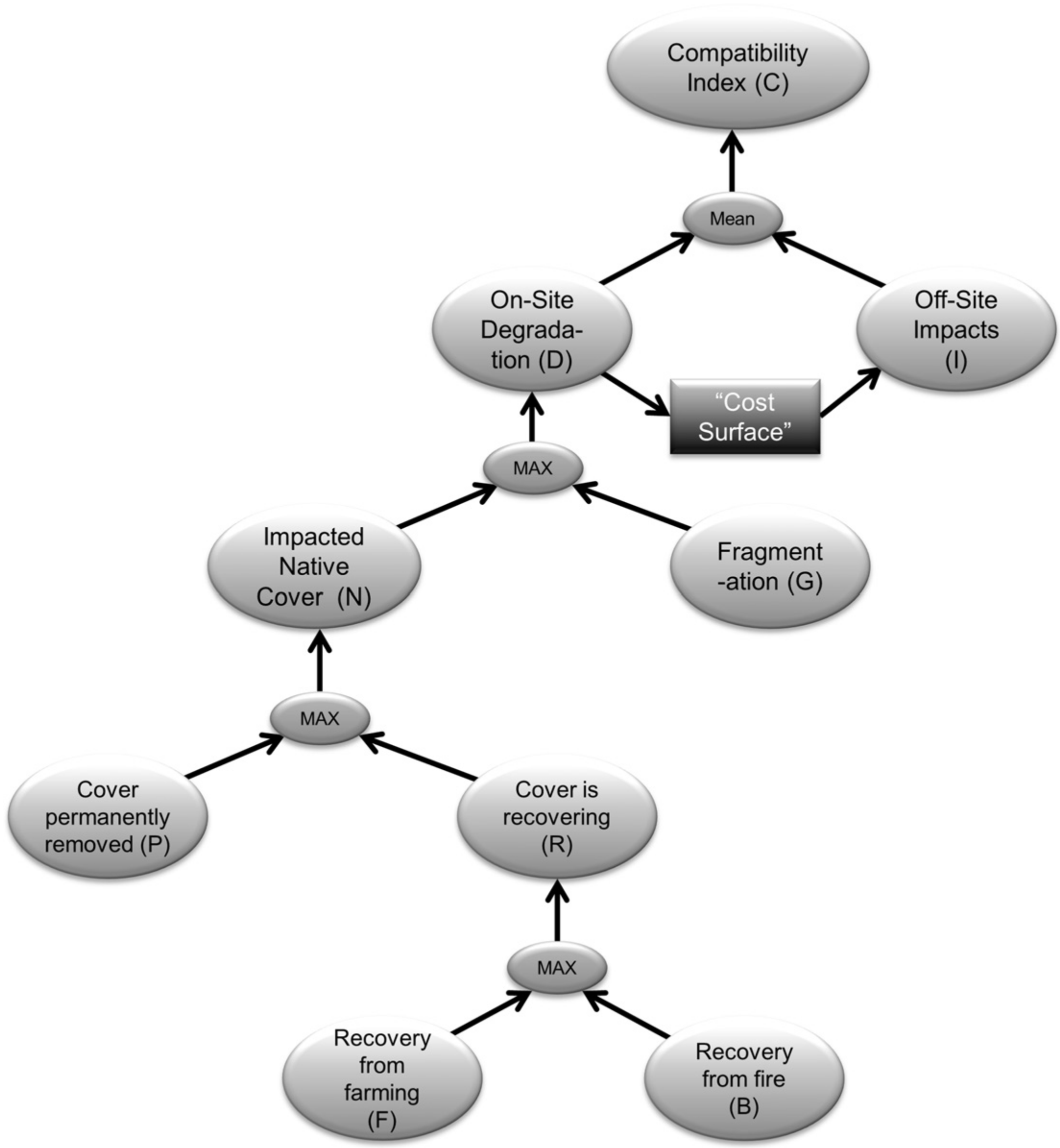

Fig. 2. Hierarchical multicriteria framework for modeling compatibility of solar energy development with biological resources.

technology and 58% for photovoltaics, requiring 2.8 ha (7 acres) per MW for each (see Ref. [17] for more about their assumptions). Until this large-scale plan is completed, the need remains to identify compatible areas of low potential conflict on both public and private lands for near-term siting [3].

The study area is based on the California portion of the American Semi-Desert and Desert province. The ecoregion was buffered by 20 km to ensure that potential solar energy sites were included. Because of data limitations, Inyo County was excluded, leaving 9.4 million ha in the study area (Fig. 1). Section 2.2 gives a top-down overview of the logic hierarchy of criteria, and Section 2.3 provides more bottom-up detail about the calculation and aggregation of criteria scores.

2.2. Logic for the multicriteria analysis framework

In fragile ecosystems such as the California deserts that have been targeted for utility-scale solar projects, the least disturbed lands are likely to be in relatively good ecological condition and 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 [1,3,18]. However, for a site to become operational, it must also be interconnected to the transmission grid and road system, requiring off-site impacts. Therefore the highest level of our hierarchical multicriteria framework evaluates the current level of degradation (*On-Site Degradation*) and how much additional degradation would be generated by connecting the site to existing road/substation/transmission line infrastructure (*Off-Site Impact*) (Fig. 2).

2.2.1. On-site degradation

Analysts frequently model land degradation from various human activities such as building roads, urban development, and agriculture. We prefer to model the level of degradation with reference to change in general ecological condition or landscape integrity [19]. We modeled current site degradation based on removal of vegetative cover (*Impacted Native Cover*) and fragmentation of habitat (*Fragmentation*; Fig. 2). Loss or reduction of vegetative cover can either be considered essentially permanent such as urban development, contaminated sites, and utilities, or

Table 1
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 cost distance (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
BLM/EPA Solar Energy Zones	http://solareis.anl.gov/maps/gis/index.cfm
Slope general exclusion area >5% (RETI)	http://www.energy.ca.gov/reti/documents/GIS/GIS_RETI_General_Exclusions.zip

temporary as vegetation recovers from past disturbance such as farming. Although native vegetative cover may eventually recover from farming, soil crust (a key component of desert ecosystem processes) is destroyed by plowing and may take decades to centuries to recover [20]. Previously tilled lands are thus given 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 [21]. Whereas *Impacted Native Cover* represents the ecological condition within an individual grid cell, landscape-scale impacts on connectivity are represented by measures of fragmentation. Habitat loss also fragments the landscape, but because it was already incorporated in the *Impacted Native Cover* score, it was not repeated in the *Fragmentation* score.

2.2.2. Off-site impacts

Most suitability and constraints analyses of renewable energy projects either rate sites according to their proximity to existing infrastructure as a surrogate for capital costs and permitting challenges or as a hard constraint with a maximum feasible geographic distance [6–8]. From an ecological perspective, the impact to the environment is a function of the distance from existing transmission infrastructure. However, just as sites vary in their current condition and the degree that solar development would cause new impacts, the condition of the landscape through which new infrastructure would be constructed also varies. Consequently we modeled *Off-Site Impact* as an impact-weighted distance associated with new infrastructure, using a cost or impact surface derived from the degradation layer (Fig. 2).

2.3. Spatial modeling

The hierarchical multicriteria framework diagram (Fig. 2) was implemented with spatial modeling tools with ArcGIS 9.3 ModelBuilder. All spatial data (Table 1) were processed into grid or raster format at 90 m resolution. Scores were scaled such that the most degraded sites were rated as highest compatibility (i.e., 100), that is, the best for solar development from the perspective of minimizing potential biological and ecological impacts. Data sets on "permanent" land use such as urban or landfills were given a score of 100 and aggregated into the *Cover permanently removed* criterion, P (Fig. 2).

Native vegetation can eventually recover from transient impacts such as farming and fire. The agricultural mapping was a 20-year time series from the Farmland Mapping and Monitoring Program with mapping in even-numbered years. Agricultural land use was dynamic, with some new tracts becoming cultivated and old farmland being abandoned over time. The score for *Recovery from farming*, F, over time based on the analysis of field data in the Mojave Desert by Webb et al. [20] was calculated as:

$$F = 100 - 13.14*\ln(2009 - y) \tag{1}$$

where y is year that the cell was last farmed. F equals 100 if the cell was farmed in 2008, the most recent year for which mapping was completed. If a cell was not mapped as farmland from 1988 through 2008, y was assumed to be zero, so that F equals 0. The score for *Recovery from fire*, B, was based on fire frequency, b, and burning after particularly wet years, w, (1999, 2005, or 2006):

$$\begin{aligned} b &= 40 \quad \text{If cell burned four or more times between 1895 through 2009} \\ &= 30 \quad \text{If cell burned three times} \\ &= 20 \quad \text{If cell burned two times} \\ &= 10 \quad \text{If cell burned one time} \\ &= \;\;0 \quad \text{If cell never burned} \end{aligned} \tag{2}$$

Table 2
Weights for linear features used in the fragmentation score.

Linear feature	Weight
Freeway and ramps	9
Highway	6
Major road	4
Local road	1
Other road	3
Pedestrian way	1
Railroad	5
Transmission line	1
Canal/aqueduct	5

$$w = 30 \quad \text{If burn year} = 1999, 2005, \text{or } 2006 \qquad (3)$$
$$\quad = 0 \quad \text{Otherwise}$$

$$B = \max(b, w) \qquad (4)$$

In our judgment, fire was less degrading than farming, so the times burned score was scaled to a maximum of 40, and burning in wet years was scaled to a maximum of 30. Thus a cell could not be considered most compatible with biological resources if the only disturbance was from fire. The *Cover is recovering* score, *R*, was calculated as the maximum of the farm, *F*, and fire recovery, *B*, scores (Fig. 2), or was set to zero if neither farming nor fire occurred. The overall *Impacted Native Cover* score, *N*, was determined by the maximum of the *Cover permanently removed* and *Cover is recovering* scores (Fig. 2). Thus in both cases, the criterion with the greatest impact on ecological condition prevails, analogous to the "law of the minimum" in ecology. This law states that plants, or biological populations, can only grow at the rate allowed by the factor (nutrients, light, water) that is the most limited [22].

Fragmentation, *G*, was modeled as a weighted line density of roads, railroads, transmission lines, and large canals or aqueducts, with higher weights for the most impactful classes of roads, e.g., multi-lane freeways (Table 2). The *On-Site Degradation* score was determined by the maximum of the two input scores, *N* and *G* (Fig. 2).

Ecological condition, the inverse of *On-Site Degradation*, was used as the basis of a *Cost-Surface* for calculating the *Off-Site Impacts* score (Fig. 2). Thus, totally degraded sites were assigned a score of zero in the *Cost-Surface* as no further loss of conservation value could occur. Sites with no degradation were initially assigned a score of 100. Furthermore, lands with special restrictions were assigned cost penalties that overrode the condition-based cost. Lands that cannot be legally used to connect new power projects, such as parks and wilderness areas, were treated as barriers by assigning them a "cost" of 10,000 per cell (no units). Designated critical habitat areas for listed species are not off-limits to infrastructure projects, but development there is considered a high risk to biological resources; therefore, a "cost" of 1000 was assigned to them. The authors chose these additional cost penalties to be sufficiently high so that the cumulative cost to circumnavigate these areas would be lower than crossing them.

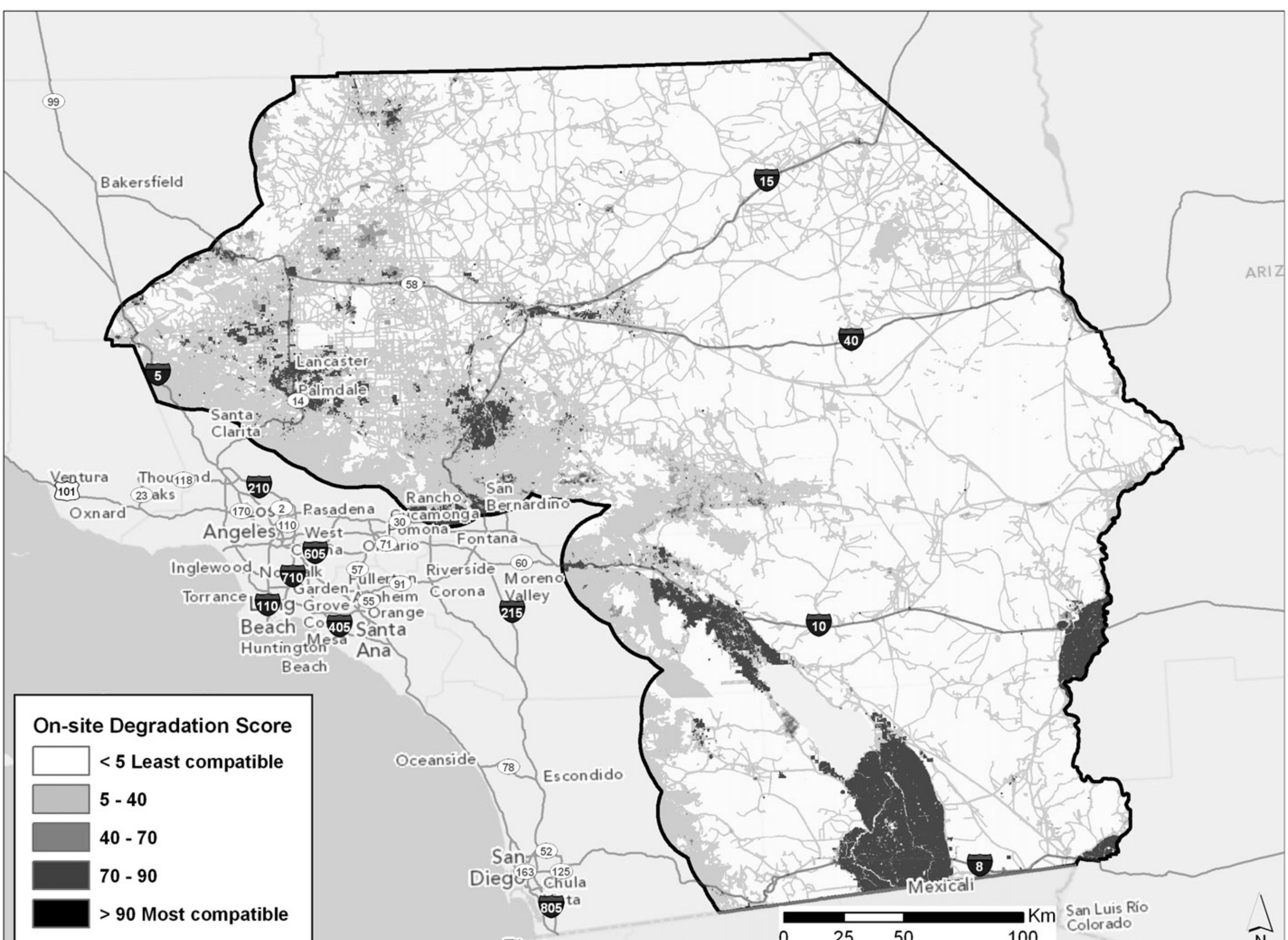

Fig. 3. Map of *On-Site Degradation* scores based on *Impacted Native Vegetation* and degree of *Fragmentation* scores.

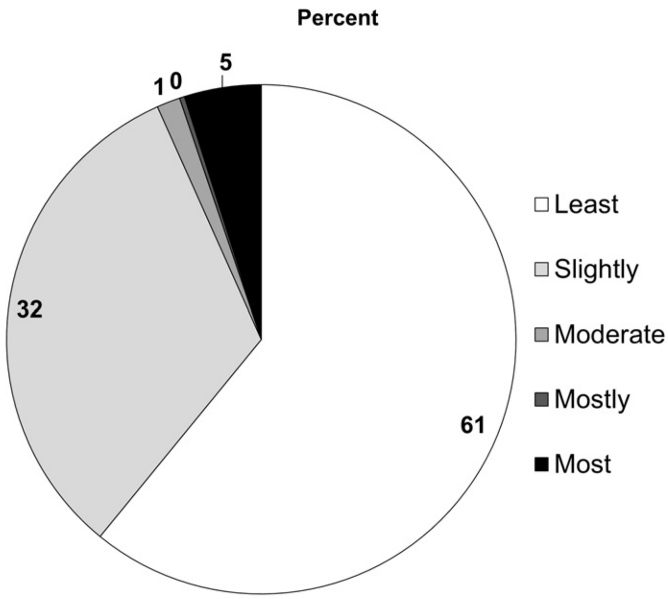

Fig. 4. Pie chart of distribution of *On-Site Degradation* scores.

The ArcGIS Cost Distance tool creates an output raster in which each cell is assigned the cumulative cost to the closest source cell. The algorithm finds the lowest cost from a source cell, in this case a paved highway, existing electrical substation, or existing transmission line, to a neighboring cell. The algorithm then proceeds iteratively to calculate the least cumulative cost (ecological impact) to every cell in the study area. Therefore the value of each cell integrates the geographic distance to infrastructure and associated environmental cost. The three cost-distance (CD) scores were aggregated by equal-weighted averaging them (Equation (5)) as there was no basis for weighting one higher than the others. Note that the overall score for *Off-Site Impacts*, *I*, represents the lowest possible cumulative impact (i.e., least environmental cost) to connect a site. The actual pathway for a project's access roads and connector lines may follow a route with a higher environmental cost, especially if the financial cost would be lower.

$$I = (\text{CD to highways} + \text{CD to substations} + \text{CD to existing transmission})/3 \tag{5}$$

The overall *Compatibility Index*, *C*, score was calculated as the mean of the *On-Site Degradation* and *Off-Site Impact* scores (Equation (6)), ranging from 0 (least compatible) to 100 (most compatible). Unlike the intermediate nodes that were based on a most limiting factor principle, the logic for the top node was that a combination of high scores in both inputs was necessary to be rated as highly compatible. Based on the dispersion of scores, we chose to assign overall scores greater than 90 to the Most Compatible class. This same scoring rule for Most Compatible applied to all intermediate nodes of the hierarchical framework. Model results at intermediate nodes of the framework were retained, both for visualization and for the validation process described below.

$$C = (D + I)/2 \tag{6}$$

Because of the large geographic extent, the analysis depends 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 compatibility of energy projects, however, such errors of omission (i.e., ground conditions are more degraded than indicated by the model) are less risky from the conservation perspective than commission errors by which the model may incorrectly identify a site as being highly degraded and of low conservation value. However, 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 permitting process. We consciously took a conservative approach in applying spatial data to attempt to minimize errors of commission.

To avoid redundancy or double-counting in the model, Pearson's correlation coefficients between some of the spatial data layers were calculated so that any highly correlated criteria could be removed from the model. We examined whether *Off-site Impacts* were correlated with *On-site Degradation*, and whether simple geographic distance was an adequate proxy for cost-weighted distance.

The purpose of the model was to map compatibility of solar energy development with biological resources, but there are many other constraints on energy project siting. For example, utility-scale solar energy projects cannot be technically or economically constructed on slopes greater than 5% [23]. Also urban residents generally oppose utility-scale renewable energy projects in or near their town [6,18] even though urban areas have low biological value. To account for these constraints, we excluded areas with slopes >5% [23] and urban regions mapped by the 2000 US Census. The area of compatible land was determined after these exclusions and compared to the projected area required to meet state renewable energy goals [17]. Because *Compatibility Index* scores are relative, we determined area at two threshold scores: >90 and more liberally, scores >70.

2.4. Model review and validation

Validation is challenging in suitability analysis because the model outcome is not directly measurable in the field. The degradation/condition layer was evaluated against a set of 381

Table 3
Comparison of model scores to photo interpreted point scores for on-site degradation. Bold font indicates agreement between model scores and photo interpreted points.

		Model degradation score				
		Not degraded	Slightly degraded	Moderately degraded	>90 most degraded	Total
Photo interpretation overall score	0 Not degraded	**128**	91	6	0	225
	1 Slightly degraded	15	**65**	8	3	91
	2 Moderately degraded	2	13	**9**	3	27
	3 Most degraded	0	4	4	**30**	38
	Total	145	173	27	36	381
	% agreement	88	38	33	83	61

Kappa Statistic: 0.40.
Model shows more degradation than photoplots 29%.
Photoplots show more degradation than model 10%.

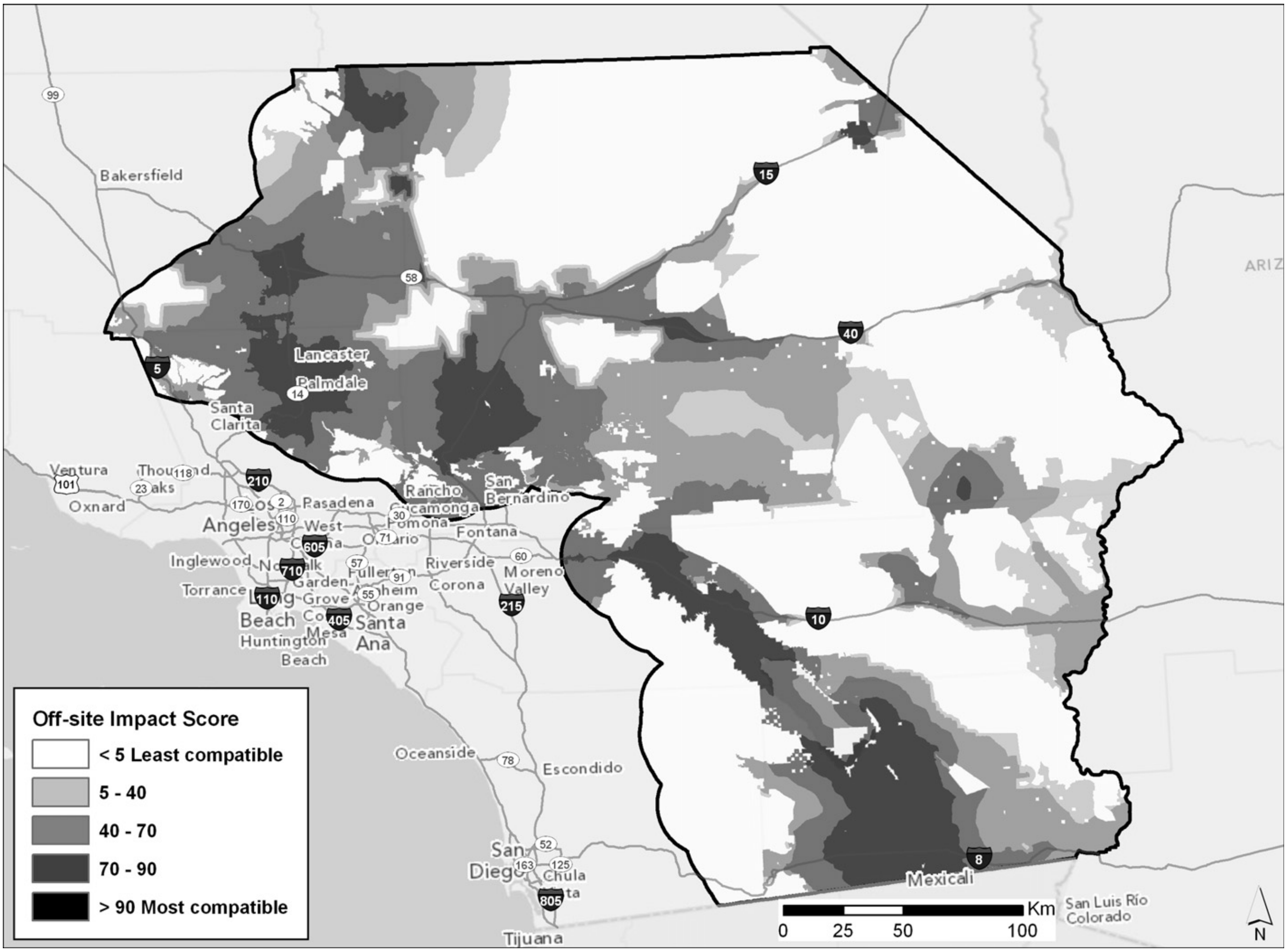

Fig. 5. Map of *Off-Site Impact* scores based on cost-distance from highways, substations, and transmission lines.

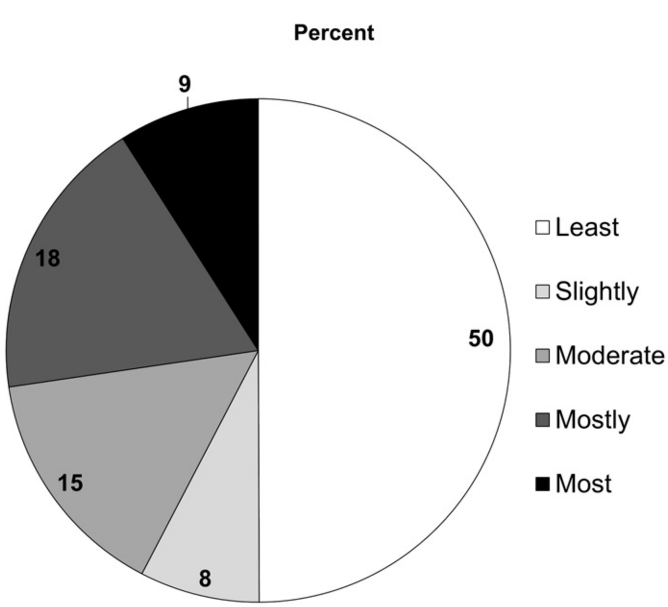

Fig. 6. Pie chart of distribution of *Off-Site Impact* scores.

random points that were photo interpreted from 2009 to 2010 National Agricultural Inventory Program 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. 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. Fragmentation scores were similarly classed into four levels, and then the Cover and Fragmentation classes were combined into the same four levels. These point values were then compared with the modeled predictions of *On-Site Degradation* in an error matrix. Investigating the mismatches between plots and the initial modeling led to several modifications in the initial model (see Ref. [24] for details).

The revised model results were distributed to a group of knowledgeable people for comment, including staff from agencies, environmental groups, and consultants involved in the DRECP. Their feedback led to several other revisions prior to the final version of the model. A new error matrix was generated for the final version, and the kappa statistic was calculated to indicate the relative level of confidence.

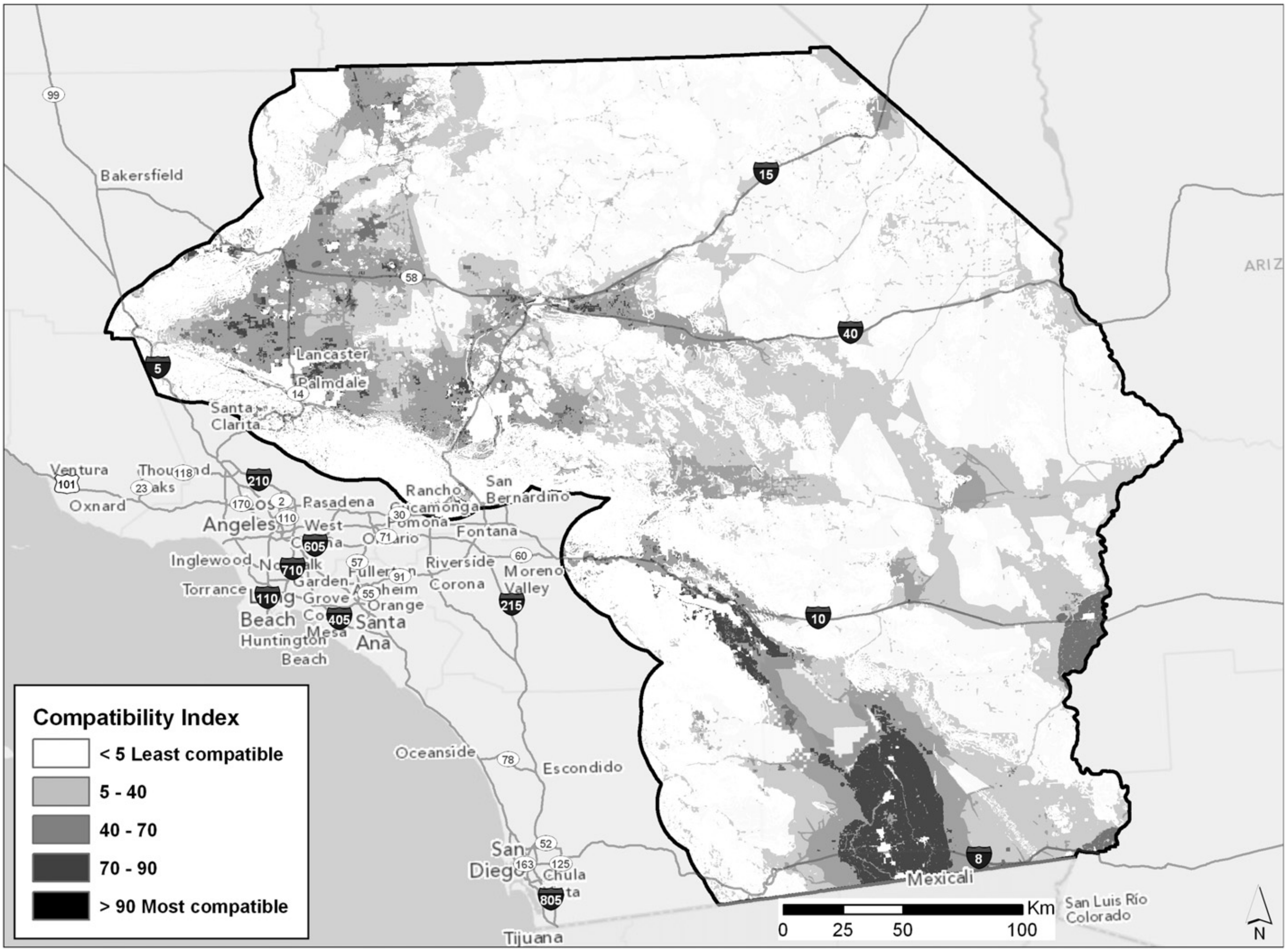

Fig. 7. Map of the *Compatibility Index* based on *On-Site Degradation* and *Off-Site Impact* scores. Urban areas and slopes >5% that were excluded in this study because they are unsuitable for solar energy development are displayed in the Least Compatible class.

3. Results

The model identified only 5% of the study area with high *On-Site Degradation* scores (>90), clumped in valley floors where urban and agricultural land use occurs (Figs. 3 and 4). Otherwise most of the study area is classed as least degraded. The main exception is where roads and other linear features fragment the habitat and yield a moderately low score. The model showed generally good agreement with the photoplots in the most (83%) and not degraded (88%) classes, but often predicted a slightly greater degree of degradation in the mid-range scores than was discerned in the photoplots (Table 3). Overall agreement was 61%, with a kappa statistic of 0.40.

Off-Site Impact scores (Figs. 5 and 6) show large core areas (9% of study area) around urban and agricultural areas that had high scores (>90). Nevertheless, the Pearson correlation between *On-Site Degradation* and *Off-Site Impact* was only 0.36, indicating that they were not highly redundant. The Pearson correlation between Euclidean or geographic distance and cost-distance was only 0.19, so including a cost associated with ecological condition added new information to the conventional approach in renewable energy suitability analysis.

Averaging the *On-Site Degradation* and *Off-Site Impact* criteria scores produced more *Compatibility Index* values near the center of the potential compatibility range with fewer grid cells in the Most

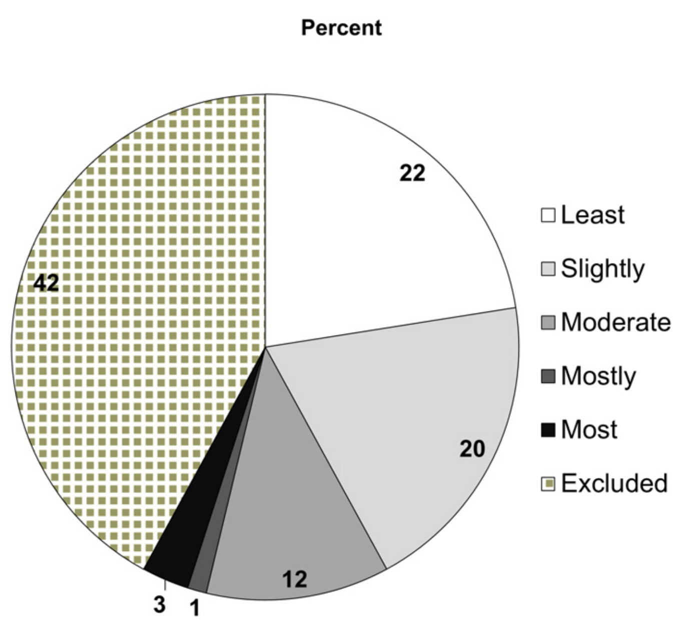

Fig. 8. Pie chart of distribution of *Compatibility Index* scores, after excluding urban areas and slopes >5%.

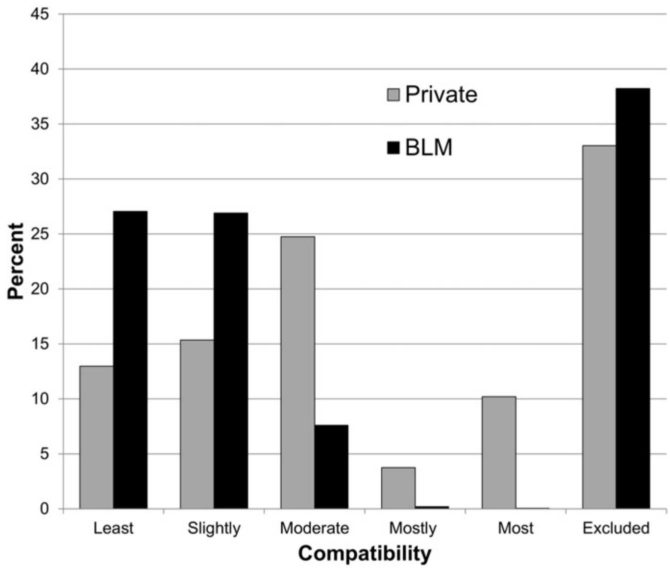

Fig. 9. Histogram of percentage of compatibility classes on privately-owned lands and federal Bureau of Land Management (BLM) lands.

or Least Compatible classes (Figs. 7 and 8). Nearly 4 million ha (42% of the study area) were excluded because of urban areas or slopes >5%. Even though only 3% of the study area has scores >90 in the "Most Compatible" class, this corresponds to roughly 282,000 ha, with 396,000 ha with scores >70 after excluding urban areas and slopes >5%. Thus there appears to be a sizeable area of degraded land close to infrastructure yet outside of towns and unsuitable terrain. In fact there is an order of magnitude more land modeled as Most Compatible than the approximately 25,000 ha required to meet California's clean energy goals [17].

Most permitting applications for solar energy projects have been filed on privately-owned lands and federal lands managed by the Bureau of Land Management. Compatibility scores are distributed quite differently between the two ownerships (Fig. 9). Even excluding urban areas, private lands tend to be much more degraded than federal lands, and therefore have a higher percentage of Most Compatible lands. Nearly all of the Most Compatible lands are privately-owned (272,000 ha), with only 1700 ha managed by BLM.

4. Discussion

The mitigation hierarchy defined in the US National Environmental Policy Act specifies four levels of dealing with environmental impacts in decreasing order of preference—avoid, minimize, restore, offset. Generally each level becomes more costly, and the probability of success becomes less certain Refs. [18,25,26]. Therefore avoidance of impacts would appear to be a prudent strategy from the perspective of any stakeholder. Mapping areas that would avoid or minimize impacts over a regional scale would be a valuable information resource for developers, permitting agencies, and conservation interests.

The framework presented here provides a transparent logic for identifying compatible, low impact sites that appear to have low conservation value because they are already degraded habitat and can be connected to existing infrastructure with minimal impact on intervening lands. It fills a gap between regional site suitability prospecting for renewable energy and systematic biodiversity conservation planning. This study assesses potential compatibility on both private and public lands. We propose that the framework could also be used to assist in prioritizing the processing of solar (and wind) energy development right-of-way applications by BLM.

The study most similar to this paper mapped disturbed lands to determine what level of wind energy penetration was possible with minimal impact on conservation values [18]. This would be similar to our *Impacted Native Cover* criterion, because that study did not include fragmentation or off-site impacts. They excluded certain areas from the disturbed category (e.g., protected areas, urban areas) that our model treated as costs or in post-analysis. The Brody et al. map [13] is similar in revealing the potential level of conflict, in their case of oil and gas extraction in the Gulf of Mexico. The main differences are that biodiversity was just one of eight marine interests that compete with energy production, and it was represented by spatial data on important habitats rather than inferred from ecological condition.

As with any spatial model, there are inherent limitations. Only mapped land uses provide evidence of degradation. Some forms of land use such as intensive grazing or off-road vehicle use often go unmapped and hence are omitted in the model. Such omissions are not risky for biological resources, however, because these sites would be erroneously labeled as least compatible. 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. Therefore not all least compatible land will prove to be of high conservation value. Conversely some agricultural land may provide more suitable habitat for some species than utility-scale energy development. We recommend that a decision process include a process for consideration of erroneously mapped least compatible sites for solar development and for denial of applications (or additional mitigation) on most compatible sites where biological value can be shown to be high.

The logic framework for the model should be transferrable to most regions, even if the data and GIS modeling might need to be adapted to each location. Modeling recovery of past agricultural activity appears to be an improvement over the conventional method of using a past snapshot of land use to model impacted natural cover in our study area. Where agricultural land use is more stable through time, it may be sufficient to use land use data for a single period, since repeating historical land use maps are not so common. The *On-Site Degradation* criterion is similar to the Human Footprint of the West [27], which was designed as a general purpose measure of degradation and not specific to renewable energy. Although developed in the context of solar energy, the framework has similar applicability for wind and geothermal energy. For instance, Janke [6] modeled site suitability for wind and solar farms in Colorado with the same set of environmental and geographic criteria for both technologies. The *On-site Degradation* information from the risk model can inform conservation planning as a factor in determining conservation value and in modeling species habitat suitability. It can be modified with scenarios of future development and transmission corridors to model future threats and cumulative impacts [19].

The convergence of the economic objectives of energy developers and conservation objectives of environmental groups is an encouraging aspect on which we based this study. Both stakeholder groups prefer that renewable energy developments be sited close to roads and transmission infrastructure, corresponding to the *Off-Site Impacts* criterion in the model. They may also agree on the use of degraded lands for energy projects to avoid or minimize impacts and potential conflict. Applying this win–win strategy demonstrated that there is ample compatible land, outside of urban areas and steep terrain, to meet the solar contribution toward 2050 greenhouse gas reduction goals at the least challenging levels of the mitigation hierarchy. Directing renewable energy development to the most compatible lands in the short-term should expedite the rapid, yet sustainable, deployment of low-carbon energy resources.

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References

[1] Audubon California, California Wilderness Coalition, Defenders of Wildlife, Desert Protective Council, Mojave Desert Land Trust, Natural Resources Defense Council, Sierra Club, The Nature Conservancy, The Wilderness Society, The Wildlands Conservancy, Renewable Siting Criteria for California Desert Conservation Area; 2009.
[2] Draft programmatic environmental impact statement (EIS) for solar energy development in six southwestern states. Washington, DC: BLM/DOE; 2010.
[3] Spencer WD, Abella S, Barrows C, Berry K, Esque T, Garrett K, et al. Recommendations of independent science advisors for the California desert renewable energy conservation plan (DRECP), Unpublished Report to the Renewable Energy Action Team (California Department of Fish and Game, U.S.) Fish and Wildlife Service, U.S. Bureau of Land Management, and California Energy Commission; 2010.
[4] Voivontas D, Assimacopoulos D, Mourelatos A, Corominas J. Evaluation of renewable energy potential using a GIS decision support system. Renewable Energy 1998;13:333–44.
[5] Baban SMJ, Parry T. Developing and applying a GIS-assisted approach to locating wind farms in the UK. Renewable Energy 2001;24:59–71.
[6] Janke JR. Multicriteria GIS modeling of wind and solar farms in Colorado. Renewable Energy 2010;35:2228–34.
[7] Carrión JA, Espín Estrella A, Aznar Dols F, Ridao AR. The electricity production capacity of photovoltaic power plants and the selection of solar energy sites in Andalusia (Spain). Renewable Energy 2008;33:545–52.
[8] Charabi Y, Gastli A. PV site suitability analysis using GIS-based spatial fuzzy multi-criteria evaluation. Renewable Energy 2011;36:2554–61.
[9] Rodman LC, Meentemeyer RK. A geographic analysis of wind turbine placement in Northern California. Energy Policy 2006;34:2137–49.
[10] Aydin NY, Kentel E, Duzgun S. GIS-based environmental assessment of wind energy systems for spatial planning: a case study from Western Turkey. Renewable and Sustainable Energy Reviews 2010;14:364–73.
[11] Nobre A, Pacheco M, Jorge R, Lopes MFP, Gato LMC. Geo-spatial multi-criteria analysis for wave energy conversion system deployment. Renewable Energy 2009;34:97–111.
[12] Defne Z, Haas KA, Fritz HM. GIS based multi-criteria assessment of tidal stream power potential: a case study for Georgia, USA. Renewable and Sustainable Energy Reviews 2011;15:2310–21.
[13] Brody SD, Grover H, Bernhardt S, Tang Z, Whitaker B, Spence C. Identifying potential conflict associated with oil and gas exploration in Texas state coastal waters: a multicriteria spatial analysis. Environmental Management 2006;38:597–617.
[14] Bailey RG. Description of the ecoregions of the United States. rev. and expanded. 2nd ed. Washington, DC: USDA Forest Service; 1995. p. 108.
[15] Black & Veatch. Renewable energy transmission initiative: RETI phase 2B final report, San Francisco; 2010.
[16] California Department of Fish and Game, California Energy Commission, United States Bureau of land management, United States Fish and Wildlife Service, Desert Renewable Energy Conservation Plan Planning Agreement, Sacramento, California; 2010.
[17] California Energy Commission. Desert renewable energy conservation plan: renewable energy acreage calculator and the 2040 revised scenario's renewable portfolio, revised July 27, 2012.
[18] Kiesecker JM, Evans JS, Fargione J, Doherty K, Foresman KR, Kunz TH, et al. Win-win for wind and wildlife: a vision to facilitate sustainable development. PLoS ONE 2011;6:e17566.
[19] Davis FW, Costello CJ, Stoms DM. Efficient conservation in a utility-maximization framework. Ecology and Society 2006;11:33 [online] URL: http://www.ecologyandsociety.org/vol11/iss31/art33/.
[20] Webb RH, Belnap J, Thomas KA. Natural recovery from severe disturbance in the Mojave Desert. In: Webb RH, Fenstermaker LF, Heaton JS, Hughson DL, McDonald EV, Miller DM, editors. The Mojave desert: ecosystems, processes and sustainability. Reno, Nevada: University of Nevada Press; 2009. p. 343–77.
[21] Brooks ML, Matchett JR. Spatial and temporal patterns of wildfires in the Mojave Desert, 1980–2004. Journal of Arid Environments 2006; 67(Suppl.):148–64.
[22] Danger M, Daufresne T, Lucas F, Pissard S, Lacroix G. Does Liebig's law of the minimum scale up from species to communities? Oikos 2008;117:1741–51.
[23] RETI Stakeholder Steering Committee. Renewable energy transmission initiative phase 1B final report, Sacramento, California; 2009.
[24] Stoms DM, Dashiell SL, Davis FW. Mapping compatibility to minimize biodiversity impacts of solar energy development in the California Deserts. Santa Barbara: Biogeography Lab, University of California Santa Barbara; 2011.
[25] Lovich JE, Ennen JR. Wildlife conservation and solar energy development in the desert southwest, United States. BioScience 2011;61:982–92.
[26] Quintero JD, Mathur A. Biodiversity offsets and infrastructure. Conservation Biology 2011;25:1121–3.
[27] Leu M, Hanser SE, Knick ST. The human footprint in the west: a large-scale analysis of anthropogenic impacts. Ecological Applications 2008;18:1119–39.