

Using GIS analytics and social preference data to evaluate utility-scale solar power site suitability



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ABSTRACT

Determining socially acceptable and economically viable locations for utility-scale solar projects is a costly process that depends on many technical, economic, environmental and social factors. This paper presents a GIS-based multi-criteria solar project siting study conducted in the southwestern United States with a unique social preference component. Proximity raster layers were derived from features including roads, power lines, and rivers then overlain with 10×10 m raster terrain datasets including slope and potential irradiance to produce a high resolution map showing solar energy potential from “poor” to “excellent” for high potential counties across the southwestern United States. Similar maps were produced by adding social acceptance data collected from a series of surveys showing the potential public resistance to development that can be expected in areas of high solar energy suitability. Applying social preferences to the model significantly reduced the amount of suitable area in each of the selected study areas. The methods demonstrated are expected to help reduce time, money, and resources currently allocated toward finding and assessing areas of high solar power suitability.

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1. Introduction

Energy demand is determined primarily by population growth, industry, and geographic distribution, whereas the amount of people that can be supported at an acceptable quality of life relies heavily on the availability, costs, and efficiency to which energy is produced [1]. Extensive, overuse of fossil fuels has been argued to be responsible for excessive levels of carbon dioxide and resulting ecologic, social, and, economic impacts [2]. This recognition drives much active research in renewable energy.

Expanded use of renewable energy is expected to increase global energy production at levels that would forego at least some use of the world's finite resources and reduce the human impact on the environment. Photovoltaic (PV) energy has lately received growing attention as a potential alternative/renewable energy source with clear advantages for regions where grid connected power is inconvenient or expensive. In spite of recent efforts to expand solar energy production, solar power presently contributes

only a small percentage of the total global energy supply. However, PV energy production has shown to produce enough power to compete in large scale markets [3]. In recent years, advanced solar panel manufacturing practices have led to a dramatic drop in costs and solar energy production has been shown to compete in price with conventional sources in some U.S. markets [4]. As the PV market grows, manufacturers will continue to standardize designs and system installation and share efficient practices to further reduce costs associated with PV energy production [5]. Paired with the falling cost of PV hardware and technology, the viability of PV utility-scale power production has the potential to capture a significant share of the energy market.

At present, only 3% of the global energy market is supplied by PV, however countries that have made renewable energy a priority demonstrate meeting more than 30% of electricity demand with wind and solar [6]. Historically, concerns regarding the long term sustainable use of solar power have included costs related to variable energy integration into the grid and the cost-to-efficiency ratio regarding the variability of solar irradiance. These concerns have considerably decreased due to advances in panel-to-grid integration technology. Advances in almost every aspect of PV technology have led to solar energy cost competitiveness.

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As advanced technologies cause physical system or “hard” costs to continue to fall, a greater share of the cost of PV deployment is associated with so-called “soft costs.” A survey directed by the National Renewable Energy Laboratory (NREL) found that non-hardware balance-of-system soft costs account for an increasing portion of PV systems by an average of 50%–64% of total installed price [7]. While the NREL study was for rooftop solar systems and surveyed installers about some soft costs such as planning, time to permit, and compliance, it is indicative of the potential for cost and time savings at the utility-scale for both developers and regulators. Improving site selection through a GIS application to decrease soft costs was specifically called out in a funding competition as part of the Department of Energy’s SunShot Initiative [8]. Recognizing that utility-scale soft costs from a survey of developers is not possible due to the reticence of industry to share competitive information with so few players, the US Department of Energy recently issued a Request for Information to glean information from stakeholders and experts in regard to soft costs of utility-scale solar on public lands [9].

The United States Department of Energy’s SunShot Initiative’s key focus is to give solar power research the boost needed to compete on the open market with other forms of energy production by the end of the decade. This includes the reduction of soft costs such as preliminary siting. According to the energy.gov web site:

“The stated goal of the SunShot Initiative is to reduce the total installed cost of solar energy systems to \$.06 per kilowatt-hour (kWh) by 2020. SunShot has achieved 60% of its goal, only three years into the program’s ten-year timeline. Since SunShot’s launch in 2011, the average price per kWh of a utility-scale photovoltaic (PV) project has dropped from about \$0.21 to \$0.11” [10].

Many of these goals are aided through freely accessible and commercial web-based mapping applications to assist analyzing solar energy project siting decisions. Examples of such web mapping applications include:

- **PVMapper** (<http://pvmapper.org>) is an open-source geographic information system (GIS)-based web application that provides utility-scale solar developers with tools and data for site selection and screening of potential PV solar energy plants. This study extensively uses PVMapper for mapping functions, modeling, and analysis.
- **The Eastern Interconnection States Planning Commission (EISPC) Energy Zones Mapping Tool** (<https://eisptools.anl.gov>) facilitates planning for clean energy zones and provides an extensive library of energy resources and other siting factors as mapping layers, models to map the suitability for solar energy and other technologies, and region-specific reports.
- **Solar Energy Environmental Mapper** (<http://solarmapper.anl.gov>) concentrates on the southwestern United States and was developed to share information relevant to siting utility-scale solar projects in the six southwestern states included in the scope of the Solar Energy Development Programmatic Environmental Impact Statement.
- **Landscape Modeler** by Esri is a commercial web based tool that allows a user to specify environmental and cultural factors considered important to decision making, select the appropriate data layers, weigh them according to importance, and then use geoprocessing tools to identify the best locations for a particular purpose.

Software tools such as these allow for the use of raster (grid-based) map data services to visualize information such as critical habitats, development risk, fire potential, and solar power potential

across the U.S., ultimately supporting optimal infrastructure siting decision-making. Advances in data processing technology and the availability of geospatial information have the potential to guide major infrastructure policy decisions [11]. Such tools help fill the need for large scale information management that weighs energy production potential and assess potential cost considerations and conflicts [12]. Indeed, the use of GIS data for renewable resource site suitability analysis has been become a trusted practice for stakeholders worldwide [13–18]. Finding a suitable location for solar energy development affects purchase price, solar power efficiency, environmental impacts, and public opinion [19]. The factors contributing to the success of solar development siting include physical characteristics such as slope, road and water proximity, land ownership and use, and grid connectivity. Developers must also avoid areas with high environmental impact [20]. Much of the data related to these factors are freely available.

In addition to physical constraints, social attitudes can also affect where and solar development occurs. While research demonstrates that majority of Americans support renewable energy generally [21–25] and solar energy in particular [26,27], development of utility-scale solar has been impeded due obstacles such as cost, efficiency, and regulations [28]. A typical explanation of slow development tended to place blame on local residents’ opposition to proposed development. However, recently researchers have found support and opposition to proposed renewable projects are the result of a variety of factors. Indeed, even environmentalists have opposed proposed projects due to the impacts of solar facilities on rare desert plants and animals [29]. In the San Luis Valley of Colorado, local residents sided with environmental groups to oppose a concentrated solar power (CSP) facility due to the impact the project would have on the local ecosystem, especially with regards to transmission line siting, and despite recognizing other benefits of solar power for the environment [27]. This example is not an isolated case; despite widespread support for renewable energy, including solar, specific projects are often met with strong opposition [30]. As Devine-Wright states, “It is widely recognized that public acceptability often poses a barrier towards renewable energy development” [22] (p. 125). Thus, an important factor to successful solar development and other renewables is to understand factors affecting public attitudes toward the resource in general, as well as those perhaps specific to place and geography.

This paper presents an approach to developing large-scale high-resolution site suitability maps of potential utility-scale PV installation locations based on both physical and social constraints. Although the approach could be applied anywhere with adequate spatial data inputs, the method is presented here with results for several counties in the southwest region of the United States. By modeling public sentiments toward potential solar PV development locations the approach can help reduce the potential economical pitfalls associated with public resistance. Public attitudes are of particular importance because they can slow or stop a project that should be permissible by law and regulation.

This approach is of particular value to developers and to government permittees and regulators, called “authorities having jurisdiction” (AHJs). Modeling public preferences in regard to siting energy infrastructure on or near specific land use or land features does not replace the importance of meaningful public engagement for a given project; rather it helps to identify where and why it is most needed. Developers must often simultaneously compare options for sites in multiple jurisdictions if not in different states. Modeling of social preferences enables utility-scale PV developers to down-select a limited number of sites for expensive interconnection studies, at which point they must begin AHJ and public engagement in earnest [31]. AHJs may use the information to identify where constituents and local stakeholders are likely to

prefer or oppose siting infrastructure, as well as the intensity of feeling as to location. This approach targets a different stage in the development process and departs from studies that use the configurative case study method which focuses on public perceptions and engagement after a renewable energy project has already been proposed or constructed [32–34].

Note that the study presented here does not account for regulations – though regulatory issues certainly play a large role in site development. Web-based GIS applications such as PVMapper use datasets that identify lands owned, regulated, or managed by state and federal agencies. Different developers interpret the regulation according to their own business plans and perceptions of risk, with some viewing it as neutral or possibly even a competitive advantage if they have experience with certain requirements, while others view a particular management classification as a “no-go” area [31]. Beyond accurate identification by the application, the varied opinions from developers make the issue of regulations difficult to score objectively and consistently.

2. Methods

Solar energy resource analysis for utility-scale development is affected by factors that can be divided into four categories: technical, economic, environmental, and social. Technical, economic and environmental factors depend on the physical terrain, existing infrastructure proximity, geographic location, and land use restrictions and regulations. The fourth category, “social”, is somewhat variable over time based on popular or cultural beliefs and perceived aesthetics regarding environmental issues, in addition to stages in the development process when opposition tends to be strongest when projects are first proposed or revealed to the public [35]. Further, the social category “manifest[s]...the public’s perception of environmental value and agencies’ valuation of ecosystem services” [36], which in turn impact the other three categories. To develop a site suitability map that adequately addresses these four main categories, we assessed and processed available datasets using ArcGIS software. We chose the southwestern region of the U.S. due to the substantial growth of commercial PV in the region, the availability of potential lands with “excellent” suitability, and the ability to test results against many existing PV sites.

The technical, economic and environmental limiting factors for preliminary PV solar siting and this study were derived from discussions and decisions made by the PVMapper Steering Committee – a group of industry professionals who guided the development of PVMapper. Preliminary terrain and proximity siting requires the consideration of existing infrastructure that affect the direct cost of utility-scale PV solar power development and potential solar irradiance that directly impacts the efficiency of an operating site [37]. Vehicle access to a developing site is essential for constructability and maintenance. Due to the high cost of road construction, proximity to existing roads is essential during preliminary siting. Proximity to grid transmission lines affects construction and development costs while proximity to a stable water source is needed for suitable maintenance. While PV power plants require minimal water resources for their operations than other solar power generation technologies (such as CSP), significant water resources are imperative during the development stages of utility-scale PV plants. Only after development is it is generally sufficient to import water via trucks to maintain operations.

For PV development, flat terrain is essential for both solar exposure and constructability while a high daily annual solar irradiance is needed for plant efficiency and stability. Terrain aspect (compass direction) could also be an important physical parameter for site selection – particularly in the case of actual site layout and design issues. However, we chose not to include aspect given the

large scale (state and county level) of this study, the predefined preference for low slopes, and the use of angled mounting brackets to overcome non-optimal slope direction. Land cover and land use are also a critical constraints in nearly every site selection problem. In the current work, land use is included in the model as part of the social acceptance constraint parameters described in Section 2.4. The final set of parameters used in the study include: distances to roads, river, and power lines together with low maximum slopes and with high average daily annual solar irradiance values. Future work could use the approach presented here with the addition of any combination of additional site selection constraints.

The following sections describe the two-phase approach to the project including: 1) large scale (multi-state) site suitability using only physical constraints as limiting factors; and 2) county level assessment of site suitability incorporating both physical constraints and social acceptance factors. Results from phase one were used to help select specific counties for further study in phase two.

2.1. Large scale site suitability map

2.1.1. Limiting factors

The commencement of this project required data for currently operating PV projects within the study area. Solar Energy Industries Association (SEIA) provided its national database of all ground-mounted solar projects, 1 MW capacity and above, that are either operating, under construction or under development. These data were collected by SEIA from public announcements of solar projects in the form of company press releases, news releases, and in some cases conversations with individual developers. Data were edited to show only PV sites in operating status within the southwest region of the U.S. The top 100 capacity sites in the region were selected to determine optimum proximity to specific features as well as slope and solar irradiance values for currently operating PV power plants.

Each selected site was processed by PVMapper [38] to analyze the maximum slope, minimum irradiance value, and distance to nearest river, road, and major grid power line. The PVMapper scorecard tool uses GIS layers to give an overview of the site terrain slope, soil, solar irradiance potential and land cover as well the distance to such features as the nearest transmission lines, rivers, and roads. Data provided by PVMapper are presented in a report for each site. Site data extracted from PVMapper reports were added to a spreadsheet giving each site a row with columns representing distance to feature values, maximum slope and minimum irradiance values for a flat plate tilted solar collector. The values for each column were analyzed and the 85th percentile value was selected to represent limiting values for the Boolean map to be built. The 85th percentile was chosen as roughly one standard deviation from the mean (z -score = 1.036). Using the 85th percentile effectively removed outlier values. The results, shown in Table 1, can be interpreted as follows: 85% of the facilities examined are within .56 km of a road and are within 17.3 km of a river, etc. In the case of the non-distance parameters, 85% of the facilities have at least 6.5 Kwh/m²/day and are on a slope of no more than 3.1°.

2.1.2. Description of data and sources

Terrain data are used to model the potential solar exposure loss due to the poor slope and aspect characteristics of the land. Also a high-resolution digital terrain model can predict constructability issues associated with steep slopes. Digital Elevation Model (DEM) data, or a digital representation of a terrain’s surface, were extracted from the “National Map Viewer” managed by the USGS National Geospatial program (NGP). Data were extracted in 10-m by 10-m cell-size (10 m) raster format and converted to slope raster data, shown in Fig. 1.

Table 1

Selected 85th percentile values for existing site data extracted from PVMapper.

Parameter	85th Percentile
Road proximity distance (km)	.56
River proximity distance (km)	17.3
Power line proximity distance (km)	32.7
Irradiance – Tilted Flat Plate (Kwh/m ² /day)	6.5
Maximum slope (degree)	3.1

Infrastructure proximity data layers used for this analysis were derived from OpenStreetMap (OSM); a collaborative editable map of the world where data is imported from digitization of aerial photography and other user-contributed sources. We chose roads and major electrical grid towers to represent the necessity for nearby grid connections and/or substation conversion potential and site accessibility. We extracted these polyline and point datasets from the study area extent to create the input data layers shown in Fig. 1. Solar irradiance data were derived from solar maps provided by the NREL online data repository. Data values represent, “the solar energy resource available to a flat plate collector, such as a photovoltaic panel, oriented due south at an angle from horizontal to equal the latitude of the collector location” (<http://www.nrel.gov/gis/solar.html>). According to NREL, “this is a typical practice for PV system installation, although other orientations are also used.” The data provide, “monthly average daily total solar resource information on grid cells of approximately 40 km by 40 km in size” [39]. This map was developed from the Climatological Solar Radiation (CSR) Model. The CSR model was derived using three parameters including cloud cover, horizontal surfaces, and trace gasses together with water vapor. Eight years of data were used to define cloud cover as monthly average percent cover per 40 km grid cell [40]. The 40 km data format was extracted as a polygon feature class containing the annual daily average irradiance values in kwh/m²/day, shown in Fig. 1.

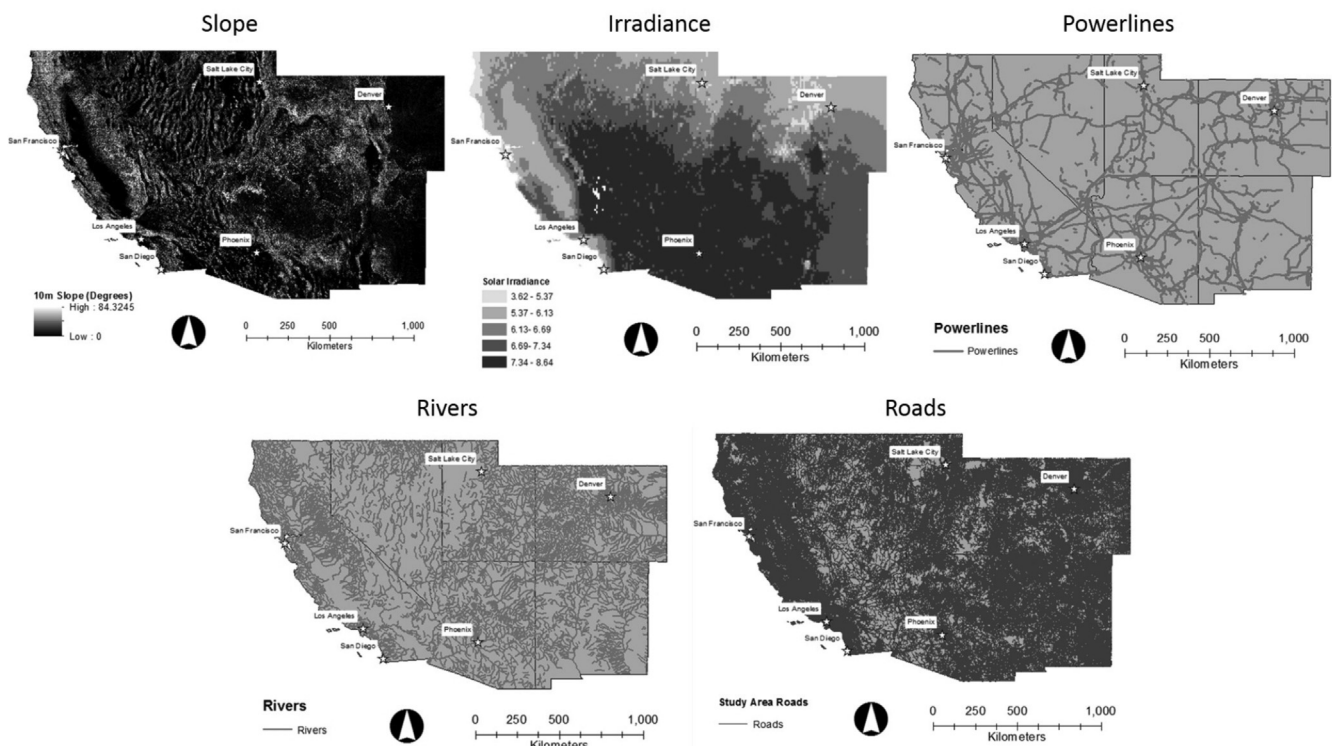
2.1.3. Data preparation

The goal of a Boolean map is to demonstrate geospatial areas that fit within given limitations of various GIS layers. The resulting map is presented in the form of a single vector dataset or “shapefile” representing the area that overlaps every layer's acceptability parameters. The area of study for this project required the infrastructure proximity layers be edited to contain the southwestern region of the U.S. We processed the road polyline data for the area of study to create a shapefile layer representing the acceptable area for PV development according to the 85th percentile values shown in Table 1. This was done using the buffer function in ArcMap that produced a polygon layer representing all area within .56 km of an existing road. We used a similar process to produce polygon layers representing the acceptable areas for development near existing rivers and power lines.

The process to prepare the slope and solar irradiance gridded datasets required the conversion of gridded data to polygons. We then selected the polygons containing acceptable values using a simple SQL expression to query the area containing the acceptable values shown in Table 1. The road, river, power line, slope, and solar irradiance layers were then intersected. The intersect tool, a part of the ArcMap analysis toolbox, computes a geometric intersection of the input features which overlap in all layers. The output produces a shapefile representing the areas that fit within the limitations of each parameter, shown in Fig. 2.

2.1.4. Zonal statistics

The Boolean map shown in Fig. 2 is a representation of suitable land for the development of utility-scale PV solar power. The five suitability factors used were determined by the PVMapper Steering Committee. We derived the parameters for each factor from the analysis done on the 100 highest capacity operational PV sites in the study area. We used the 85th percentile values as limiting values for each factor to produce for the reasons given in 2.1.1. The

**Fig. 1.** Geospatial input data used for site suitability assessment.

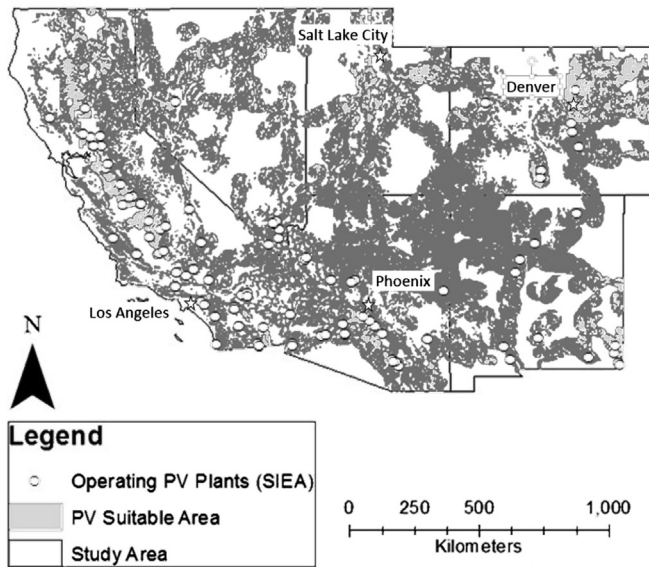


Fig. 2. Acceptable areas for PV development based on large-scale assessment.

Boolean map we created was used for visual suitability analysis and to assess the highest concentration of area suitable for PV development. Using ArcGIS and this map, we calculated the zonal statistics for each county in the southwestern U.S. The results of this analysis are shown below in Table 2.

Table 2 shows the five counties in each state with the highest concentration of suitable area in order of most total suitable area as defined by the Boolean map and the zonal analysis we prepared using ArcMap. This preliminary breakdown returned the counties

Table 2
Results of the zonal statistical analysis showing percent and total suitable area.

State	County	Total area (Km ²)	Suitable area (Km ²)	Percent suitable area
Arizona	Apache	43,123	21,010	49%
Arizona	Navajo	38,463	16,146	42%
Arizona	Maricopa	34,074	15,411	45%
Arizona	Pinal	19,609	9352	48%
Arizona	Cochise	22,466	9223	41%
California	Modoc	19,422	8309	43%
California	Lassen	21,057	12,424	59%
California	Merced	7954	5618	71%
California	Butte	7251	4041	56%
California	Stanislaus	6348	3356	53%
California	Nevada	4214	2875	68%
Colorado	Kit Carson	9359	7436	79%
Colorado	Elbert	7866	6160	78%
Colorado	Arapahoe	3481	2827	81%
Colorado	Alamosa	2892	2180	75%
Colorado	Denver	683	675	99%
Nevada	Pershing	26,836	10,898	41%
Nevada	Eureka	18,313	7818	43%
Nevada	Lyon	8762	4082	47%
Nevada	Storey	1136	579	51%
Nevada	Carson City	695	358	51%
New Mexico	San Juan	22,203	12,936	58%
New Mexico	Chaves	22,647	11,213	50%
New Mexico	Guadalupe	11,606	5874	51%
New Mexico	Valencia	4218	2877	68%
New Mexico	Bernalillo	4476	2438	54%
Utah	Uintah	19,982	9104	46%
Utah	Duchesne	14,451	6510	45%
Utah	Sanpete	6784	3137	46%
Utah	Carbon	6722	2987	44%
Utah	Rich	4750	2240	47%

in the southwestern region of the U.S. that are most suitable for further analysis. We selected the top two counties in each state with highest total suitable area for high-density suitability analysis including social factors.

2.2. Solar PV site suitability analysis

A GIS site-suitability analysis is a process used to determine the appropriateness of a given area for particular use based on a calculated raster or gridded values. The basic principle behind a suitability analysis for the purposes of this project is to determine the degree to which each area is suitable for solar PV development on a utility-scale. Suitability was determined through a multi-factor analysis of landscape characteristics derived from the parameters suggested by the PVMapper Steering Committee including: proximity to roads, rivers, and power lines; low slope; and high solar irradiance.

2.3. Geoprocessing model

High density 10 m cell-size raster layers were produced for each suitability parameter. Proximity-to-feature layers were converted from the vector format provided by OSM to 10 m raster data layers using ArcGIS. Each 10 m raster layer created was built to exactly match the 10 m slope layer raster cells for ease in layer calculations performed at a later stage. Raster input data layers were reclassified and combined using a weighted sum on a cell-by-cell basis using map algebra [41]. We built and organized these operations using a visual programming application called ModelBuilder included in Esri's ArcGIS software package. ModelBuilder allows processes to be organized together in sequences of geoprocessing tools, linking the output of one tool into another tool as input as shown in the geoprocessing workflow in Fig. 3.

To evaluate each area according to its distance to a specific infrastructure feature, we derived a Euclidean distance raster from each road, river, and power line raster using the Euclidean Distance tool in ArcMap to evaluate proximity. The output of this process is then used as the input for a reclassify function that groups distance values into 9 bins and gives each bin an integer ranging from 1 to 9. We chose 9 bins based on the Rice Rule for histogram binning which suggests that the number of bins be equal to twice the cube root of the number samples – in our case, 100 samples. In this way a new output raster is created for each parameter containing only integer values from 1 to 9, each representing a step scale of distances to existing roads. We defined the distribution of bins or categories for each parameter based on common maximum distances for each infrastructure feature. For roads, the 9 categories were reclassified from a range of 0 km–6 km, rivers ranged from 0 km to 45 km, and power line distances ranged from 0 km to 85 km. The workflow diagram for the full suitability assessment process is shown in Fig. 3.

When classifying distances to features it is important to expand the processing extent to include features just beyond the county borders. Fig. 3 shows the county mask feature buffered by 1 km to include nearby features just outside county boundaries. The buffered shape was then used as the extent to which processing occurred. To restore the raster extent to the area of study, a mask of the original county shape was applied during map algebra calculations.

Slope and solar irradiance data were also reclassified to create 10 m raster layers containing integers ranging from 1 to 9. Solar irradiance values were redefined by 9 evenly distributed categories from 3 to 8 kWh/m²/day. We also assigned reclassified values to slope characteristics into 9 evenly distributed categories ranging from 0 to 90°. Cells with a value of 9 represent area of flat terrain or

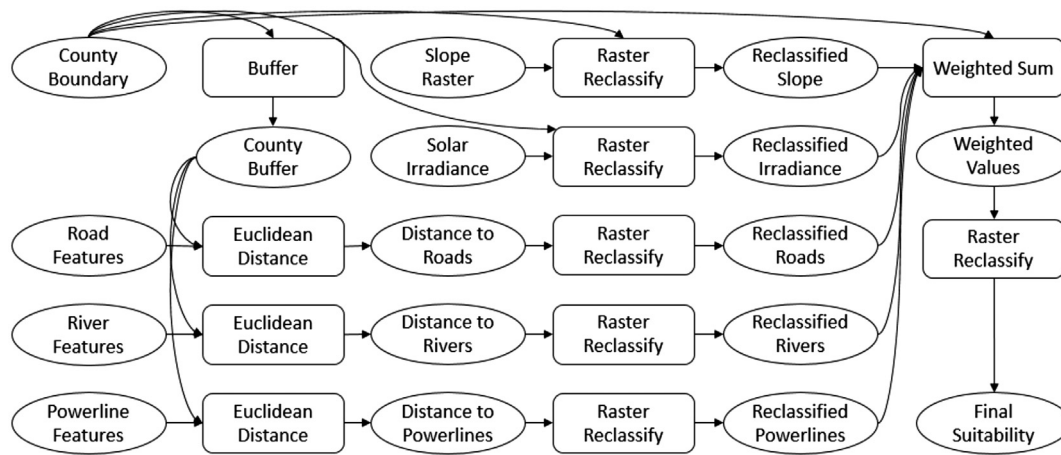


Fig. 3. Geoprocessing workflow including data pre-processing, raster reclassification, and weighted suitability analysis.

high irradiance value. Cells with a value of 1 represent terrain containing steep slopes and areas of low solar exposure.

The reclassified raster datasets shown in Fig. 3 each contain integer values ranging from 1 to 9 representing the suitability inside each layer. The next process, Weighted Sum, combines each of these raster index layers based on the relative value each parameter brings to PV development and operational costs. This step is required because the index values of each parameter do not necessarily correspond to each other directly in terms of actual costs. Weights were developed using the 85th percentile values shown in Table 1 – comparing the cost to construct .56 km of road with the cost to install 17.3 km of water line and 32.7 km of power line. A comparison shows that the needed power line and water line construction cost are similar and about 80 percent of the cost of building the needed road length. The cost associated with the constructability issues that arise from steep slopes is difficult to weigh, so we chose the weighted value for this parameter to be equal to that of building a .56 km stretch of road. The value of solar irradiance is also difficult to determine due to future advancements in technology, but because solar exposure affects plant efficiency for the entire design life of the facility, we chose to weight it 10 percent higher than road construction. Table 3 shows the weighted values.

We determined a weighted sum model or multi-criteria decision analysis was the best method for analysis since each layer has been evaluated cell by cell with an integer value from 1 to 9 that denotes the benefits of each parameter. This model multiplies the weighted value by each raster layer value that sums each corresponding cell. The result is a raster layer containing values ranging from 4.7, the lowest possible product, or 42.3, the highest possible product of the weighted sum model. The weighted sum model result was reclassified as “Poor”, “Good”, or “Excellent” suitability to simplify display and interpretation in the final result maps.

Table 4 shows the weighted sum value ranges and associated reclassified values. Note that the “Excellent” category was defined

at the boundaries of values for all existing sites (i.e. all of the existing sites had weighted sum suitability values between 32 and 42.3). The “Good” and “Poor” value ranges were chosen to split the remaining land areas of the total study area evenly into these two categories (i.e. half of the non-“Excellent” areas had weighted sum suitability values between 26 and 32 and the remaining half of the non-“Excellent” areas had weighted sum suitability values between 4.7 and 26). These values were determined from the results of the physical constraints model (Fig. 3), not including any social acceptance constraints.

The geoprocessing workflow linking the weighted sum analysis to the reclassify tool is shown in Fig. 3. The weighted sum tool was restricted to process only within the confines of the original county boundary. This ensures that final map results show only suitable area inside the area of study, but still include the distance to features outside the extent.

2.4. Public acceptance model

2.4.1. PVMapper survey

The integration of social attitudes moves beyond simplistic “not in my backyard” (NIMBY) explanations that have been intensively criticized in the renewable energy siting literature for assuming opposition comes from ill-informed and purely provincial attitudes and is largely a function of a project’s proximity to a person’s home [25,26,42–44]. Stakeholders’ motivations and reasons for both opposition and support for particular projects are complex and hinge on many factors such as informed knowledge of environmental impact and land use [42]; visual disturbance [45]; trust, perceived equity and fairness [46]; “framing,” [47] local economic development and jobs [48]; and as many recent studies have investigated, attachment to place [26,49].

The present study’s approach focuses on one aspect, and extends the concept of place attachment from “place protective” to “land use and feature protective.” This approach is additionally novel because widespread utility-scale solar development globally is a new phenomenon in just the last few years; most siting

Table 3

Weighted values used to determine suitability.

	Weighted Value
Existing road proximity	1
Existing power line proximity	.8
Existing water source proximity	.8
Slope	1
Solar irradiance	1.1

Table 4

Weighted site suitability status values.

Weighted sum values	Reclassified values
4.7–26	Poor
26–32	Good
32–42.3	Excellent

research has focused on wind energy because it is the most prevalent around the world. Solar research has tended to focus on public support for solar as a technology and at the national level [50].

Included in the scope of the PVMapper project is the formal integration of socio-political attitudes and economical solar site suitability designed from data retrieved from a specially designed 2012 public opinion survey. The survey was administered to a national sample with oversampling in the southwestern US, where large MW utility-scale development was beginning to occur and future projects were being proposed. This population was most apt to have knowledge of solar technology and had experienced the effects of development.

Part of the public opinion survey was designed to gauge the public's preferred distances or buffers, between solar facility and a variety of land features including residential areas, agricultural lands, cultural resources, wildlife breeding grounds, recreation areas, and existing solar facilities. The survey questions defined 4 categories of distances for response: less than a mile, 1–5 miles, 6–10 miles, and more than 10 miles. These categories define the minimum acceptable distance between the land feature and a potential solar facility. For example, if a respondent chose less than a mile, the minimum acceptable distance between the feature and the solar generation facility was less than a mile, and any distance greater was acceptable. The responses for preferred buffer distances also acted as a measure or proxy for intensity of feeling. For example, a majority of responses at a more than a 10 mile distance from a given land use or feature inferred a high level of opposition intensity if infrastructure was to be sited in close proximity.

Fig. 4 shows the results representing minimal acceptable distances from each feature to solar power plant construction. For

residential areas, a solar power plant built more than 6 miles away is supported by 72% of those surveyed. For breeding or nesting sites, a large majority of respondents believe that only 10 or more miles away is suitable for PV development and about 49% of those surveyed believe a solar development location needs to be at least 6 miles away from recreational areas. Sixty-five percent of the public believe solar power development within 5 miles of agricultural land is acceptable.

The PVMapper survey allows for site suitability based on technical, economical, and environmental factors to be analyzed according to the potential social acceptance as a function of feature proximity. The method used to locate areas of high suitability with high percentage of public acceptance was to build a public acceptability layer. The goal of a public acceptance model is to build a raster that contains the lowest percentage of potential social acceptance in each cell according to the proximity of the five features of study outlined by the PVMapper survey. This model was designed to produce a high-density result that matches the suitability raster already created. This was done specifically to overlay the suitability layer and social acceptance layer to demonstrate areas of high suitability and high social acceptance contrast to areas of high suitability and potential public resistance.

2.4.2. Model details

Data used to define locations of residential area and agricultural area were derived from land use raster data retrieved from the U.S. Department of Agriculture's National Agricultural Statistics Service. We extracted cells containing values that represent residential areas and agricultural areas to create a residential data layer and an agricultural data layer. Breeding and Nesting location data was

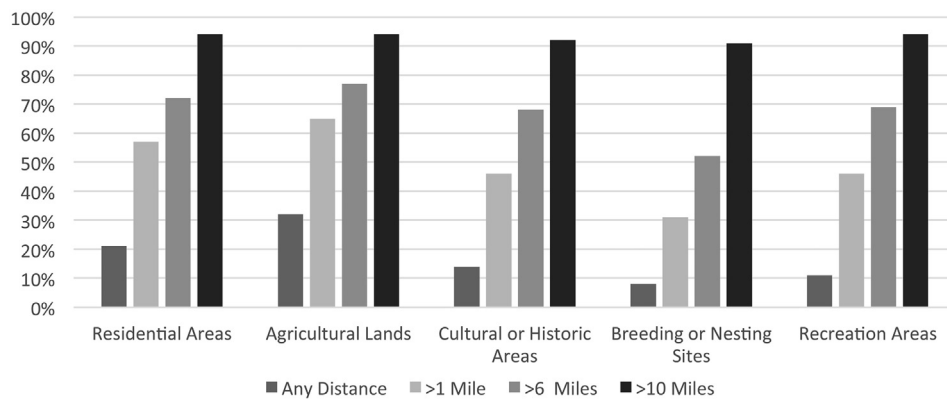


Fig. 4. Survey results for support distances between solar facility and land uses.

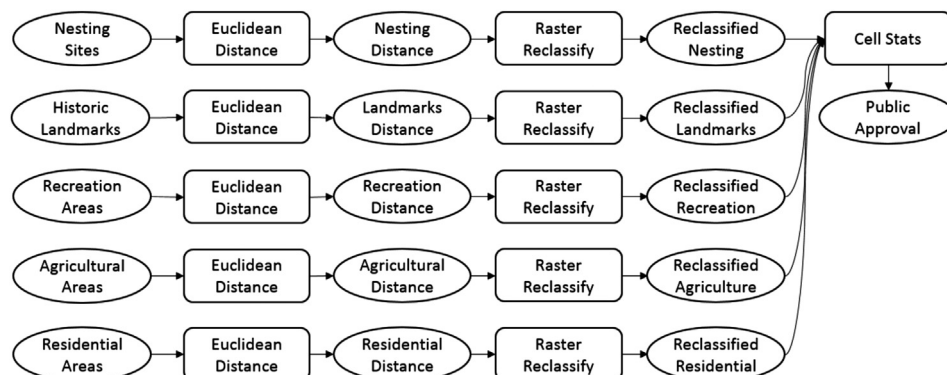


Fig. 5. Geoprocessing workflow for social acceptance model.

defined by the U.S. Fish and Wildlife Services' Geospatial Services and was extracted as polygon shape files. Recreational Boundaries were defined by the U.S. Department of the Interior Bureau of Land Management. The National Register of Historic Places containing geographical locations of registered historic sites was downloaded from the U.S. National Park Service.

We built the social acceptance model using ModelBuilder within the area of study defined for this project as the southwestern U.S. We used each feature layer collected to create 5 Euclidean distance raster datasets with 10 m cell-size and snapped to site suitability raster. The distance raster datasets were reclassified to represent the categorical public acceptance percentages for each cell. For

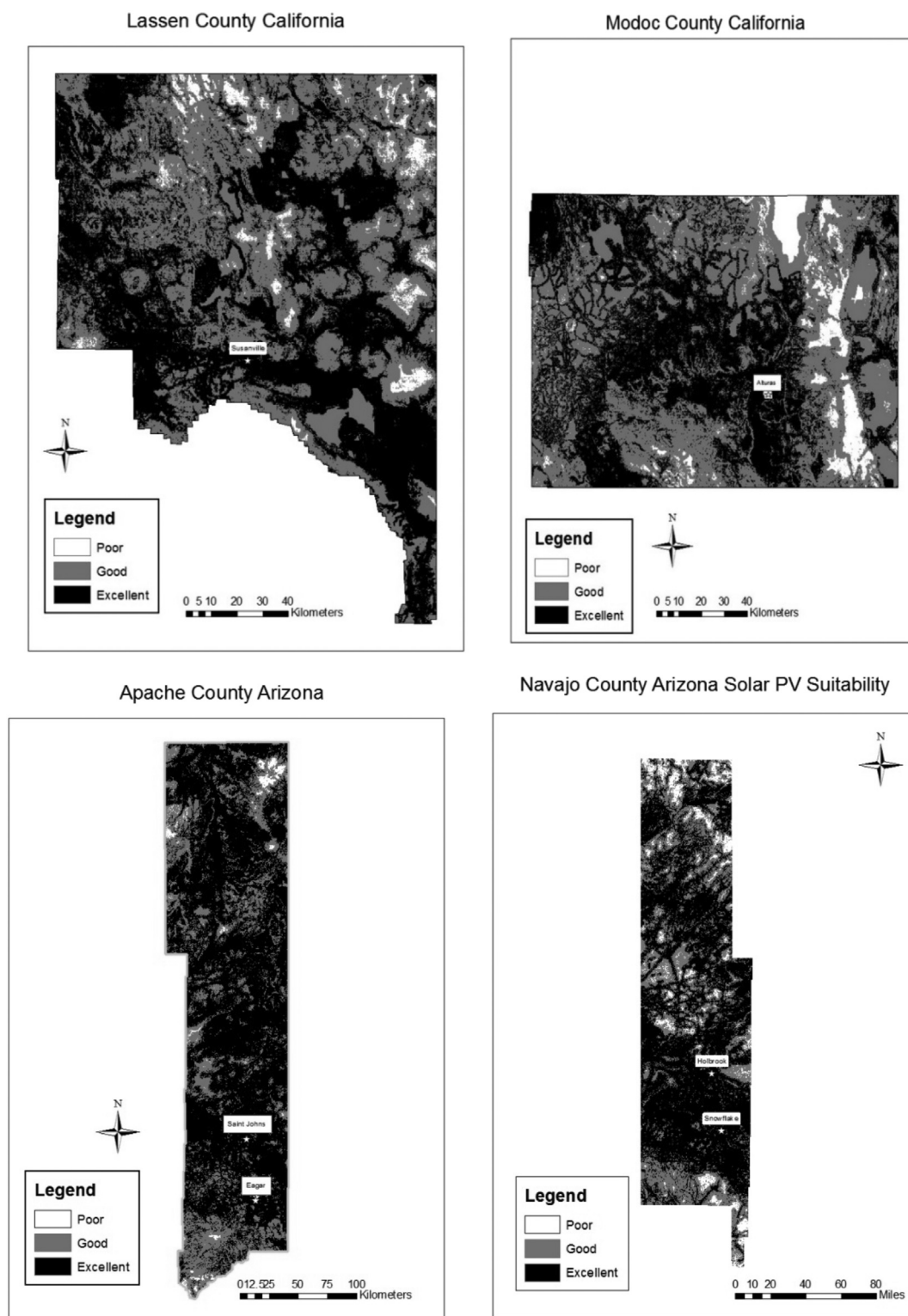


Fig. 6. Site suitability based on physical constraints for Lassen County, Navajo County, Apache County, and Modoc County.

example, we reclassified the distance from residential areas such that all cells within 1 mile of a residential area were replaced with a value of .21 to represent 21% of respondents that feel areas of 1 mile or less to be acceptable for solar site development. Similarly, all areas between 1 and 5 miles of residential areas are represented

with a .57 to show that 57% of people believe 5 miles or less to be acceptable area for solar power development, this was continued for the other values.

After reclassification there were five raster datasets that represent the public acceptance percentage according to proximity to

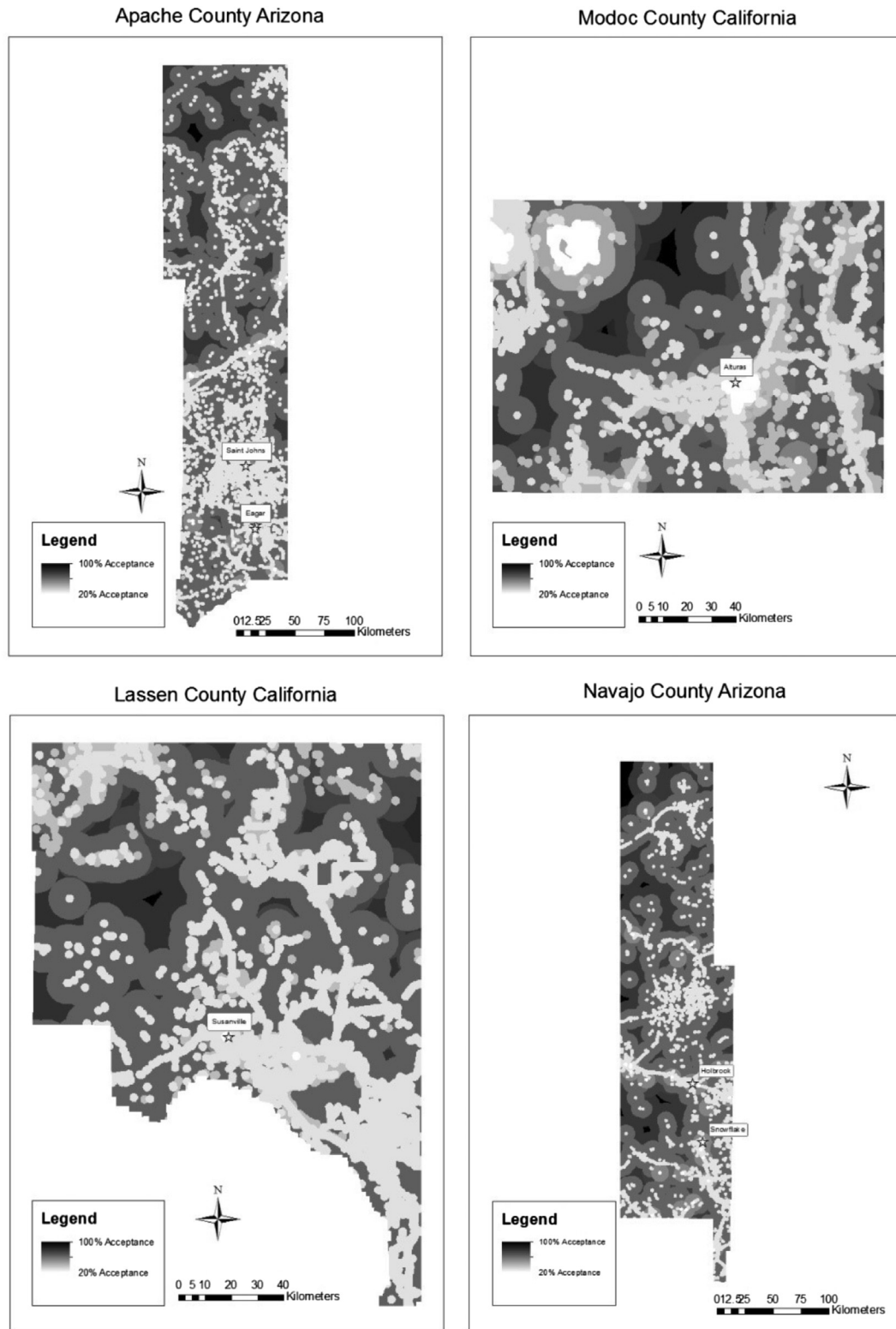


Fig. 7. Results of social acceptance model showing low acceptance (light areas) to high acceptance (darker areas).

each respective feature. We then combined these datasets into one layer using the minimum value of acceptance for each location as the output. This meant that for any location in the area of study there is a value representing the least accepted area for all five input factors. Fig. 5 shows the geoprocessing work for these steps.

The completed Social acceptance model represents the minimum percentage of public acceptance for each area according to

the proximity to certain features such as endangered species habitat and nesting sites, historical landmarks, residential area, agricultural area and recreational area. This model is useful in combination with the suitability model developed. The goal is to analyze the social acceptance of areas with high geographical and economical suitability for solar PV plant development. This goal was satisfied by using simple map algebra to multiply the weighted

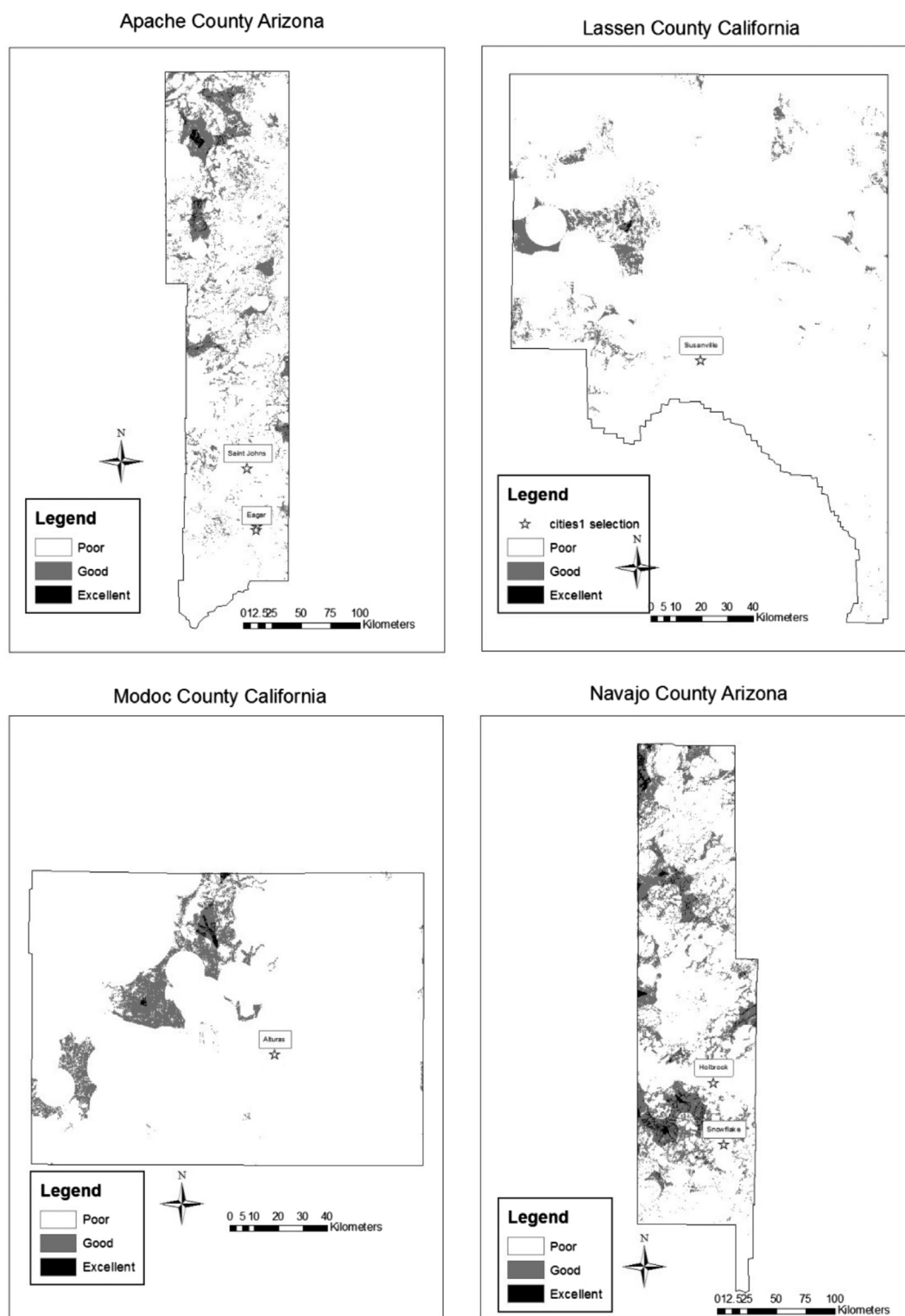


Fig. 8. Site development suitability including social factors.

sum value data produced by the suitability workflow by the social acceptance percentage before categorizing suitability according to Table 4. For example, if an area suitability value was calculated to be 42, a high suitability value, it was then multiplied by its social acceptance percentage value of .4 or 40% to be equal to 16.8. In this way an area of high suitability with low percentage of acceptability becomes an area of low suitability. The resulting map produced can help developers find suitable areas while avoiding areas that could produce public push back or general social disapproval.

3. Results and discussion

3.1. PV suitability results

The PV site suitability model and map product defines the areas of the southwest U.S. region that satisfy the technical, economical, and environmental goals of this study. The weighted values of potential irradiance, slope considerations, and necessary existing infrastructure show areas with high potential output relative to constructability and cost efficiency. Weighted values produced based on this model are shown in terms of “poor”, “good”, and “excellent” for four specific counties in Fig. 6. Note that these initial results do not include social acceptance factors, but are strictly representative of physical constraints.

3.2. Social acceptance model results

The lasting implications of this study reside in the dynamic of predicting likely public acceptance or resistance in regard to land use and land features, or more accurately, public preferences. The social acceptance model presented here is intended to attach values representing the absence of public resistance to visually definable geographical coordinates. The reverse is also true because the model may be used to ascribe resistance values to visual maps; a map incorporating both visualizes public preferences.

The 2012 PVMapper survey used as the underlying source for this model was designed to capture American sentiments toward solar development in general. However, this study was directed specifically at the proximity of suitable land to areas of high environmental controversy. The value of this model is in the identification of the seemingly excellent potential in any siting model that may intrude on areas that can spark public resistance. Developers are made aware early in their own internal decision process as to potential controversy, allowing them to look for alternatives or to place special attention on public engagement and discussions for that use and location. AHJs can use the information to provide meaningful input and guidance to developers seeking to obtain permits and local assent. In sum, public attitudes toward solar development are essential to cost efficiency of PV production and to gain momentum in the continuing battle for energy market share. The map shown below in Fig. 7 shows the gradient of expected public resistance values.

3.3. Resulting county overlay

Table 2 shows counties with high suitability density and total area selected for further, high resolution analysis. For each selected county, the suitability data were extracted and multiplied by the public acceptance factor defined above. The result of this operation can be interpreted as the suitable area for solar PV development that has the least risk of encountering public resistance. The distinction between high economic, environmental, and technical potential and that same potential demonstrated with limited negative public attitudes is essential to the financial success of solar power production. By comparing Fig. 8 to Fig. 6, one can readily see

Table 5

Comparison of models with and without social considerations.

	Suitability Category	Results without social data		Results including social data	
		Area (km ²)	Percent of total area	Area (km ²)	Percent of total area
Apache AZ	Poor	512	1%	36,922	86%
	Good	11,286	26%	5986	14%
	Excellent	31,325	73%	215	<1%
Navajo AZ	Poor	1934	5%	29,531	77%
	Good	12,647	33%	8284	21%
	Excellent	23,880	62%	646	2%
Lassen CA	Poor	721	3%	20,321	97%
	Good	9925	47%	729	3%
	Excellent	10,409	50%	5	<1%
Modoc CA	Poor	1197	6%	18,153	94%
	Good	9871	51%	1230	6%
	Excellent	8353	43%	38	<1%
Duchesne UT	Poor	3133	22%	14,423	100%
	Good	6810	47%	27	0%
	Excellent	4506	31%	0	<1%
Uintah UT	Poor	2395	12%	19,916	100%
	Good	10,225	51%	65	0%
	Excellent	7361	37%	0	<1%
Eureka NV	Poor	1427	8%	17,114	93%
	Good	8408	46%	1195	7%
	Excellent	8408	46%	4	<1%
Pershing NV	Poor	2062	8%	23,582	88%
	Good	12,878	48%	3135	12%
	Excellent	11,895	44%	117	<1%
Elbert CO	Poor	16	<1%	7835	100%
	Good	2614	33%	31	<1%
	Excellent	5236	67%	0	<1%
Kit Carson	Poor	4	<1%	9355	100%
	Good	1698	18%	4	<1%
	Excellent	7656	82%	0	<1%
Chaves NM	Poor	68	<1%	20,417	90%
	Good	4594	20%	2020	9%
	Excellent	17,984	80%	209	1%
San Juan NM	Poor	0	<1%	18,926	85%
	Good	2354	11%	3219	15%
	Excellent	19,847	89%	56	<1%

the high percentage of otherwise suitable area should be avoided in light of potential public resistance. The social acceptance factor is presented here as very conservative to avoid the unpredictable culture of public opinion. In this way the models outlined in this paper lead to defining areas carrying all the criteria necessary with a high degree of confidence.

The amount of suitable area categorized as “Excellent” is significantly reduced by current public attitudes toward utility scale PV development. Although this study does not cover all possible public concerns regarding solar development, it does allow for future developers to consider aspects to siting that could cause significant public outcry. An important finding of this study and addition to the field of knowledge is that public concerns are to be far reaching and have reduced the amount of suitable area by as much as 78% in some counties. Table 5 compares the output of the models with and without social data.

4. Conclusions

The goals of this study included determining likely acceptable and economically viable locations for utility-scale solar projects. By developing models with and without multi-criteria social acceptance, in-depth preliminary siting analysis can be done that allows for the avoidance of solar development from areas that can cause constructability and public issues. These issues hamper the solar PV industry with both added cost and decreased efficiency. This paper

presented the methods and results from a GIS-based spatial multi-criteria solar siting assessment study done for the southwest U.S. region. Suitability was assessed through economic, technical, environmental, and social factors to determine areas of the study region that contain both excellent terrain with proximity to features that reduce the cost of construction and are in harmony with the environmental sentiments of the public. Using this model developers will understand the limitations associated with current social opinion regarding environmental issues. Avoiding unforeseen public resistance will overall reduce the soft costs associated with solar development.

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References

- [1] Holdren J. Population and the energy problem. *Popul Environ* 1991;03/01;12: 231–55.
- [2] Coyle E D A S, Richard A. Understanding the global energy crisis (knowledge unlatched open access edition ed.). 2014.
- [3] Darling SB, You F, Veselka T, Velosa A. Assumptions and the leveled cost of energy for photovoltaics. *Energy & Environ Sci* 2011;4:3133–9.
- [4] Drury E, Brinkman G, Denholm P, Margolis R, Mowers M. Exploring large-scale solar deployment in DOE's SunShot vision study. In: Photovoltaic specialists conference (PVSC), 2012 38th IEEE; 2012. p. 000763–8.
- [5] Goodrich A, James T, Woodhouse M. Residential, commercial, and utility-scale photovoltaic (PV) system prices in the United States: current drivers and cost-reduction opportunities. 275–3000 Contract 2012;303.
- [6] Nichols W. IEA: expanding wind and solar power does not mean additional costs. March 19, 2014. Available: <http://www.businessgreen.com/bg/analysis/2331389/iea-expanding-wind-and-solar-power-does-not-mean-additional-costs>.
- [7] Ardani K, Barbose G, Margolis R, Wiser R, Feldman D, Ong S. Lawrence Berkeley National Laboratory. In: Golden CO, editor. Benchmarking non-hardware balance-of-system (Soft) costs for US photovoltaic systems using a bottom-up approach and installer survey. Berkeley, CA: National Renewable Energy Laboratory; 2012.
- [8] U. D. o. Energy. In: Funding opportunity announcement – Sunshot initiative – reducing market barriers and non-hardware balance of system costs; 2011.
- [9] U. D. o. Energy. Close Date. In: Request for information: reducing the soft costs for utility-scale solar installations on public lands; January 2013.
- [10] Energy gov. (2013, March 17, 2014). Available: <http://energy.gov/eere/sunshot/mission>.
- [11] Stein EW. A comprehensive multi-criteria model to rank electric energy production technologies. 6// *Renew Sustain Energy Rev* 2013;22:640–54.
- [12] Calvert K, Pearce JM, Mabey WE. Toward renewable energy geo-information infrastructures: applications of GIScience and remote sensing that build institutional capacity. 2// *Renew Sustain Energy Rev* 2013;18:416–29.
- [13] Dawson L, Schlyter P. Less is more: strategic scale site suitability for concentrated solar thermal power in Western Australia. 8// *Energy Policy* 2012;47:91–101.
- [14] Gastli A, Charabi Y. Solar electricity prospects in Oman using GIS-based solar radiation maps. 2// *Renew Sustain Energy Rev* 2010;14:790–7.
- [15] Aydin NY, Kentel E, Sebnem Duzgun H. GIS-based site selection methodology for hybrid renewable energy systems: a case study from western Turkey. 6// *Energy Convers Manag* 2013;70:90–106.
- [16] Omitaomu OA, Blevins BR, Jochem WC, Mays GT, Belles R, Hadley SW, et al. Adapting a GIS-based multicriteria decision analysis approach for evaluating new power generating sites. 8// *Appl Energy* 2012;96:292–301.
- [17] van Haaren R, Fthenakis V. GIS-based wind farm site selection using spatial multi-criteria analysis (SMCA): evaluating the case for New York State. 9// *Renew Sustain Energy Rev* 2011;15:3332–40.
- [18] Hossain J, Sinha V, Kishore VVN. A GIS based assessment of potential for windfarms in India. 12// *Renew Energy* 2011;36:3257–67.
- [19] Kuiper J, Ames DP, Koehler D, Lee R, Quinby T. Web-based mapping applications for solar energy project planning. 2013.
- [20] Stoms DM, Dashiell SL, Davis FW. Siting solar energy development to minimize biological impacts. 9// *Renew Energy* 2013;57:289–98.
- [21] Bell D, Gray T, Haggett C. The 'social gap' in wind farm siting decisions: explanations and policy responses. *Environ Polit* 2005;14:460–77.
- [22] Devine-Wright P. Beyond NIMBYism: towards an integrated framework for understanding public perceptions of wind energy. *Wind Energy* 2005;8: 125–39.
- [23] Klick H, Smith ER. Public understanding of and support for wind power in the United States. *Renew Energy* 2010;35:1585–91.
- [24] Warren CR, Lumsden C, O'Dowd S, Birnie RV. 'Green on green': public perceptions of wind power in Scotland and Ireland. *J Environ Plan Manag* 2005;48:853–75.
- [25] Wolsink M. Wind power and the NIMBY-myth: institutional capacity and the limited significance of public support. *Renew energy* 2000;21:49–64.
- [26] Carlisle JE, Kane SL, Solan D, Joe JC. Support for solar energy: examining sense of place and utility-scale development in California. 9// *Energy Res Soc Sci* 2014;3:124–30.
- [27] Farhar B, Hunter L, Kirkland T, Tierney K. Community response to concentrating solar power in the San Luis Valley. 2010.
- [28] Montgomery J. In: Brightsource mothballs Rio Mesa solar thermal project, refocuses on pipeline. *Renewable Energy*; 2013. World.com.
- [29] Cart J. In: Oil industry to profit from Ivanpah solar project. *Mojave Desert Blog*; 2012.
- [30] Klick H, Smith ER. Public understanding of and support for wind power. 2009.
- [31] E. P. Institute. PVMapper: final technical report DE-EE0005351. Boise State University; 2014.
- [32] Swofford J, Slattery M. Public attitudes of wind energy in Texas: local communities in close proximity to wind farms and their effect on decision-making. *Energy Policy* 2010;38:2508–19.
- [33] Devine-Wright P. Place attachment and public acceptance of renewable energy: a tidal energy case study. *J Environ Psychol* 2011;31:336–43.
- [34] Devine-Wright P, Howes Y. Disruption to place attachment and the protection of restorative environments: a wind energy case study. *J Environ Psychol* 2010;30:271–80.
- [35] Van der Horst D. NIMBY or not? Exploring the relevance of location and the politics of voiced opinions in renewable energy siting controversies. *Energy Policy* 2007;35:2705–14.
- [36] Solan D. From federal preemption politics to regional transmission planning and policy integration. 11// *Electr J* 2012;25:25–36.
- [37] Janke JR. Multicriteria GIS modeling of wind and solar farms in Colorado. 10// *Renew Energy* 2010;35:2228–34.
- [38] Peery B, Alessi RS, Lee R, Vang L, Brown S, Solan D, et al. Enhancing user customization through novel software architecture for utility scale solar siting software. In: 7th international congress on environmental modelling and software. San Diego: California; 2014. p. 215–21.
- [39] NREL. (2013, November 7, 2013). Solar Maps. Available: <http://www.nrel.gov/gis/solar.html>.
- [40] Maxwell E, George R, Wilcox S. A climatological solar radiation model," presented at the American solar energy society, Albuquerque NM. 1998.
- [41] Tomlin DC. Geographic information systems and cartographic modeling. 1990.
- [42] Michaud K, Carlisle JE, Smith ER. Nimbyism vs. environmentalism in attitudes toward energy development. *Environ Polit* 2008;17:20–39.
- [43] Jones CR, Eiser JR. Understanding 'local'opposition to wind development in the UK: how big is a backyard? *Energy Policy* 2010;38:3106–17.
- [44] Dear M. Understanding and overcoming the NIMBY syndrome. *J Am Plan Assoc* 1992;58:288–300.
- [45] Haggett C. Over the sea and far away? A consideration of the planning, politics and public perception of offshore wind farms. *J Environ Policy & Plan* 2008;10:289–306.
- [46] Wolsink M. Wind power implementation: the nature of public attitudes: equity and fairness instead of 'backyard motives'. *Renew Sustain Energy Rev* 2007;11:1188–207.
- [47] Walker BJ, Wiersma B, Bailey E. Community benefits, framing and the social acceptance of offshore wind farms: an experimental study in England. *Energy Res Soc Sci* 2014;3:46–54.
- [48] Haggett C. Understanding public responses to offshore wind power. *Energy Policy* 2011;39:503–10.
- [49] Devine-Wright P. Explaining "NIMBY" objections to a power line: the role of personal, place attachment and project-related factors," *Environment and behavior*. 0013916512440435. 2012.
- [50] Carlisle JE, Kane SL, Bowman M, Joe J, Solan D. Public attitudes towards large-scale solar energy development in the US," presented at the 19th annual meeting of the international symposium on society and resource management, Estes Park Center, Colorado. 2013.