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# Mapping suitability areas for concentrated solar power plants using remote sensing data

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**Abstract.** The political push to increase power generation from renewable sources, such as solar energy, requires knowing the best places to site new solar power plants with respect to the applicable regulatory, operational, engineering, environmental, and socioeconomic criteria. Therefore, we present applications of remote sensing data for mapping suitable areas for concentrated solar power (CSP) plants. Our approach uses satellite data from National Aeronautical and Space Administration's Global Energy and Water Cycle Surface Radiation Budget project at a resolution of 1 deg for estimating global solar radiation for the study area. Then we develop a computational model built on a geographic information system (GIS) platform that divides the study area into a grid of cells and estimates the site suitability value for each cell by computing a list of metrics based on applicable site requirements using GIS data. The computed metrics include population density, solar energy potential, federal lands, and hazardous facilities. Overall, some 30 GIS datasets are used to compute eight metrics. The site suitability value for each cell is computed as an algebraic sum of all metrics for the cell with the assumption that all metrics have equal weight. Finally, we color each cell according to its suitability value. We present results for CSP that drives a stream turbine and parabolic mirror connected to a Stirling engine. © The Authors. Published by SPIE under a Creative Commons Attribution 3.0 Unported License. Distribution or reproduction of this work in whole or in part requires full attribution of the original publication, including its DOI. [DOI: [10.1117/1.JRS.9.097697](https://doi.org/10.1117/1.JRS.9.097697)]

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## 1 Introduction

Concentrated solar power (CSP) is expected to grow as a clean and affordable source of energy in the next few decades. Studies<sup>1</sup> have shown that solar energy can be used to supply up to 35% of the total energy requirements by 2050 with huge reductions in greenhouse gas emissions. Nine CSP plants<sup>2</sup> were built in the time period from 1980 to 1990 with a total capacity of 354 MW. This was followed by a period of skepticism about the viability of solar power generation. In 2000, the National Academies' National Research Council<sup>3</sup> recommended that the Solar Energy Technologies Program should abandon further research and development of solar technologies as it would not lead to deployment and there was not enough economic scope in such a deployment. This was followed by a U.S. Department of Energy report<sup>2</sup> in 2002, which concluded that with proper government incentives, over 1000 MW of solar power could be generated within a 10- to 20-year time frame. Due to the conflicting conclusions of the reports, DOE hired an independent firm to assess the feasibility of solar power plants in the US. The firm again concluded that CSP is economically feasible and viable if taken up on a large scale.<sup>4</sup>

The interest in CSP has been revived again and the US Department of Interior approved the largest solar energy project to be built on public lands in Riverside, California, in October 2010. With its vast expanse of lands, especially in the western half of the country, the US has a huge potential for CSP. The first task in building CSP is to identify potential sites where these plants

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can be built, and it is no surprise that GIS has been used in some of the national evaluations for CSP locations.<sup>5</sup> Available tools include a GIS map,<sup>6</sup> which allows a static view of a few map layers overlaid on top of each other. GIS modeling and analysis would be the best tool to delineate sites for CSP locations, since these plants are expected to be built on unused, degraded, or marginal lands where GIS modeling can be very useful for locating the sites. GIS modeling enables the combination of environmental parameters (e.g., solar radiation, water availability) with physical parameters (e.g., land use, land cover, etc.) and the infrastructure facilities (e.g., roads, grid lines, etc.) to identify suitable lands for siting CSP plants.

GIS modeling has traditionally been used for site selection but not much work has been done in locating sites for large-scale solar plants. A survey of literature indicates the modeling of solar radiation advanced very rapidly starting from 1980 and by the late 1990s models, such as SolarFlux, Genasys Solar Analyst, and r.sun, were available in open and commercial GIS packages which could very accurately estimate solar radiation at various spatial and temporal resolutions. However, there is a lack of good modeling tools to site CSP plants even though the concept has gained importance recently due to concerns of depleting fossil fuels, greenhouse gas emissions, and the political instability in some of the regions which are the highest producers of oil and gas. In the following section, an exhaustive literature review has been provided which traces the development of solar radiation models followed by some very recent work on locating CSP locations.

## 2 Literature Review

Gautier et al.<sup>7</sup> were one of the first to develop a simple physical model to estimate surface solar radiation from geostationary operational environmental satellite data. This physical model used satellite data to calculate incident solar radiation for an area of interest and it provided a quick and fast estimation of solar radiation over large areas. This had a distinct advantage over using conventional pyrometer networks in that it provided better temporal and spatial resolution, while the advantage of using a physical model over a statistical one was that it allowed continuous modeling of the surface rather than doing it on smaller discrete regions. These models were refined over time by Cano et al.,<sup>8</sup> Beyer et al.,<sup>9,10</sup> and Becker.<sup>11</sup> These led to more accurate estimation of solar radiation as the refined models had better algorithms and used more variables to calculate solar radiation.

SolarFlux<sup>12</sup> was one of the first solar radiation models that were developed and it was developed on the ARC/INFO platform. Compared to the previous solar radiation models which allowed the users to estimate solar radiation values based primarily on satellite data, SolarFlux provided users with the flexibility to model solar radiation based on various parameters like surface orientation, time interval and spatial coordinates. Arc Macro Language was used to develop the programming environment and consisted of four modules to perform four tasks, which were later integrated into a single model. These were followed by development of Genasys<sup>13</sup> and Solei,<sup>14</sup> which was linked to the GIS software IDRISI. These models used digital elevation models (DEMs) to calculate solar radiation and enabled the users to perform statistical calculations.

The first independent modeling tool was developed as an ArcView GIS extension module.<sup>15</sup> Instead of using the simple interpolation techniques used in the previous models, they used optimized algorithms to account for influences of viewshed, surface orientation, elevation, and atmospheric corrections. The Solar Analyst combined the strengths of both point and area-based models and enabled the user to create maps of direct, diffuse and global radiation for various time resolutions. It also allowed viewers to calculate viewsheds and horizon angles. The interface with ArcView software enabled querying, graphing and statistical analysis. The model generated an upward looking hemispherical viewshed based on a digital terrain model. Some of the inputs required for the model included a DEM, spatial coordinates of the study area, sky size, transmittivity, and time configuration.

In 2004, Suri and Hofierka<sup>16</sup> developed a GIS model known as r.sun which runs on the open source GRASS GIS software; this was an extension of the earlier work of Hofierka.<sup>17</sup> The model enabled users to calculate all three components of the solar irradiance for clear as well as cloudy

skies, whereas previous Hofierka's earlier model did not allow for calculations of atmospheric transmissivity and the diffuse proportions. The r.sun model worked in a two-mode system: in mode 1, it created rasters of selected components of solar irradiance for a particular time; whereas in mode 2, it created daily raster maps which are based on the integration of irradiance values. The model required fewer input parameters and derived the remaining parameters from the given inputs, thus allowing users to model at different scales ranging from local to global. The model was found to be very sensitive to elevation effects and viewshed directions. The r.sun model has been expanded<sup>18</sup> to take into consideration 3-D surfaces like facades and shadows which capture the temporal and spatial variation of solar radiation in urban environments with tall buildings. More recently, r.sun has been coupled with a canopy openness index derived from light detection and ranging (LiDAR) data to produce a subcanopy solar radiation model.<sup>19</sup>

Recently, Kodysh et al.<sup>20</sup> presented a methodology that advances previous efforts by estimating solar radiation potentials on multiple rooftops in an urban area for photovoltaic (PV) applications using DEM from LiDAR data and an upward looking hemispherical algorithm. Their methodology considers input parameters such as surface orientation, shadowing effect, elevation, and atmospheric conditions that influence solar intensity on the Earth's surface; it was implemented for some 212,000 buildings in Knox County, Tennessee, United States.

Once solar GIS models were developed, solar radiation maps for a particular region could be easily and accurately calculated. As technology moved forward, the focus shifted from single PV installations which could power individual houses or street lights, to larger CSP plants which could: (a) produce larger amounts of power; (b) be operational after sunset; and (c) could be connected to the national grid. This called for the development of siting models, which could take in various parameters and produce optimal sites for construction of CSP plants.

The work of Broesamle<sup>21</sup> was one of the first which used GIS modeling to assess the solar electricity potential in North Africa. Unlike earlier studies which focused more on estimating solar radiation, this work was focused on selecting sites in North Africa where solar thermal power plants could be located. The system that developed was known as STEPS, which consisted of a main module and five-linked submodules. The main module allowed users to control spatial and temporal resolutions along with some environmental analysis. The submodules were used to: (1) assess geographical conditions, (2) assess meteorological conditions, (3) load country infrastructure database, (4) perform economic analysis, and (5) perform power block simulation. This model was the first to use a variety of input data and integrate them to produce siting results. Geographic data used in this model included land use/land cover data, DEM and slope. The model enabled users to perform solar radiation resource assessment using meteorological data, simulate power plant performance and provide a cost estimate of a solar thermal power plant. It also allowed users to calculate infrastructure costs based on distances from roads, power lines, and the availability of water for cooling. Broesamle et al.<sup>22</sup> extended this framework to include desalination plants along with solar plants for the Mediterranean region. Additional variables were included in the siting study, including risk factors and performance parameters for CSP plants.

Carrion et al.<sup>23</sup> developed a decision support system for optimal site selection for grid-connected PV power plants. They used environmental, orography, location, and climate criteria to build the decision support system. Their model used a system which was based on multicriteria analysis (MCE) with a single objective and several criteria. They used an analytic hierarchy process developed by Saaty<sup>24</sup> to assign weights to each criteria, factor and indicator. This enabled them to determine the relative importance of each factor and criteria for selection of solar sites, thus weights could be assigned based on their relative importance. They also used the consistency ratio to determine if the values were sufficiently consistent to establish the weights. Once weights were determined, the criteria and factors were ordered according to their degree of importance and then normalized on a scale of 1 to 10. These normalized values were then used to make a model using Model Builder in ArcView.

With reference to the studies of identifying suitability sites for CSP plants in the US, Fthenakis et al.<sup>1</sup> did a technical, geographical and economical feasibility study which was more statistical in nature. Using past statistical solar radiation data and worst case climate scenarios, they showed that CSP would be economically viable in the US by 2020. They also performed an economic analysis to predict future costs of solar power generation for the next 50

years and showed that it had the potential to meet most of the energy demands of the US based on land and solar radiation supplies in the southwest. Fadare et al.<sup>25</sup> used artificial neural networks to model solar potential studies in Africa. Using satellite data for 172 locations for a period of 22 years and geographical and meteorological data, they produced monthly solar radiation intensity maps. They used a multilayer, feed-forward and back-propagation network consisting of three layers for their model.

As the CSP technology advances, there are not many models or tools which can be used to assess the availability of sites for CSP on a variety of scales starting from local to global. However, a few recent studies have attempted to do so in localized regions. Anders et al.<sup>26</sup> did a study for the San Diego region, whereas Bravo et al.<sup>27</sup> did studies in Spain; Fluri<sup>28</sup> did a study for South Africa; and Clifton and Boruff<sup>29</sup> have also used GIS tools to estimate areas of potential CSP development in rural regions of western Australia. Gastli et al.<sup>30</sup> did a GIS-based assessment of a CSP plant in Duqum, Oman. All these models used very simple overlay techniques to estimate areas for optimal location of power plants; the only difference in these studies are the number of layers used (minimum 5, maximum 10) for determining suitable sites.

A different approach was used by Badran et al.<sup>31</sup> who used fuzzy logic to assess solar sites in Jordan. Using fuzzy logic, the authors could best estimate benefit and cost parameters for siting CSP plants. Janke,<sup>32</sup> on the other hand, used multicriteria analysis to locate wind and solar farms in the state of Colorado. Datasets, including solar potential (obtained from the National Renewable Energy Laboratory, land cover, distance to roads, population density, and distance to transmission line) were scaled from 0 to 1 with a gradational rating of excellent to poor and overlaid to produce maps which showed the suitability of areas for wind and solar farms. Comparison of existing facilities showed that the wind farm locations matched the model while there was poor correlation between existing solar facilities and predicted areas. This could be due to the fact that solar facilities were not planned properly or the model needs to be reevaluated for its effectiveness.

### 3 Methodology

The methodology presented here is a two-stage process. First, global solar radiation in Wh/m<sup>2</sup>/day is calculated using the satellite data obtained from the National Aeronautical and Space Administration (NASA) Global Energy and Water Cycle (GEWEX) for the entire continental United States. Second, using eight metrics defined for some 30 GIS data sets and a grid divided into 100 m cells, the study area is classified with respect to its degree of site suitability. Based on these outputs, two applications of solar power plants are analyzed.

#### 3.1 Study Area and Data Set

The methodology is implemented for the entire contiguous United States (CONUS). For suitability mapping, a spatial database including planimetric and altimetric data was used. The solar radiation data were obtained from the NASA/GEWEX surface radiation budget (SRB) project.<sup>33</sup> The NASA/GEWEX SRB project provides global shortwave (SW) and longwave (LW) data at 1-deg resolution every 3 h and is available from July 1983 to December 2007. The reported uncertainty for the LW data is around  $\pm 5$  W/m<sup>2</sup> while that for the SW can be as high as  $\pm 20$  W/m<sup>2</sup>. A detailed assessment of the data can be found in Raschke et al.<sup>34</sup>

#### 3.2 Estimating Global Solar Radiation

We used monthly averages of the SW downward flux data to create seasonal averages for the summer months (June, July, and August) as well as the winter months (December, January, and February). The averages were computed over the last 7 years. The rationale for this decision is because we expect low solar radiation during the winter months and high solar radiation during the summer months. The data are produced based on the Pinker/Laszlo SW algorithm,<sup>35</sup> which uses the Edington model to compute transmitted fluxes. Later, the Langley parameterized SW algorithm<sup>36</sup> was used to minimize errors due to scattering and other absorptive processes and improved the estimation of the top of the atmosphere fluxes.

### **3.3 Metrics for Assessing Site Suitability**

To map suitability areas for siting CSPs in the study area, we proposed eight metrics that consider regulatory, engineering, operational, environmental, and socioeconomic criteria. However, only those criteria that are appropriate for spatial modeling are implemented in this paper. The criteria are translated into a computational framework by dividing the study area into 100 m cells. To define these metrics, we use insights from well regulated industries such as the nuclear industry.<sup>37</sup> The summary of the eight metrics is presented in the following sections.

#### **3.3.1 Population density**

For this metric, the idea is that we do not want to site CSPs in urban areas. Population density is a metric for achieving this objective. For the population metric, the following definition of a population exclusion area is proposed: "A CSP plant should preferably be located such that, at the time of initial plant operation and within about 5 years thereafter, the population density, including weighted transient population, averaged over any radial distance out to 20 miles (cumulative population at a distance divided by circular area at that distance), does not exceed 500 persons per square mile." This definition is adapted from the Nuclear Regulatory Commission definition of population exclusion areas for siting nuclear power plants; it assumes that population densities >500 people per square mile begin to transition into an urban setting. Therefore, cells with population density >500 people per square mile within a 20-mile radial distance are excluded. By engineering judgment, this population guidance was determined appropriate for CSP applications. The population exclusion is based on LandScan Global 2011 data obtained from Oak Ridge National Laboratory.<sup>38</sup> LandScan is already in raster format with a 30" (arc sec) resolution. The first step is to project the data by converting the nonzero cells to points and projecting these points. The projection used for all the data layers is the Lambert Conformal Conic. The projected points are converted back to raster using the population value. We then aggregate and sum the cells of this newly created raster. We aggregate the cells up to 1600 m (~1 mile) cells. The result is a population grid whose cells represent density in population per square mile and the sum over the entire raster should be equal to the original population total. Then we process the data to identify the exclusion areas based on the proposed population exclusion definition stated above.

#### **3.3.2 Protected lands**

These are lands designated as national parks, historic areas, Indian lands, and wildlife refuges. For health and safety concerns, cells that overlap with areas designated as protected lands are excluded. The full list of the GIS data that falls in this category includes national parks, national monuments, national forests, wilderness areas, state parks, wild and scenic rivers, wildlife refuges, Indian lands, hospitals, schools, colleges, correctional facilities, inventoried roadless areas, and areas of critical environmental concern. This is a composite metric that combines at least 14 datasets. The data are obtained from different sources including the National Forest Service, Bureau of Land Management, US Fish and Wildlife Service, National Wild and Scenic Rivers, National Atlas of the USA, and some commercial sources.

#### **3.3.3 Wetlands and open water**

Land classified as wetlands or open water are excluded. For safe operation of facilities, wetlands, open water, and the Great Salt Lake are avoided. The datasets are obtained from the US Geological Survey (USGS) and the US Department of the Interior.

#### **3.3.4 Landslide hazards**

Land with moderate or high landslide hazard susceptibility as defined by USGS is excluded.

### 3.3.5 Flood hazards

External flooding could affect the safe operation of a solar power plant; therefore, we adopt a simple area exclusion approach by excluding cells that overlap with areas classified as being within a 100-year flood zone by the Federal Emergency Management Agency.

### 3.3.6 Slope

Another metric is to exclude cells that overlap with areas with more than 5% (~3 deg) slope. While the optimum slope value is site dependent, a 5% threshold for slope should be applicable for most applications. The slope data were obtained from the National Geospatial-Intelligence Agency.

### 3.3.7 Stream flow

Solar power plants that drive steam engines will require water that could come from streams, oceans or other sources. In this paper, we consider water from streams. According to a Department of Energy report to Congress, CSP uses ~800 gallons of water per megawatt-hour. Therefore, for a representative plant size of 100 MW(e), about 15,000 gpm of water is needed. For this metric, we exclude cells that overlap areas with less than 15,000 gpm of stream-flow within 20 miles from the water sources. This metric will not apply to CSPs that are connected to a Stirling engine since they use minimal water only for cleaning the solar array.

As a result of the many uses of water from the streams, periodic droughts or dry seasons may excessively strain water supplies, which may negatively impact the stream environment and leave a solar plant with insufficient cooling water.<sup>39</sup> Therefore, accurate data on stream flows, particularly at the low-flow levels, are needed to evaluate candidate areas for new solar plants. Hence, a database of low-flow estimates (that is, a 7-day annual minimum stream flow average, 10-year return period) is developed and used for this analysis. The steps involved are summarized as follows:

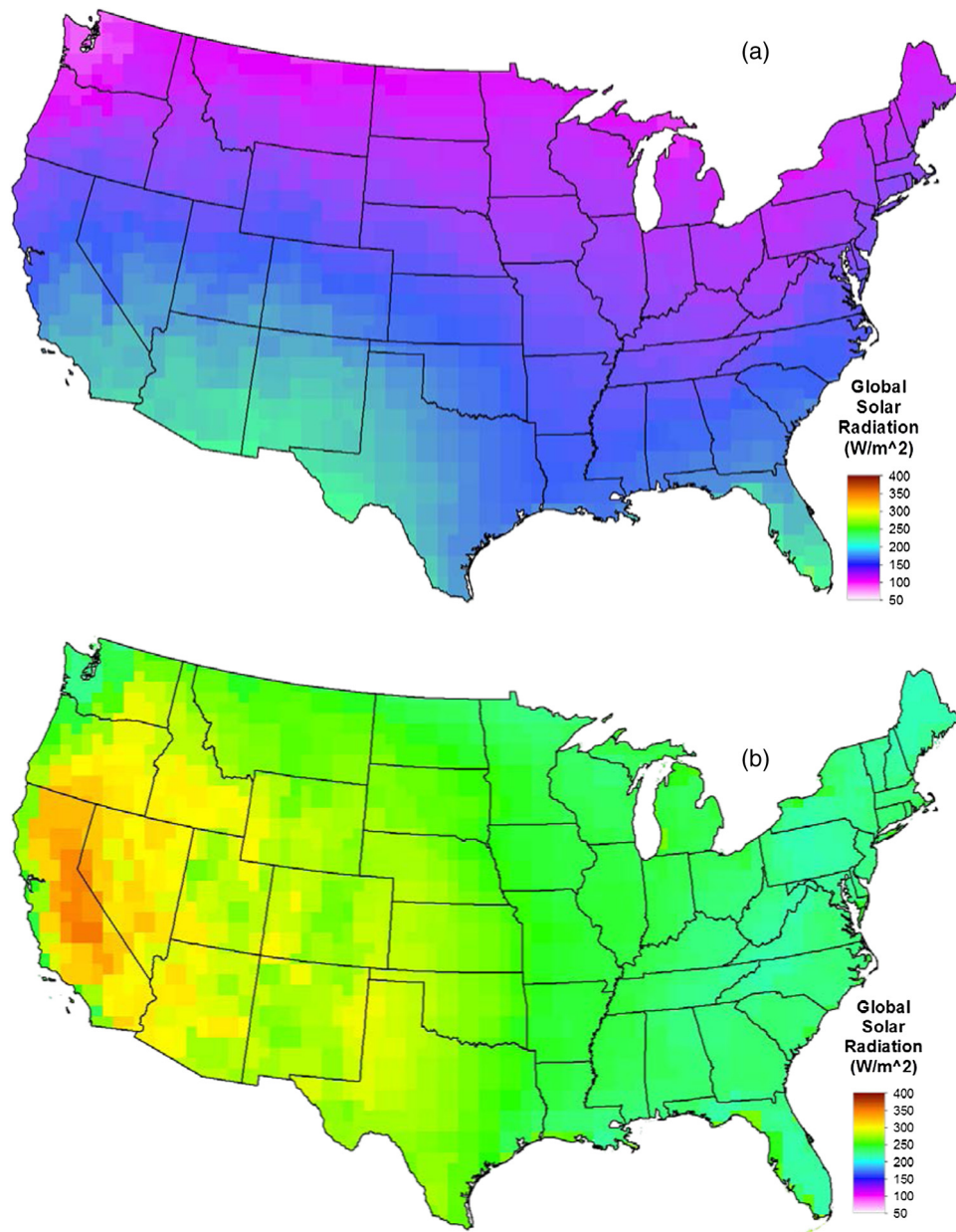
- (1) Real-time stream flow data are first collected from the USGS National Water Information System (NWIS).<sup>40</sup>
- (2) Low-flow statistics are computed for gauges that have at least 10 years of daily stream flow observations (unit in ft<sup>3</sup>/s). For quality assurance purposes, there must be at least 300 days of valid records within 1 year; otherwise the entire year is discarded.
- (3) Within each calendar year, the annual minimum 7-day mean flow is computed. By collecting all annual minimum flows, the lower 10% quantiles are computed for each of the selected USGS gauges. The 10% quantile is statistically equivalent to the 10-year return threshold, in which it represents the low flow value that is expected to occur once in every 10 years.
- (4) The low-flow statistics are estimated for ungauged locations using nearby stream gauging stations that have been calculated in the previous steps.
- (5) The Environmental Protection Agency-USGS National Hydrography Database Plus (NHDPlus),<sup>41</sup> is used as the framework for identifying and spatially locating stream segments and gauging stations and performing upstream and downstream navigation tasks.
- (6) For a given ungauged stream segment of interest, a list of the nearest gauging stations is identified by navigating upstream into all tributaries and downstream of the stream segment. The closest gauges with drainage areas between 0.5 and 1.5 times the location of interest's drainage area are used. If suitable upstream and downstream gauges are found, the flow per unit drainage area at the gauges are averaged and multiplied by the drainage area of the ungauged location to estimate the flow. This methodology is similar to the methods<sup>42,43</sup> described and implemented in some USGS StreamStats State applications.<sup>44</sup>
- (7) In order to develop a complete database of flow estimates, the above process is repeated for each stream segment where the NHDPlus estimates a mean annual flow greater than 15 cubic feet/s. Additionally, low flows are only estimated at locations where suitable gauges can be identified. The smaller streams are discarded from consideration as

locations of interest because they are unlikely to meet cooling water requirements for solar plants. However, the smaller streams are replaced with lakes and reservoirs with sufficient cooling water requirements (annual flow rate) for solar plants.

The developed dataset provides a realistic estimate of potentially available stream flows and conditions that could impact site suitability and have been created in a consistent and unified format for the study area. The methodology assumes a natural flowing stream (not regulated streams where a dam regulation could change the flows).

### 3.3.8 Solar radiation

According to the US Department of the Interior, a potential CSP plant should receive at least 5.0 kWh/m<sup>2</sup>/day to be economically viable. However, with improvements in solar technology,



**Fig. 1** Average global solar radiation for the (a) winter months (December, January, and February) and (b) summer months (June, July, and August), respectively.

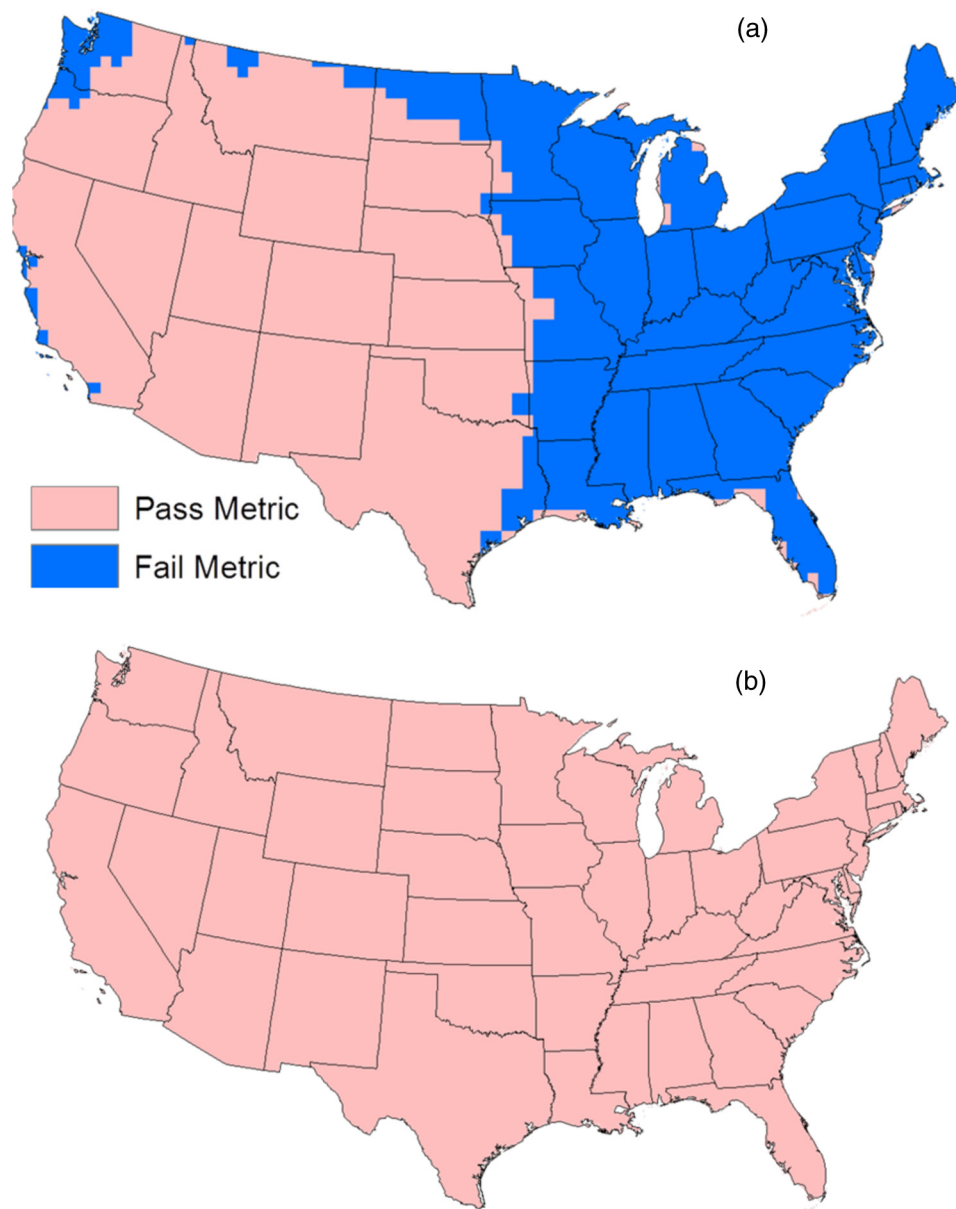


practitioners are beginning to evaluate the economic feasibility of accepting lower global solar radiation values. In this paper, we consider two cases—average global solar radiation of at least 4.8 and 6.0 kWh/m<sup>2</sup>/day—for our analysis. The actual data given in W/m<sup>2</sup> are multiplied with 0.024 to convert to kWh/m<sup>2</sup>/day.

Each metric is used to characterize the cells in the study area. For each metric, a binary classification is used. Cells that meet the limit for each metric are classified as 0 and cells that did not meet the limit for each metric are classified as 1.

## 4 Results

Figure 1 shows the average global solar radiation for the winter (a) and summer (b) months. According to the data, we can easily conclude that using the results for the summer months is a good representation of the average global solar radiation and that setting the minimum global



**Fig. 2** Excluded solar radiation data layers. (a) Minimum global solar radiation set at 4.8 kWh/m<sup>2</sup>/day. (b) Minimum global solar radiation set at 6.0 kWh/m<sup>2</sup>/day.

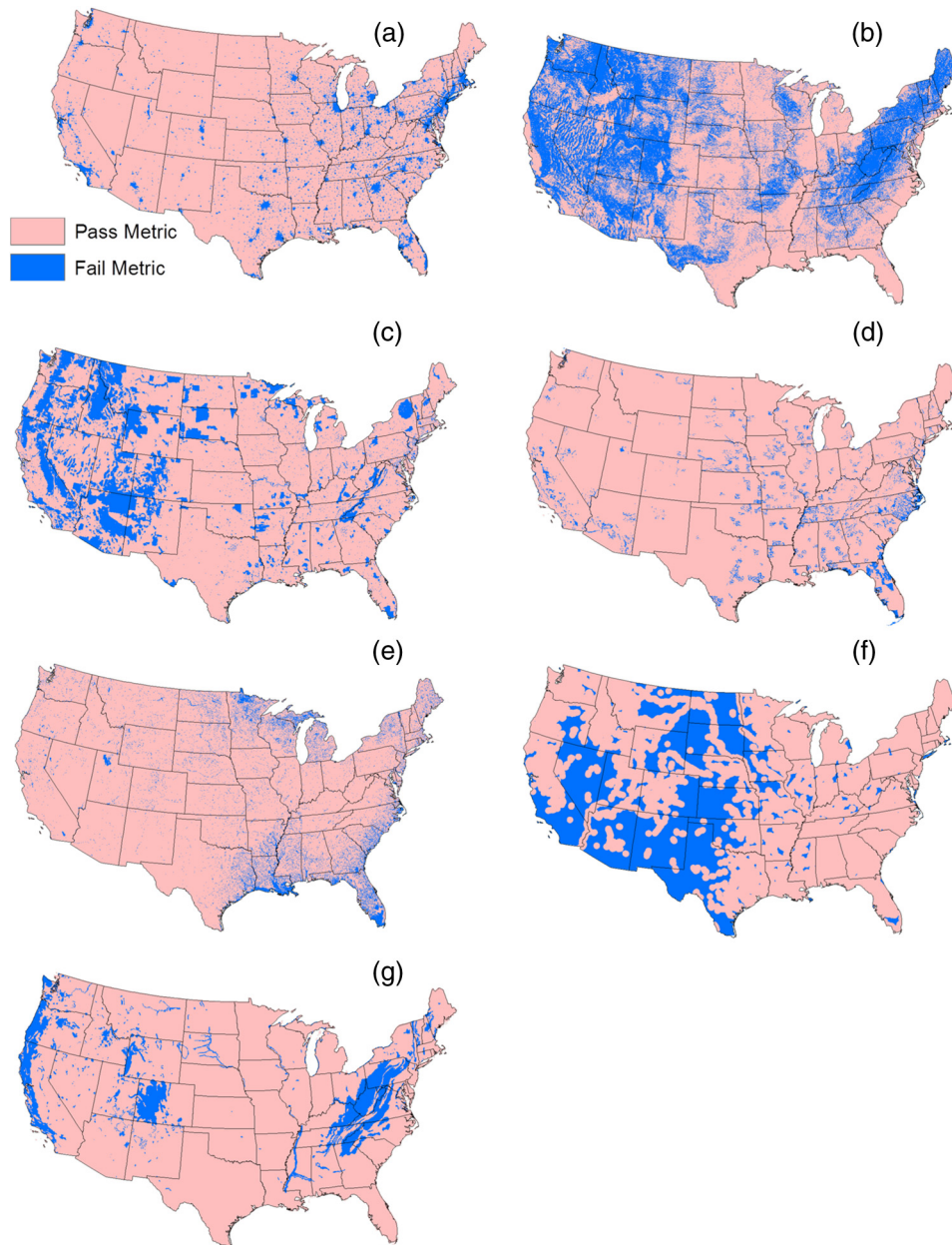
solar radiation at 4.8 kWh/m<sup>2</sup>/day for one case and 6.0 kWh/m<sup>2</sup>/day for another case provides an opportunity to explore potential land areas all over the CONUS.

The excluded data layers for these two cases based on the solar radiation metric are shown in Fig. 2. Excluded areas are areas that are not suitable for siting CSP based on the criteria for the respective metric (fail) and nonexcluded areas are areas that are suitable for siting CSP based on the criteria for the respective metric (pass).

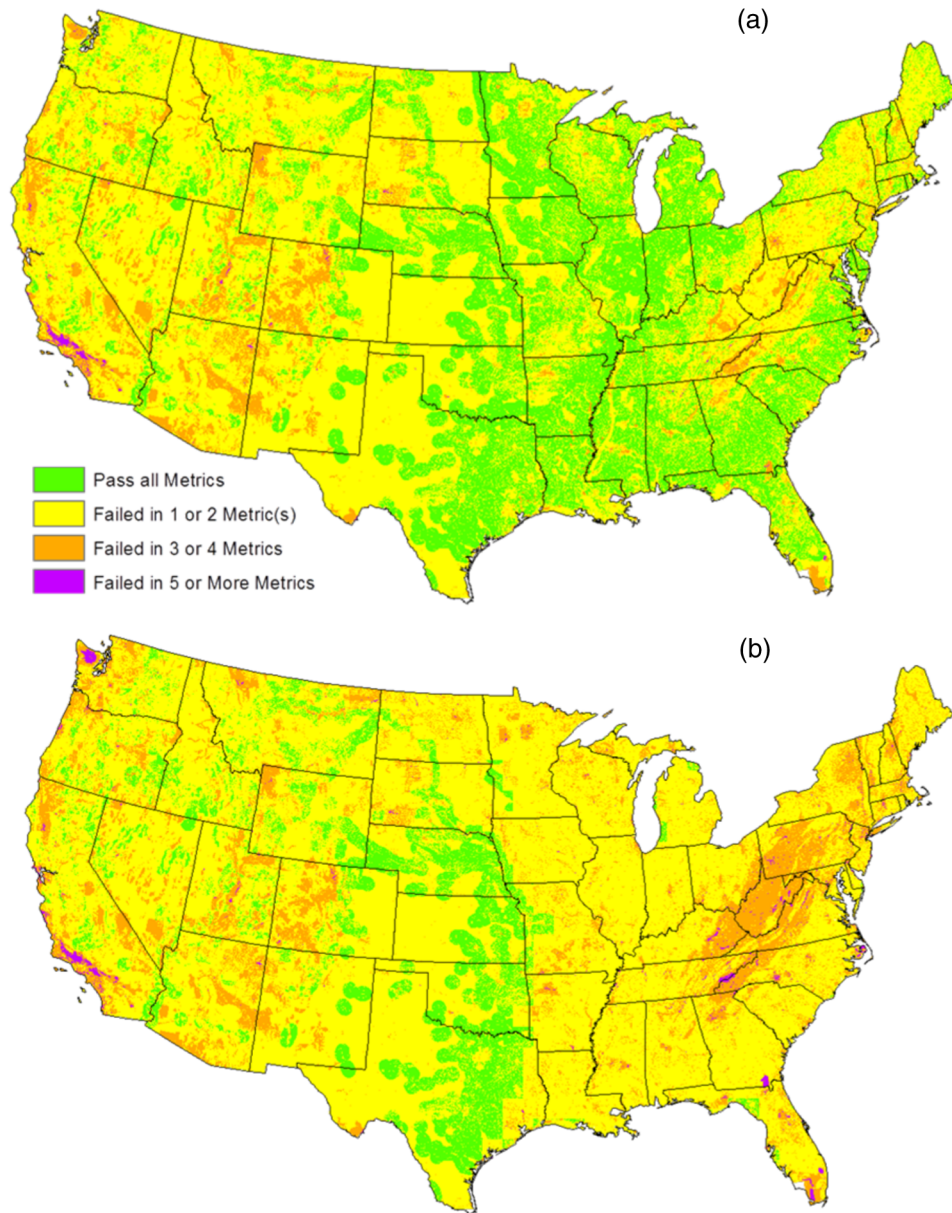
The excluded areas and nonexcluded areas for each of the other metrics are shown in Fig. 3.

#### 4.1 Suitability Areas for CSP Plants that Drive Steam Turbine

An algebraic combination of the data layers representing all the metrics resulting in the outputs is shown in Fig. 4. The green areas are areas that meet all metrics threshold and are completely



**Fig. 3** Individual data layers representing the other seven metrics for CSP site suitability in the following order: (a) population, (b) protected lands, (c) wetlands and open water, (d) landslide hazards, (e) 100-year floodplain, (f) 5% slope, and (g) 15,000 gallons/min stream flow.



**Fig. 4** Results of the map algebra of the eight metrics for CSP (wet options) with (a) global solar radiation set at 4.8 kWh/m<sup>2</sup>/day and (b) global solar radiation set at 6.0 kWh/m<sup>2</sup>/day.

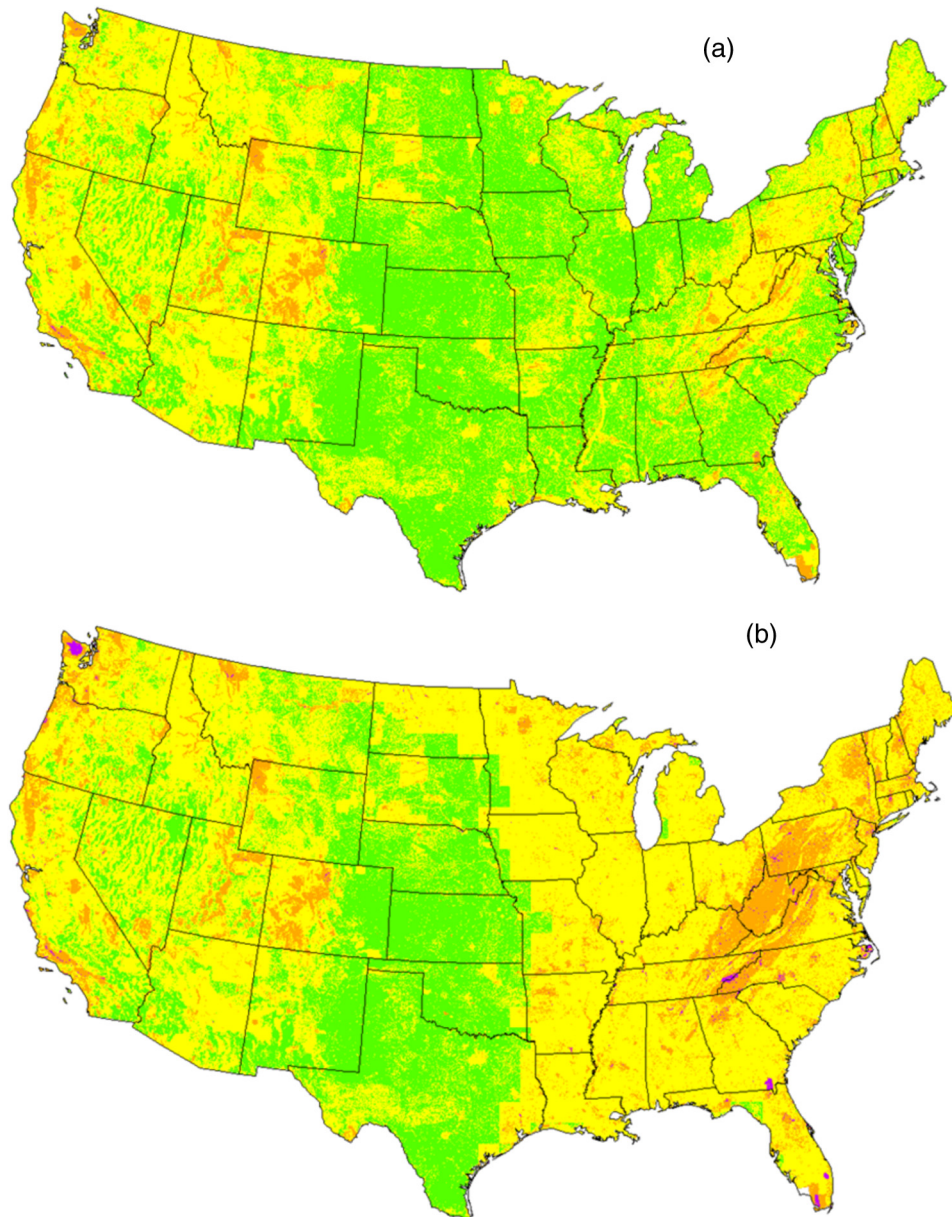
suitable. The other areas are partially suitable because they failed in at least one metric as follows: the yellow areas are areas that failed on one or two metrics; gold areas failed on three or four metrics; and purple areas failed on at least five metrics. Let us call the results obtained by setting the minimum global solar radiation at 4.8 kWh/m<sup>2</sup>/day our case-1 and the results obtained by setting the minimum global solar radiation at 6.0 kWh/m<sup>2</sup>/day are our case-2.

The green areas for case-1 represent 28.1% of the total land area in CONUS and 10.9% of the total land area for case-2. The difference in land area between the two cases is more than 17%, which is almost two times the size of the suitable land area for case-2. One implication of these results is that with improved technology that could make lower global solar radiation more economical for CSP applications, more land areas, especially in the eastern half of CONUS, could become more suitable. Looking at the results for case-2, most of the suitable land areas are in the midwestern states from Texas to North Dakota. Some of these areas may also be suitable for other renewable or no-carbon energy sources, such as wind and natural gas. Hence, different energy sources may be competing for land in these areas. On the other hand, the impact of

climate change with regard to seasonal drought is another concern for these areas. Our future studies in this area will model the implications of these interdependencies.

#### 4.2 Suitability Areas for CSP Plants that Drive Sterling Engine

Looking at the results in Fig. 4, we can conclude that one of the two major limiting factors is cooling water. Therefore, if we perform a sensitivity analysis by not including the streamflow metric, that is considering CSP plants that drive a Sterling engine, the outputs of the algebraic combination of the data layers are shown in Fig. 5. The different colors have the same interpretation as the outputs in Fig. 4. The green areas for case-1 for the Sterling application represent about 43.5% of the total CONUS land area; for case-2, it is about 24.3%. The difference in suitable land area for this application is about 19%, almost the same as the land area for case-2.



**Fig. 5** Results of the map algebra of the eight metrics for CSP (dry options) with (a) global solar radiation set at 4.8 kWh/m<sup>2</sup>/day and (b) global solar radiation set at 6.0 kWh/m<sup>2</sup>/day.

## 5 Conclusions

The increasing environmental cost of fossil fuels is driving policy makers in the United States to promote electricity generation from renewable energy sources, such as solar. We have presented a methodology for identifying a CSP siting suitability index for the contiguous United States. This is achieved by dividing the entire country into a grid of 100-m cells. We proposed eight metrics that use about 30 GIS data layers to characterize each cell and identify areas with the highest suitability index. The solar radiation potential data uses a remote sensing data derived from the NASA/GEWEX (Global Energy and Water Cycle) Surface Radiation Budget project. The methodology was implemented for two applications of CSPs—CSPs that drive steam turbines and CSPs that drive a Sterling engine. The results show that about 11% and 24%, respectively, of the CONUS area have the highest suitability index for CSP (steam turbine and Sterling engine) applications if the minimum global solar radiation is set at 6.0 kWh/m<sup>2</sup>/day, whereas, about 28% and 44%, respectively, of the CONUS area have the highest suitability index for the two CSP applications if the minimum global solar radiation is set at 4.8 kWh/m<sup>2</sup>/day.

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