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# A large scale multi criteria suitability analysis for identifying solar development potential: A decision support approach for the state of Illinois, USA

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ABSTRACT

The State of Illinois is examining prospects to increase the development of in-state renewable energy resources on public lands. In response, this research develops a scalable decision-support tool for identifying suitable areas for solar energy generation in the state. This paper provides guidance for state agency-driven solar development by evaluating the suitability of potential generation areas in terms of environmental impact, socioeconomic costs, and energy productivity, and providing a forum for critical decision-making. More specifically, geospatial technologies are combined with a suitability analysis to reveal the potential for solar energy generation on public lands. This study demonstrates the usefulness of the resulting information for supporting both regional and local decision-making as a Planning Support System (PSS). Our analysis suggests that the large-scale analysis using fine resolution data is useful for comparison and site-specific decision making - with site verification protocols in terms of physical implementation. We find that planning decisions for solar development should use a fine-grained suitability approach at a large scale and a feasibility analysis at a specific scale. We present our findings in statewide application along with a scalable PSS tool to optimize and support solar decision-making process and democratize the information for engaging a broader audience.



## 1. Introduction

By the year 2050, solar energy generation is projected to climb to 48% of the total electrical energy produced in the U.S. (up from 11% in 2017) [1]. California is projected to increase its solar energy generation to 60% by 2030 [2]. Illinois (in 2019), the fifth-largest energy-consuming state, produces only 10% of its electricity from renewable sources (primarily wind). In comparison, 53% is produced by nuclear power, 30% coal-fired, and 7% is from natural gas [3]. When compared with other states or some European countries of similar size, it is apparent that the utilization of renewable energy in Illinois is still at the early stages of development. To help begin to rectify this, the state seeks to increase the use of renewable energy, envisioning that it will play a vital role in climate mitigation, advancing the local economy, and improving public health [4,5]. An important consideration in these efforts is the identification of suitable places in the state for generating this type of energy.

The current Illinois renewable energy portfolio standard requires the state of Illinois to acquire 25% of energy from renewable sources by 2025, although projections show them falling short of that goal [6,7]. A bill currently being debated, the Clean Energy Job Act would require the state to obtain 100% of its electricity from renewable sources by 2050 [8]. These legislative activities have prompted state agencies to take a more active role in renewable energy procurement. For example, the Illinois Department of Natural Resources (IDNR) is exploring an increase in in-state solar development activity by analyzing which state land assets are compatible for renewable energy generation. The agency notes that in order to achieve ecologically and economically sustainable development, it is crucial to evaluate the potential for locating solar and other renewable energy resources on existing state assets. It is also important to engage and facilitate the decision-making process for the physical implementation of these resources at both the state and local levels.

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**Abbreviations**

| | |
|---|---|
| IDNR | Illinois Department of Natural Resources |
| MCDA | Multi-Criteria Decision Analysis |
| PSS | Planning Support System |
| AHP | Analytical Hierarchy Process |
| GIS | Geographic Information System |

In this work, we develop a scalable decision-support tool for determining the relative suitability of different locations for solar energy generation in the state of Illinois. The purpose of our work is to provide guidance for state agency-driven solar development by evaluating the suitable of potential areas in terms of environmental impact, socioeconomic costs, energy productivity, and critical decision-making. More specifically, this paper combines geospatial technologies with Multi-Criteria Decision Analysis (MCDA) to reveal the potential for solar energy generation on public lands in Illinois at a large scale using a fine-grained resolution (30 m $\times$ 30 m). We highlight the spatial explicitness of our state-wide analysis. It offers a wide range of opportunities to evaluate and spatially compare locations at multiple scales. The resolution and scale also foster stakeholder engagement through its visual accessibility. We also consider some of the critical planning and design implications of using the MCDA approach as part of a broader Planning Support System (PSS).

A spatially explicit MCDA using a variety of sustainability factors is used to determine the overall solar suitability across Illinois. An Analytical Hierarchy Process (AHP) helps to sort and weigh the variables. The MCDA methodology has been extensively reviewed and applied in the literature for various purposes [9–11]. Few of these studies, however, link the method to advanced decision-making technologies for real-world action, and even fewer link larger-scale assessment to smaller-scale decisions. This is important given that some of the urgent energy demands necessitate immediate, strategic policy decisions, and regional or national scale analyses may not adequately respond to the political context in which policy implementation takes place. Vonk [12] and Kwak et al. [13] note a wide 'implementation gap' between analysis and the 'on-the-ground' planning decisions. Our approach attempts to address this gap through the development of an interactive, spatially explicit, and scalable PSS tool for presenting and articulating the analysis for non-technical decision-makers. The tool allows for an interactive viewing and collaborative exchange between stakeholders that helps facilitate a deeper understanding of specific suitability issues [14].

Our analysis is conducted at a 30 m $\times$ 30 m resolution at a statewide scale (162,112,061 total cells). The high resolution enables a fine-grained comparison and evaluation of multi-scalar state property assets for their potential to contribute to state renewable energy goals. The approach examines large-scale solar energy suitability, suggests *in situ* details for real-world action, and presents a PSS tool that can facilitate interdisciplinary collaboration and strategic decisions. We believe that this work will be a valuable contribution to the solar energy and decision-making literature and to the improvement of the renewable energy profiles in Illinois.

The remainder of the paper is organized as follows. Section 2 presents the relevant literature and the rationale for this study. Detailed descriptions of our method and data for an application to the state of Illinois are presented in Section 3. The descriptions presented highlight procedures for selecting and weighting (sustainability organized) suitability criteria. Results from our suitability and subsequent sensitivity analysis are presented in Section 4. In our discussion section (Section 5), the implications of the study are proffered, including a small case study analysis. A proposal for a PSS tool for presenting and democratizing the analysis is also presented. Finally, Section 6 concludes the paper with a discussion of the major findings and suggestions on improvements and potential future work.

## 2. Literature review

MCDA has aided decision-making in a variety of fields because of its ability to handle multiple criteria simultaneously. It supports decision-making in helping to select the best option among several alternatives. It can help assess suitability over a given area by determining the relative importance among the criteria [15,16]. MCDA is considered a powerful tool for identifying optimal site locations. The use of Geographic Information System (GIS) with MCDA methods has gained attention as spatial computational technologies have evolved [15]. Geospatial technologies can process and analyze large quantities of spatial data and provide visual information that helps increase a comprehensive understanding of the areas being studied. More importantly, when equipped with decision support systems, they can help facilitate communication between experts and non-experts by delivering information in an understandable and intuitive graphic manner.

### 2.1. Spatial explicit decision-support systems

The literature on PSS suggests that large-scale analysis should incorporate contextually explicit information that allows policy-makers to determine suitability, project relevant demands, and inform localized decisions [17]. These tools are typically asked to help facilitate a consensus-driven decision-making process [18]. According to Geertman [19], this is highly dependent on the ability of the PSS tools to represent the specific context of the application. He notes that this ability to contextualize information influences how and to what degree the tool will be utilized. Similarly, Andrews [20] argues that effective planning models must be locally credible in order to successfully support decisions. Good PSS tools therefore, should be capable of contextualizing the characteristics and demands of specific sites as part of a larger analytical or planning process [20,21]. Contextualization, however, can be a challenging task when analyses are conducted at a regional (or larger) scale with varying layers of interactions [21].

Highly scalable PSS modeling systems can convey spatially explicit information from a variety of sources in a readily understandable and contextual form that enables decision-making based on site conditions [22]. They enable a fine-grained spatial assessment, comparison, and site identification in support of very local decision-making. Some systems (such as the one presented here) also allow users to test multiple alternative solutions (scenarios) iteratively as well as interactively [22,23]. This allows quick analysis of a range of potential state changes. It also allows, with visual representation functions, an ability to govern multi-scalar systems collectively [24], suitable locations for development activities (e.g., solar development), for example, and other planning suitability questions [25].

PSS usefulness is a topic of note in the current literature. Pan and Deal [26] note that a credible PSS requires objectiveness, reasonableness, understandability in order to be classified as 'useful.' PSS operationalization, according to te Brömmelstroet [27] is a function of the quality of analytic outcomes and quality of communicative processes in operationalizing a PSS. Generally, a credible PSS must produce quality analyses, effectively communicate outcomes to non-experts (e.g., stakeholders) in understandable manners, and well account for the local condition [20,26]. Decisions made through a credible PSS with explicit contextual information are more understandable to the user, more easily replicable, and quicker to track and manage [28,29].

### 2.2. Suitability optimization

Various GIS-based MCDA methods have been deployed and visualized to select development locations in the energy literature. Choudhary and Shankar [30] adopted Technique for Order Preference by Similarity to Ideal Solution (TOPSI) to rank the alternative locations for thermal power plants, Sánchez-Lozano et al. [31] combined GIS and the Elimination and Choice Translating Reality (ELECTRE-TRI) for solar farms site selection, Szurek et al. [32] used Weighted Linear Combination (WLC) to develop a wind farm suitability map. Charabi and Gastli [33] applied Fuzzy Logic Ordered Weight Averaging (FLOWA) to photovoltaic site suitability analysis. Of the variations of MCDA, AHP is an extensively used, robust approach in energy decision-making [34]. AHP weighs the MCDA variable and enables a reliable evaluation of the complex MCDA data for producing reasonable outcomes [11,35]. GIS-based AHP offers an important advantage over other methods, especially for spatial decisions, to easily obtain the relative importance weights of a large number of criteria through pair-wise comparison [33,36]. This study employs AHP and spatially presents the results using geospatial technologies.

In the study of solar energy development using MCDA, it is critical to optimize the analysis process for given study areas because the energy potential is subject to different environmental, economic, and social settings [15,33,37–42]. Different contexts, such as available natural resources, cultural assets, and developmental statuses, necessitate different optimizations in the criteria setting process. Majumdar and Pasqualetti [37] select nine evaluation criteria for solar development in Arizona. In their MCDA process, five distance criteria, such as distance from recreational areas, are selected based on the public opinion survey, and different combinations of the criteria are used to establish multiple scenarios. Noorollahi et al. [39] use eleven criteria, including solar radiation and distance from transmission lines, for identifying suitable development locations in Iran. They especially include average dusty days as a criterion with respect to the metrological conditions of Iran. Both Watson and Hudson [16] and Doorga et al. [38] highlight the importance of solar radiation in identifying the suitability for solar development in south-central England and Mauritius, respectively. Both assign more than 40% of the total weights to a criterion of solar radiation.

The ability of the method to flexibly reflect diverse contextual settings in the optimization process makes the method still useful in decision-making. In this paper, we established the evaluation and exclusion criteria based on solar development literature. Table 1 summarizes the top three highly weighted evaluation criteria and exclusion criteria in the literature.

## 3. Materials and methods

This study identifies suitable areas for solar development at a statewide scale to provide spatially explicit information. The suitability score for each cell (30 m × 30 m) is calculated by:

$$S_k = \sum_{j=1} C_{jk} W_j E_k \tag{1}$$

where $S_k$ is the suitability of cell $k$, $C_{jk}$ is a ranked value of cell k in criterion $j$, $W_j$ is the assigned weight of criterion $j$, and $E_k$ is a binary value of whether cell $k$ is located inside (0) or outside (1) of the constraint areas. Optimizing criteria and weights is a key process of MCDA because it greatly affects the discovery of the energy potential of the study areas [11,40,45]. In addition, by varying criteria or weights, multiple scenarios can be generated to test the robustness of the outcomes through sensitivity analyses. An overview of the process of this research is displayed in Fig. 1. Criteria data generation and map visualization were processed by ESRI's ArcMap 10.7. The MCDA modeling process was written in R (https://www.r-project.org/) for replicability. R is a programming language and open-source software environment for statistical computing.

### 3.1. Selection of criteria and materials

Solar development success is heavily influenced by the amount and duration of sunlight. Important for influencing costs are the project location and its proximity to existing infrastructure. Many studies consider solar radiation, distances from transmission lines, and -use as important criteria or use them to mask out the constraint areas (as shown in Table 1). Criteria selected in this work are based on the literature and input from the IDNR. For example, Crop Productivity (C9) is selected in this study because the IDNR expressed an interest in identifying and assessing state-held agricultural lands. We divide the selected criteria into three categories according to the three sustainability elements: environment, society, and economy (Table 2). A combination of environmental, social, and economic concerns has been identified as critical component considerations for solar system sustainability [46].

Each evaluation criterion is comprised of different units and plays a different role in determining overall suitability. Therefore, this study rescales each criterion into five ranks (1–5) for standardization (Table 3). Rescaling the values is also based on the literature review and communication with the IDNR. Rescaled maps of the criteria are shown in Fig. 2. The rationales for criterion selection and ranking are described in Supplementary Materials.

### 3.2. Identification of weights: the analytic hierarchy process

We use Saaty's [35] AHP method to estimate the weights of the criteria for suitability evaluation. AHP operates through pairwise comparison within a reciprocal matrix that uses a scale of absolute judgment representing how much one criterion dominates another [53]. The process involves two stages: 1) determining the relative importance of each criterion and 2) calculating the relative weight. In performing a pairwise comparison matrix, the relative importance values are ranked from 1 to 9. Once weights are computed based on relative importance, a consistency ratio (CR) is calculated to check the degree of consistency.

After normalizing entries in the pairwise comparison matrix, relative weights were calculated using equations (2) and (3). The sum of all criteria weights is 1; a larger weight represents a greater influence on solar development.

$$\overline{P}_{ij} = P_{ij} / \sum_{l=1}^{n} P_{lj} \tag{2}$$

$$W_i = \sum_{j=1}^{n} \overline{P}_{ij} / n \tag{3}$$

where $P_{ij}$ is the relative importance, $n$ is the number of criteria (9 in this research), $\overline{P}_{ij}$ is the normalized relative importance, and $W_i$ is the weight of criterion $i$, which is obtained by averaging across the rows.

CR was checked using equations (4) and (5). A CR smaller than 0.1 signifies acceptance. A CR larger than 0.01 suggests

**Table 1**
Top 3 criteria and weights used in the previous studies.

| Literature | Top 3 Evaluation Criteria | Weights | Exclusion Criteria | Study Area |
|---|---|---|---|---|
| [16] | Solar radiation | 0.49 | Historical areas, residential areas, wildlife designations, etc. | South Central England |
| | Distance from transmission lines | 0.26 | | |
| | Distance from roads and train lines | 0.07 | | |
| [38] | Solar radiation | 0.23 | Residential areas, reservoirs, national parks, etc. | Mauritius |
| | Sunshine duration | 0.07 | | |
| | Slope | 0.05 | | |
| [43] | Land use | 0.41 | Private lands | Karapinar region, Turkey |
| | Distance from transmission lines | 0.37 | | |
| | Distance from residential areas | 0.14 | | |
| [15] | Solar radiation | 0.35 | Protected areas, high slope area, urban areas, and major roads | Saudi Arabia |
| | Temperature | 0.24 | | |
| | Slope | 0.16 | | |
| [44] | Solar radiation | 0.3 | – | Colorado, U.S. |
| | Distance from transmission lines | 0.2 | | |
| | Distance from roads | 0.1 | | |
| [42] | Solar radiation | 0.39 | Residential areas, conservation areas, water bodies, etc. | Ulleung Island, Korea |
| | Sunshine duration | 0.27 | | |
| | Distance from transmission lines | 0.16 | | |
| [41] | Solar radiation | 0.32 | Forests, water bodies, protected areas, road networks, etc. | Serbia |
| | Sunshine duration | 0.18 | | |
| | Slope | 0.15 | | |

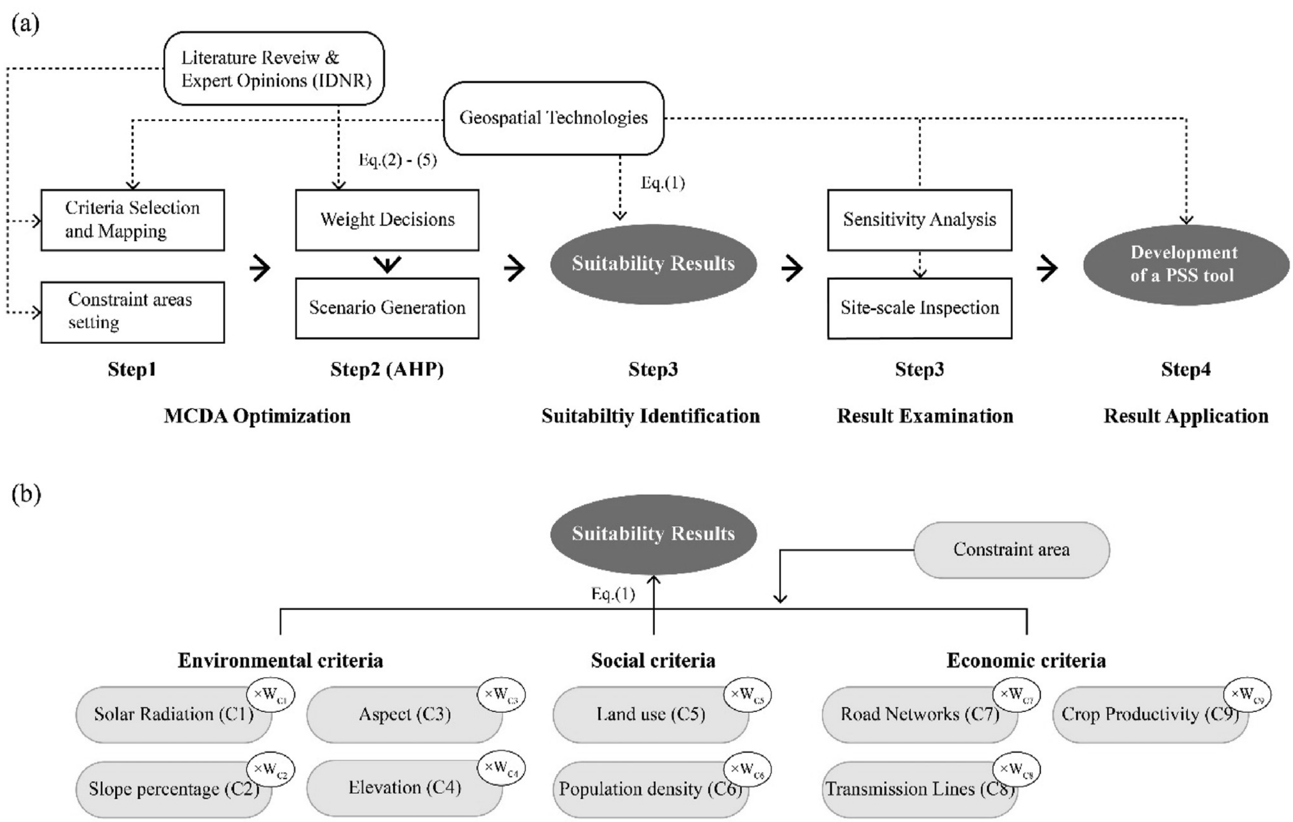


**Fig. 1.** (a) Research Framework, (b) Process of MCDA modeling. The equation applied to this is presented in Equation (1). The equations for AHP are presented in Equations (2)–(5).

inconsistencies that require the pairwise comparisons to be revised.

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{4}$$

$$CR = \frac{CI}{RI} \tag{5}$$

where CI refers to the consistency index for calculating CR, $\lambda_{max}$ represents the maximum eigenvalue of the pairwise comparison matrix, and RI is the random consistency index [35] describing how the values vary across the criteria. The value of RI for nine criteria is 1.45.

**Table 2**
Evaluation criteria selected in this study.

| Category | Criteria | Data sources |
|---|---|---|
| Environmental criteria | Solar radiation (C1) | [47] |
| | Slope percentage (C2) | |
| | Aspect (C3) | |
| | Elevation (C4) | |
| Social criteria | Land use and land cover (C5) | [48] |
| | Population center density (C6) | [49] |
| Economic criteria | Connectivity to road networks (C7) | [50] |
| | Distance from transmission lines (C8) | [51] |
| | Crop productivity (C9) | [52] |

The relative importance values were established based on the literature at the initial stage of the process and the revised discussion with the experts from the IDNR. The final decisions are presented in Table 4.

### 3.3. Exclusion criteria

Exclusion criteria represent constraint areas for solar development. In this study, they include 1) water bodies, 2) 100-year floodplain, and 3) ecologically sensitive or protected areas [54] that include conservation areas. It is worth mentioning that we include urban areas, forests, and parks in the analysis, which are typically designated as constraint areas in many studies [15,16,38,40,41]. We believe that the highest and best use criteria should be applied to all development decisions – determined by local stakeholders. Exclusion datasets were merged and rescaled using a binary scale, where 1 represents a viable location for development while 0 is an unavailable one.

### 3.4. Sensitivity analysis

A sensitivity analysis testing the model's robustness was conducted by comparing the effects on suitability between variables to help reduce uncertainty in MCDA [36]. We generated four additional scenarios with respect to the three sustainability categories used in this research. The scenarios include: 1) Environment-focused scenario (SA1), 2) Socials/development-focused scenario (SA2), 3) Economy-focused scenario (SA3), and 4) Scenario with equal weights (SA4). Except for SA4, where the weight of 0.111 was equally assigned, we re-applied AHP to determine the new weights. The highest importance was given to criteria under a specific category. For example, in SA1, we considered that the four criteria under the environmental category are ‘extremely more important than any other criteria, so we inputted values of 9 in a pairwise comparison matrix (see **Supplementary Materials**). The approach enables emphasis on the impact of a particular category while maintaining the relative importance between the criteria. Comparing the outputs between the scenarios generated through this process will provide a greater understanding of the importance of each category while avoiding some inconsistency.

## 4. Results

### 4.1. AHP scenario results

The AHP technique helps to determine the weights of the evaluation criteria in each scenario analysis. In our study, we first establish a Base Run scenario where the weights are based on ‘business as usual’ criteria using the existing literature and IDNR preferences. The result of this scenario establishes our baseline from which to compare other scenarios. The maximum eigenvalue for the scenario ($\lambda_{max}$) 9.566, resulting in a CR of 0.049. This value is below the 0.01 significance threshold, indicating that our base scenario shows a highly acceptable consistency and does not require an amendment.

This study generates four additional scenarios for sensitivity analysis by re-applying the process of pairwise comparisons. As criteria under a specific category are emphasized respectively, the most important criterion of each scenario is computed differently. This result coins with our intention of sensitivity analysis to find out which criterion is the most or the least sensitive to change, which will help facilitate sensible planning decisions for solar development in response to varying focuses of different government agencies. The weight values of each scenario are presented in Table 5.

### 4.2. Combined suitability scores

An overlaid set of our nine criteria produced a final suitability map of solar development for the whole of Illinois (Fig. 3). We rescaled the values of each criterion to a range from 1 to 5 (Table 3). 5 indicates the most suitable locations implying that there is the highest potential for solar development, while 1 indicates the least suitable locations where the installation is not recommended. Constrained areas were scored as 0. In the Base Run scenario, final suitability scores range from 1.08 to 4.19.

A visual inspection of the result shows the central region of the state, especially around Decatur, Champaign, and Bloomington, with higher suitability scores. The areas just south of Chicago also show higher potential. Given the roads and transmission lines that are densely located around the metropolitan area (Fig. 2g and h), the finding indicates that the solar is generally economically viable and can efficiently transmit electricity to some urban centers.

Morphologically, most of the highly suitable areas are on flatlands that can garner a larger amount of solar radiation (Fig. 2a, b,

**Table 3**
Ranking of evaluation criteria.

| Criteria | Rank[a] | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| Solar Rad. ($kWhm^{-2}yr^{-1}$) | <1200 | 1200–1300 | 1300–1400 | 1400–1500 | >1500 |
| Slope Percent (%) | >10 | 5–10 | 3–5 | 1–3 | <1 |
| Aspect | N | NE, NW | Flat, E, W | SW, SE | S |
| Elevation (m) | <400 | 400–600 | 600–800 | 800–1000 | >1000 |
| LULC | Wetlands/waters, and Forest | Urban areas | Herbaceous and Agricultural uses | Shrubland and Open space | Barren land |
| Population Density | Quantile method | | | | |
| Road Networks | Quantile method | | | | |
| Transmission Lines (m) | >20000 | 10000–20000 | 1600–4800 | 800–1600 | <800 |
| Crop Productivity | Quantile method | | | | |

[a] Higher rank indicates higher suitability. Each criterion exhibits a rough assessment of the potential for solar development.

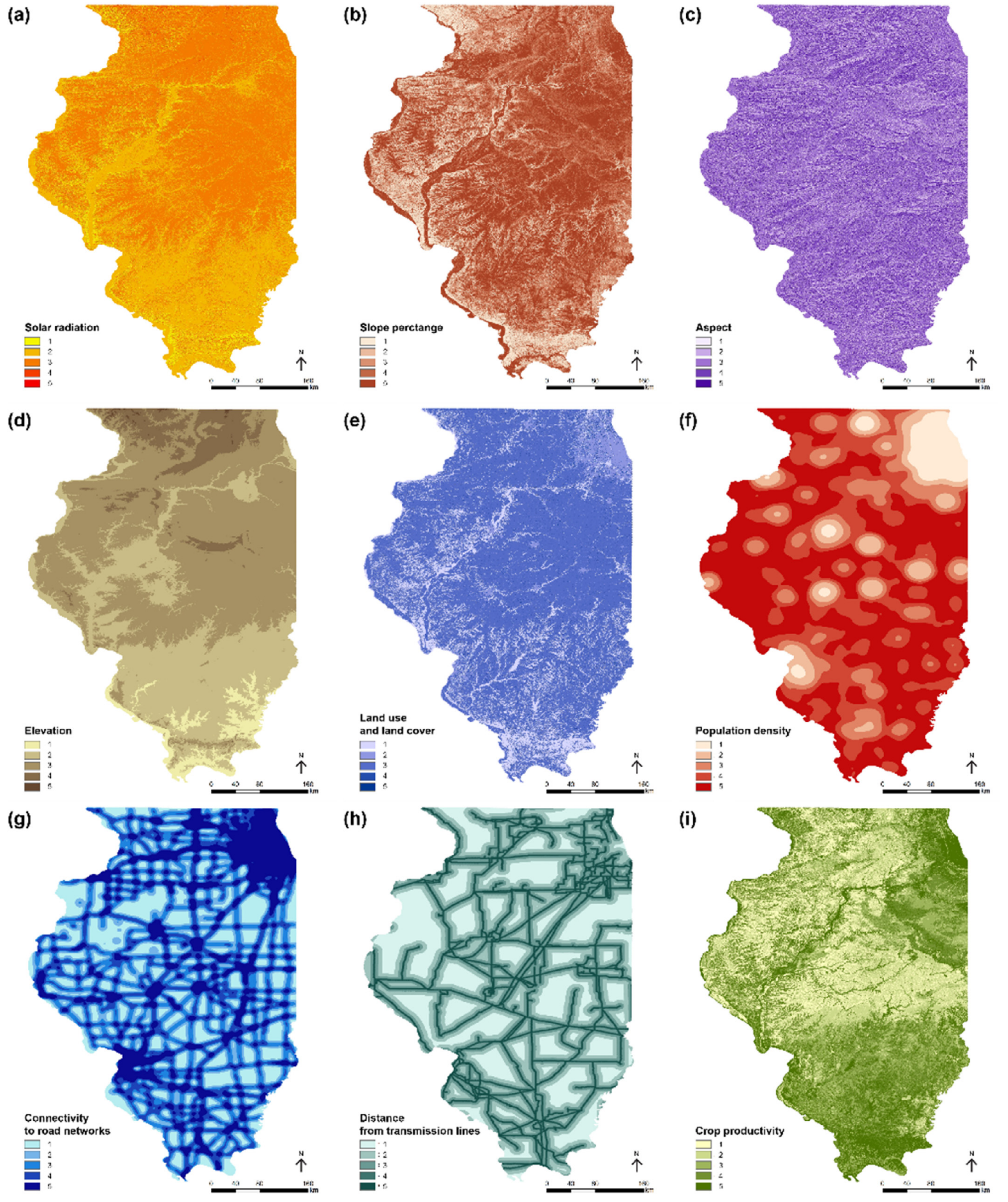


**Fig. 2.** Nine evaluation criteria selected in this study. The criteria are classified into three categories. 1. Environmental category: (a) solar radiation, (b) slope percentage, (c) aspects, and (d) elevation. 2. Social category: (e) land use and land cover, and (f) population center density. 3. Economic category: (g) connectivity to road networks, (h) distance from transmission lines, and (i) crop productivity.

**Table 4**
Pairwise comparisons of the evaluation criteria.

| Criteria | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 |
|---|---|---|---|---|---|---|---|---|---|
| Solar Rad. (C1) | 1 | 5 | 8 | 7 | 5 | 9 | 7 | 5 | 9 |
| Slope (C2) | 1/5 | 1 | 5 | 3 | 3 | 7 | 5 | 1 | 7 |
| Aspect (C3) | 1/8 | 1/5 | 1 | 1 | 1/2 | 3 | 1 | 1/3 | 5 |
| Elevation (C4) | 1/7 | 1/3 | 1 | 1 | 1/2 | 3 | 1 | 1/3 | 5 |
| LULC (C5) | 1/5 | 1/3 | 2 | 2 | 1 | 5 | 3 | 1/2 | 7 |
| Pop. Den. (C6) | 1/9 | 1/7 | 1/3 | 1/3 | 1/5 | 1 | 1/3 | 1/5 | 3 |
| Road Net. (C7) | 1/7 | 1/5 | 1 | 1 | 1/3 | 3 | 1 | 1/3 | 4 |
| Trans. Lines (C8) | 1/5 | 1 | 3 | 3 | 2 | 5 | 3 | 1 | 8 |
| Crop Prod. (C9) | 1/9 | 1/7 | 1/5 | 1/5 | 1/7 | 1/3 | 1/4 | 1/8 | 1 |

*$P_{ij}$ refers to the relative importance of criterion $i$ over criterion $j$, and $P_{ij} \times P_{ji}$ should be equal to 1. For example, $P_{19} = 9$ signifies that solar radiation is judged to be extremely more important than crop productivity in determining the suitability of solar development.

**Table 5**
Weights of the evaluation criteria under the scenarios generated.

| Criteria | Weight | | | | |
|---|---|---|---|---|---|
| | Base Run | SA1 | SA2 | SA3 | SA4 |
| Solar Rad. (C1) | 0.390 | 0.364 | 0.142 | 0.101 | 0.111 |
| Slope (C2) | 0.169 | 0.200 | 0.071 | 0.057 | 0.111 |
| Aspect (C3) | 0.054 | 0.137 | 0.030 | 0.023 | 0.111 |
| Elevation (C4) | 0.057 | 0.140 | 0.031 | 0.024 | 0.111 |
| LULC (C5) | 0.098 | 0.046 | 0.367 | 0.035 | 0.111 |
| Pop. Den. (C6) | 0.027 | 0.019 | 0.256 | 0.014 | 0.111 |
| Road Net. (C7) | 0.051 | 0.028 | 0.028 | 0.229 | 0.111 |
| Trans. Lines (C8) | 0.136 | 0.052 | 0.061 | 0.341 | 0.111 |
| Crop Prod. (C9) | 0.017 | 0.014 | 0.013 | 0.176 | 0.111 |
| Sum | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |

and d). Southern Illinois generally presents the lower scores, mainly because of vegetative cover and steeper slopes (Fig. 1a and b). Allerton Park, our case site in the center of the state, is an appropriate site to explore details since it is located between Decatur and Champaign, where we identify a high potential to produce electricity from solar energy (Fig. 3).

### 4.3. Sensitivity analysis results

The results of our four additional scenarios are shown in Fig. 4. Table 6 summarizes the descriptive statistics of 10% randomly sampled data, and the percentage of cells in each suitability score of all scenario results. This shows that the differences in the mean, minimum, and maximum values between the Base Run result and others are not greater than one suitability rank. Assuming that a score of 3, the median value of the score range (1–5), is a threshold that we can use to determine whether or not the location is suitable, 46.27% of Illinois (cells with a score >3) appears suitable in the Base Run scenario. The mean score for the state is 2.86.

Comparing Base Run with SA2 shows the most significant change in both the percentage of suitable cells (68.08%) and the mean value (3.11). Specifically, the score ranging from 3.5 to 4 mainly accounts for this change, given that its percentage increases remarkably by 13.31%. We also find that the spatial distributions of LULC and population density (C5 and C6) greatly affect this result: most of the urban centers are less suitable. Notably, both Chicago and East St. Luis areas represent lower scores plausibly because of their highly developed lands and concentrated population (Fig. 4b).

SA3 results in the lowest percentage of suitable cells (37.92%) and the smallest mean value (2.83). The biggest variation in scores also is observed in this scenario, with the largest maximum score of 4.76 and the smallest minimum score of 1.07 scores. Unlike SA2, in scenario SA3, Chicago displays a huge potential for solar development, which is attributed to the densely constructed roads (C7) and transmission lines (C8). This indicates that the area would be more viable when it comes to economic aspects.

The results of different scenarios offer various distributions of suitability scores and reveal the sensitivity of each category. SA2, where we assign the higher weights to the social category, generates the largest changes in the result. In other words, the criteria for our social categories (C5 and C6) are the most sensitive to changes in suitability among all criteria. SA2 also results in larger potential areas than any other scenario. On the other side, SA1 produces the smallest change compared to Base Run, connoting that the environmental criteria (C1, C2, C3, and C4) are the least sensitive.

## 5. Discussion

### 5.1. Solar development potential in Illinois

We highlight that our finding largely corresponds to the real-world undertaking of solar development occurring in Illinois. In January of 2019, the Champaign County Board agreed to build a utility-scale solar farm that is designed to generate 150 MW in association with the Future Energy Jobs Act incentives. Our analysis shows a correspondingly high suitability score in Champaign County. It is likely attributed to its flatness, its relatively high solar radiation, and good proximity to roads and transmission lines (Fig. 2a, g, and h). The mean suitability score in Champaign County appears 3.19, which accounts for the top 4 mean scores among all counties in the state (see Table 7).

Fig. 5 displays the spatial distribution of the mean scores across the counties, providing a rough insight into where decision-makers should prioritize solar projects. De Witt, Douglass, Champaign, and Will counties present the highest potential, whereas most of southern Illinois are less suitable. Our analysis suggests that central areas of Illinois can arguably be the optimal areas for maximizing solar energy potential. The results validate that the actual solar projects for the Champaign area are helping shape the behavior of the state to move toward better levels of sustainable energy systems.

Our sensitivity analysis shows that the social category criteria are the most sensitive to the changes in suitability results. With a greater weight is assigned to C5 (LULC), we find that LULC is the most sensitive criterion. This has some implications. For example, if social criteria are given more weight in the decision-making process, the distribution of suitable locations will change significantly for fast-growing places. This leads to a future extension of this work regarding the influence of land-use change. Indeed, the unintended consequences of proposed development policy and choices often result from seemingly reasonable decisions. Anticipating the potential consequences of land-use change is challenging [55]. Understanding the dynamic of urban systems and how future land-use change, in particular, will affect the solar developmental potential would improve our MCDA model outcomes.

### 5.2. Scale and feasibility

In order to provide practical guidance in detail to related stakeholders and developers, it is important to discuss the feasibility of real-world actions, which cannot be evaluated through a large-scale suitability analysis. We take Allerton Park, near Monticello, Illinois, as our case study area to discuss the feasibility (Fig. 6). The left image shows a map of the park with the suitability scores. The right one shows satellite imagery for comparison. Four locations are identified as higher suitable areas for solar development (blue circles in Fig. 6a). We highlight that our identification corresponds to the implementation in reality – a spot where solar

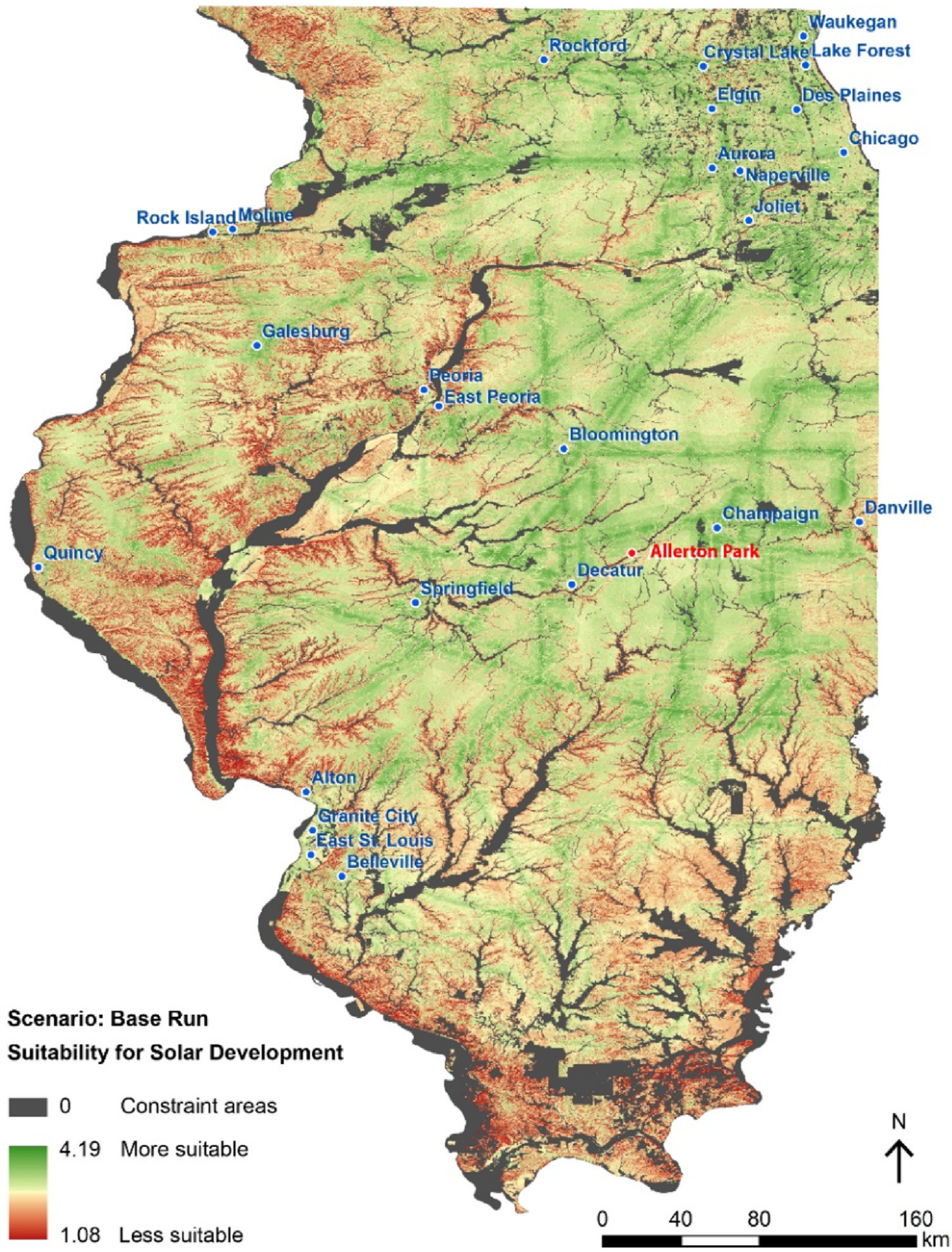


**Fig. 3.** Result of MCDA for 'Base Run' scenario.

panels were installed in 2014 (Fig. 6c). However, we also note that the suitable locations identified through the statewide analysis do not always indicate 'feasible' locations. In terms of feasibility, a (smaller scale) implementation necessitates consideration of construction details, types of solar panels, and current contexts. For example, the very left circle in Fig. 6a is a large cleared area for the Sun Singer statue, one of the most recognizable features of the park [56].

The case application for the Allerton park reveals a possible caveat that the large-scale suitability analysis can fail to identify feasible locations in terms of physical implementation. This informs decision-makers that site-specific details, including cost, design, and micro-climate, should be carefully explored when applying the resulting information to real-world actions.

### 5.3. MCDA as a PSS decision-support tool

The suitability evaluation necessitates a broad range of considerations, including the amount of solar radiation, closeness to the implanted transmission lines and roads, and the growth status of neighboring cities. Additionally, detailed sociocultural factors that are not revealed from this type of analysis are also critical. In order to facilitate solar development efficiently and escalate sustainable growth sensibly, the processes from identifying potential sites to deciding specific locations should be undertaken with interdisciplinarity and local input. The MCDA can be a valuable planning tool for undertaking such exercises, especially when presented in the form of PSS. A PSS can provide sharable and scalable outputs allowing dynamic interaction with users, facilitating input from non-technical disciplines and local stakeholders.

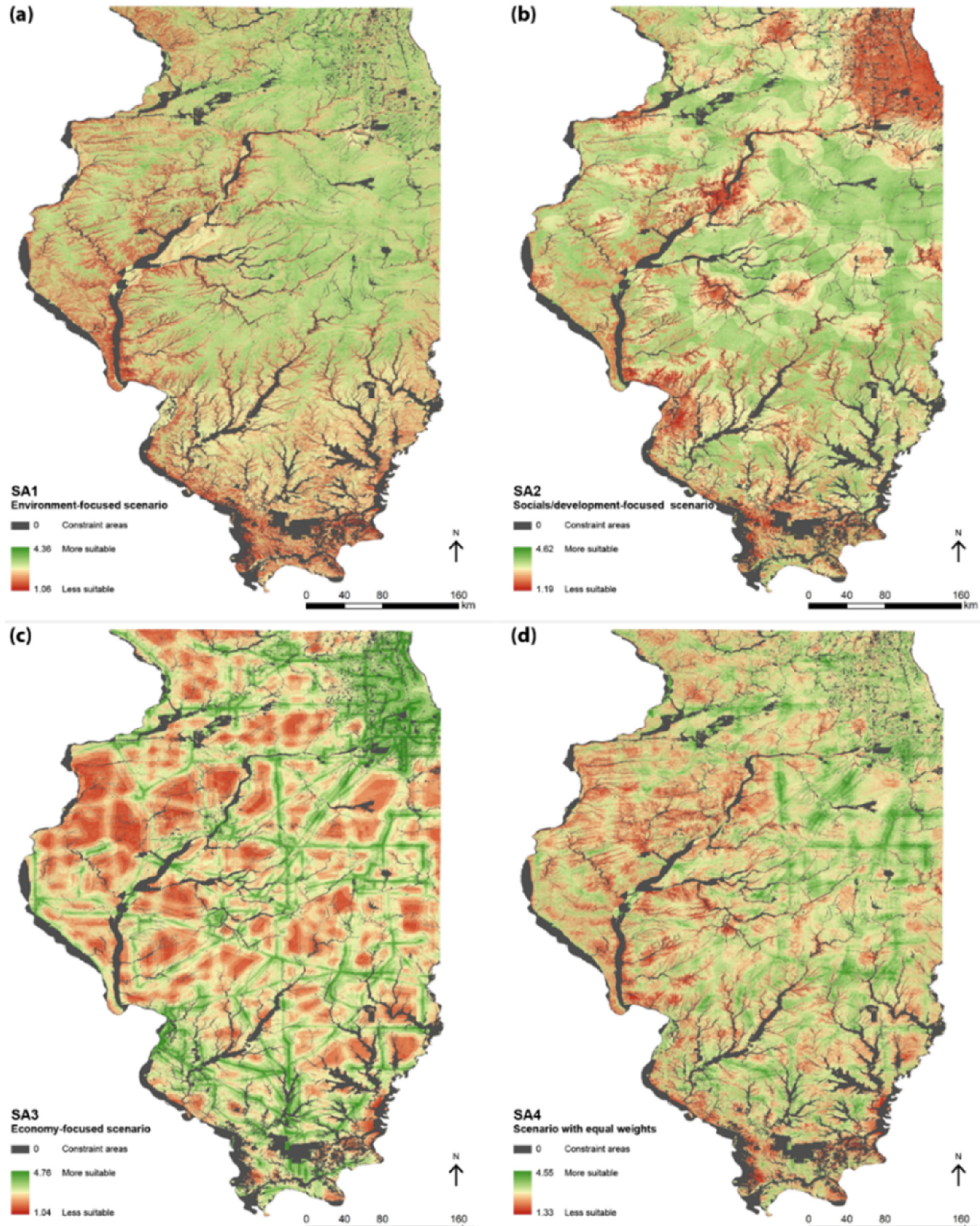


**Fig. 4.** Results of MCDA for the four additional scenarios. (a) represent the suitability result of SAI (Environment-focused scenario), (b) is the result of SA2 (Socials/development-focused scenario), (c) is the result of SA3 (Economy-focused scenario), and (d) is the result of SA4 (Scenario with equal weights).

**Table 6**
Summary table of each scenario result (10% randomly sampled data).

| | Descriptive Statistic | | | | Suitability Score (% of cells) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Scenario | Mean | Min. | Max. | SD. | 1–1.5 | 1.5–2 | 2–2.5 | 2.5–3 | 3–3.5 | 3.5–4 | 4–4.5 | 4.5–5 | Over 3 (suitable) |
| BASE | 2.86 | 1.08 | 4.13 | 0.49 | 1.45 | 5.80 | 12.64 | 33.84 | 41.15 | 5.12 | 0 | 0 | 46.27 |
| SA1 | 2.93 | 1.08 | 4.29 | 0.53 | 1.14 | 6.25 | 11.77 | 27.25 | 44.74 | 8.88 | 0 | 0 | 53.59 |
| SA2 | 3.10 | 1.20 | 4.52 | 0.46 | 0.08 | 1.89 | 11.9 | 18.04 | 49.58 | 18.28 | 0.22 | 0 | 68.08 |
| SA3 | 2.83 | 1.07 | 4.76 | 0.63 | 0.51 | 8.30 | 23.76 | 29.52 | 27.87 | 11.95 | 3.83 | 0.26 | 37.92 |
| SA4 | 3.03 | 1.33 | 4.44 | 0.34 | 0 | 0.49 | 6.54 | 43.18 | 41.98 | 7.79 | 0.03 | 0 | 49.80 |

*SAI = Environment-focused scenario, SA2 = Socials/development-focused scenario, SA3 = Economy-focused scenario (SA3), and SA4 = Scenario with equal weights.

**Table 7**
Top 10 counties for suitability of solar development.

| County | Min. | Max | Mean | S.D. |
|---|---|---|---|---|
| Dewitt | 1.37 | 4.02 | 3.22 | 0.35 |
| Douglas | 1.40 | 3.95 | 3.21 | 0.26 |
| Will | 1.37 | 4.00 | 3.21 | 0.37 |
| Champaign | 1.32 | 3.97 | 3.19 | 0.29 |
| Lee | 1.30 | 4.13 | 3.15 | 0.36 |
| Boone | 1.33 | 4.03 | 3.15 | 0.32 |
| Mclean | 1.19 | 4.07 | 3.14 | 0.33 |
| DuPage | 1.59 | 4.05 | 3.13 | 0.34 |
| Dekalb | 1.22 | 4.01 | 3.13 | 0.28 |
| Grundy | 1.40 | 3.94 | 3.13 | 0.34 |

An example of such a tool is described in Fig. 7. In order to make inclusive decisions on solar development, the expected users (stakeholders) need to comprehend 'where things are' and 'what accounts for the suitability' both spatially and quantitatively and should be allowed to control criteria and their weights responding to a variety of local policies. As noted, although the Base Run scenario presented in this paper is generated through the extensive literature review and discussions with the government agencies, the statewide assessment still has several caveats in terms of implementation at smaller scales. The suggested web-based tool, which is under construction, is aimed to minimize the 'implementation gap' by providing process scalability and encouraging stakeholder engagement. Users will be able to control the weights by adjusting the slide bars (Fig. 7) and get a resulting map with high resolution that is scalable enough to discuss smaller-scale implementations. This tool addresses the utility of scalable PSS for better decisions while providing stakeholders with information that pertains to local communities and policies in a usable, useful, and interactive manner.

In the following, we consider 4 criteria (from Pan and Deal [26]) for evaluating our Solar Suitability PSS: *objectiveness, reasonableness, understandability,* and *usefulness*.

### 5.3.1. Objectiveness

Visual inspection is a widely used method for evaluating PSS outcomes. The method is simple to understand (and execute) and can be helpful in engaging non-technical PSS users. It is not however, an objective measure since validity is determined in large part by who is doing the assessment. The visual approach can be influenced by opinions and biases and is not testable or replicable. Its subjectivity can cause conflicts among the actors in plan or decision-making [57]. Objective and quantifiable approaches are inherently valid. To increase our PSS model objectiveness, we utilize a multi-criteria approach with AHP in determining the weights of the criteria to represent solar suitability in a quantifiable and replicable way. The subjectiveness inherent in the AHP process is offset by the contextualization it affords in presenting the outcomes and the ability of the user to modify and adjust the weighting variables.

### 5.3.2. Reasonableness

Reasonableness emerges when the results of a PSS model can be widely understood and accepted. For this reason, in typical PSS model applications, a reasonable outcome can be more important than mathematical exactness [26]. The perception of reasonableness however, may be scale dependent and contextual. For example, watershed-based models do not work at a small resolution and therefore accuracy is applied only to the watershed scale. It would be unreasonable to try to depict the accuracy of the model at a fine resolution. The spatial explicitness of our large-scale PSS offers a wide range of opportunities to foster stakeholder engagement and spatially compare locations at multiple scales. Its scalability, contextual specificity, and visual accessibility improve its reasonableness, as does the use of sustainability as a metric for suitability criteria.

### 5.3.3. Understandability

Delivering the modeled outputs to untrained stakeholders in an understandable way is essential in collaborative plan-making. Unintuitive results with quantitative analyses hamper communication and negotiation. PSS data visualization techniques have been shown to promote both more *and* less transparency and public trust, depending on whether the information is complemented by interpretation techniques [21]. In this sense, to promote a PSS practicality, its outputs must be represented in a graphic manner, be interactive, readily interpretable, downloadable, and accompanied by a written explanation. GIS-based MCDA methods have been widely applied in various decision-making fields explicitly because of its ability to produce easily understandable spatial information. In addition, we add a spatial viewer window built upon a google map API, so that it is zoomable referenceable and scalable. We expect this strength of MCDA in combination with our advanced PSS visualization techniques to bolster the accessibility and understandableness of our outcomes.

### 5.3.4. Usefulness

Generally, model usefulness is preferred in planning processes while accuracy is more highly valued in validation exercises [28,58]. When the models convey information that can inform decision-making successfully, they can be considered useful to the process. In this case, usefulness is determined by the ability of the solar suitability analysis and PSS to inform practical decision-making. Our experiences in working with the IDNR on the use of the tool to evaluate the solar suitability of public lands has proven its usefulness in that context. IDNR decision-makers were able to quickly grasp the situation in each parcel and compare suitability scores. The tool also provided a forum for discussion on agency priorities and a path forward toward their next steps in acquiring solar resources – namely economic and feasibility analysis on specific sites. In the process of planning for a state agency the tool has proven extremely useful.

This paper suggests our statewide analysis as a decision-support tool that delivers spatial and quantifiable information from

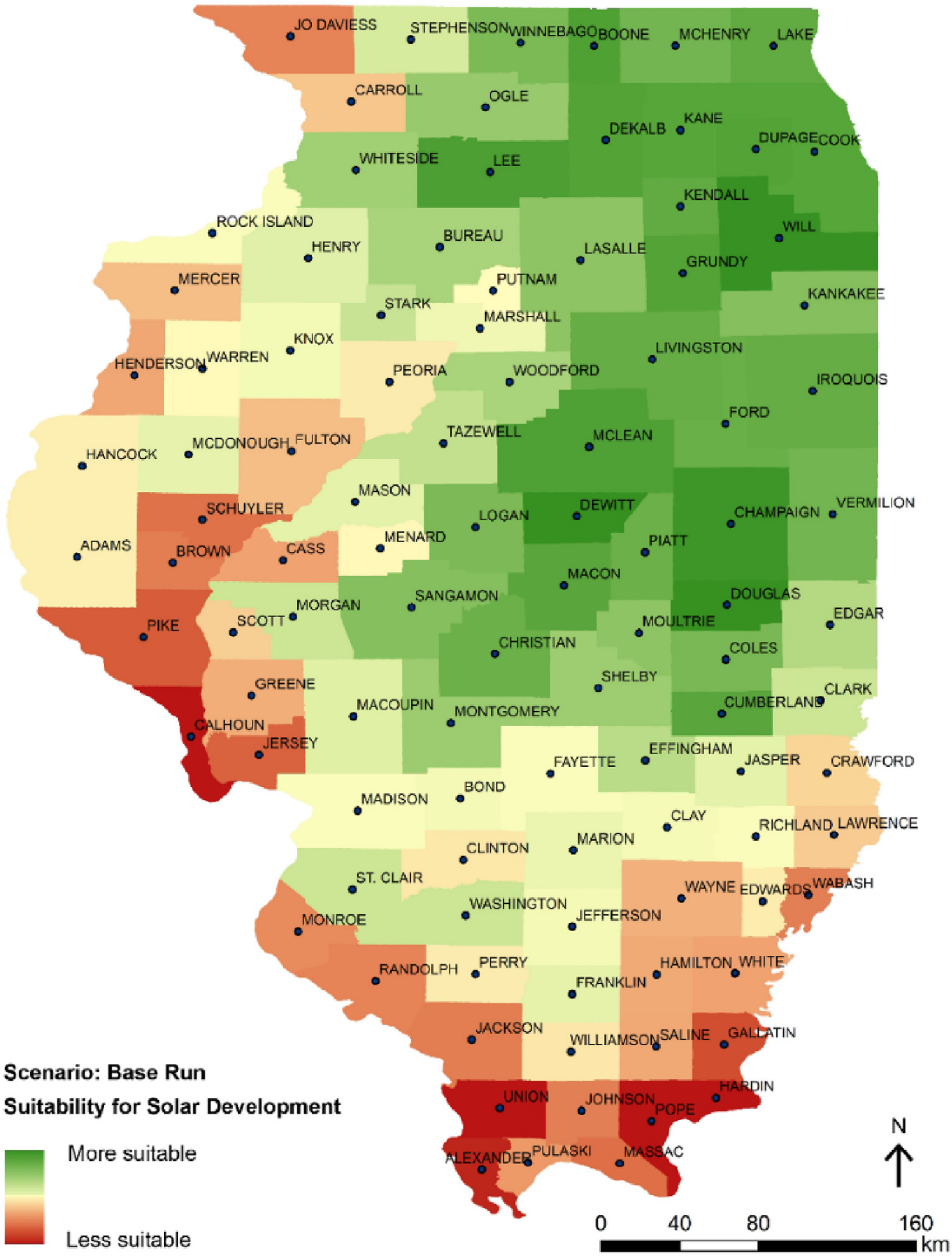


**Fig. 5.** Map of zonal statistics of suitability.

manifold criteria, is highly scalable with spatial explicitness and fosters stakeholder engagement through its practical application. The analysis and PSS delivery have proven objectively valid, reasonable in its approach and outcome, understandable to the users, and useful in the process of planning for solar implementation.

### *5.4. Limitations*

There are several limitations that should be addressed in future research. First, a verification of model accuracy is important. Although our results generally suggest corroboration with real-world policy initiatives in Illinois, our case study at Allerton Park describes the importance of physical verification in application. However, since Illinois is at the early stage of solar development and state currently lacks a statewide solar assessment program, we cannot broadly test the accuracy of our model. We do suggest however, that our results can serve to ignite cross-scale (from statewide to site-specific) dialogue with a range of public land-holders using our navigable PSS tool. We also expect the results to be verified with real-world solar installation cases in the future. Second, as described in the previous section, further steps for model contextualization and localization are required to connect our MCDA model to local realities. Consideration of contextual or qualitative factors, such as social preference [59], community ownership [60], and characteristics of spaces [61], can be utilized to help make the model practically more useful.

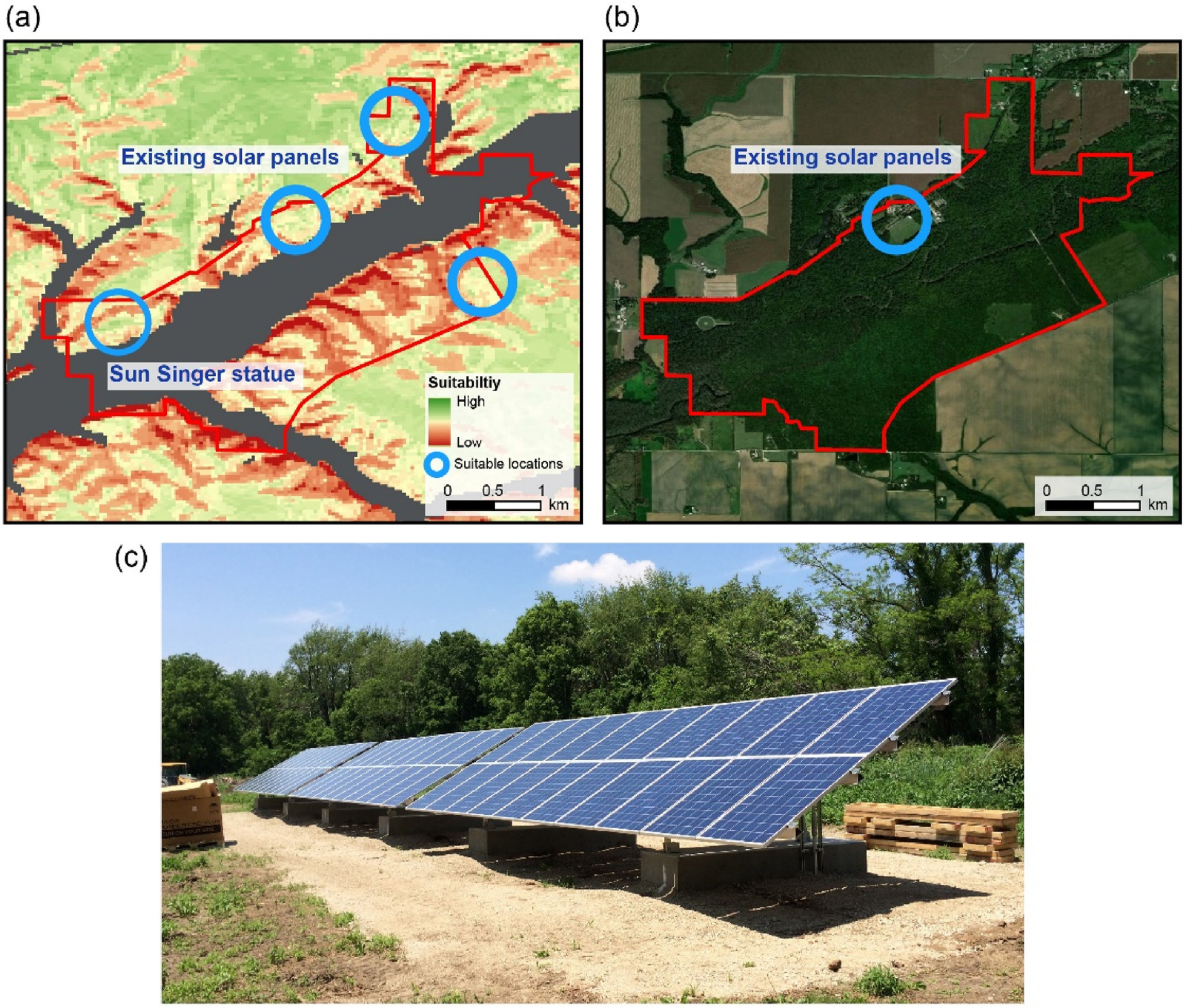


**Fig. 6.** Case application to the Allerton Park. Fig. 6c shows the existing solar panels in the park. The image is obtained from the Illinois Climate Action Plan (https://icap.sustainability.illinois.edu/).

## 6. Conclusion

Electricity generation in Illinois currently relies heavily on coal and nuclear power plants. As the fifth-largest state in the nation in terms of energy consumption, the potential for renewable energy in Illinois is great. State government agencies are beginning to recognize the potential. However, the state needs a deeper understanding of its unrevealed renewable energy potential to make strategic decisions for harnessing energy resources more efficiently and sustainably. Solar development requires interdisciplinary collaboration to assess potential, create plans, and decide specific locations and sizes for implementation. This research suggests that planning decisions for solar development should be incorporated with suitability at a large scale and feasibility at a specific scale, considering a wide array of sustainable factors. We also suggest that the analysis should be done in a democratic and engaged decision-making process using accessible and understandable PSS systems.

The tool presented in this study is based on PSS evaluation criteria suggested in the PSS literature [26]. Multiple objective criteria along with AHP help remove bias from the analysis, advancing *objectiveness*. Scalability, multiple scenarios emphasizing sustainability elements, and a sensitivity analysis help reduce uncertainty and improve the *reasonableness* of the analysis. A web-based interactive platform where outputs, as well as inputs, are visualized in an easy to navigate and accessible platform promotes *understandability*. Finally, the PSS tool has been developed in cooperation with a state agency and successfully utilized in a real-world planning process – testing its *usefulness*.

In this paper, we also emphasize the need for analytical and PSS tool flexibility. This flexibility allows for contextualization to the specific application. In this work, selecting evaluation criteria and determining the weights are highly contextual. This enables policymakers to analyze the solar development potential on a wide range of sites quickly and objectively. More work is needed in criteria analysis and objective weighting processes. In this study, we also compared the results of different scenarios to reflect varying solar development policies and found that the suitability score for solar development is most sensitive to land use. Further research on the impact of land-use change will add to the reasonableness of our approach and outcomes. Additional work is also needed on the PSS tool's ability for replication and further scale-dependent refinement.

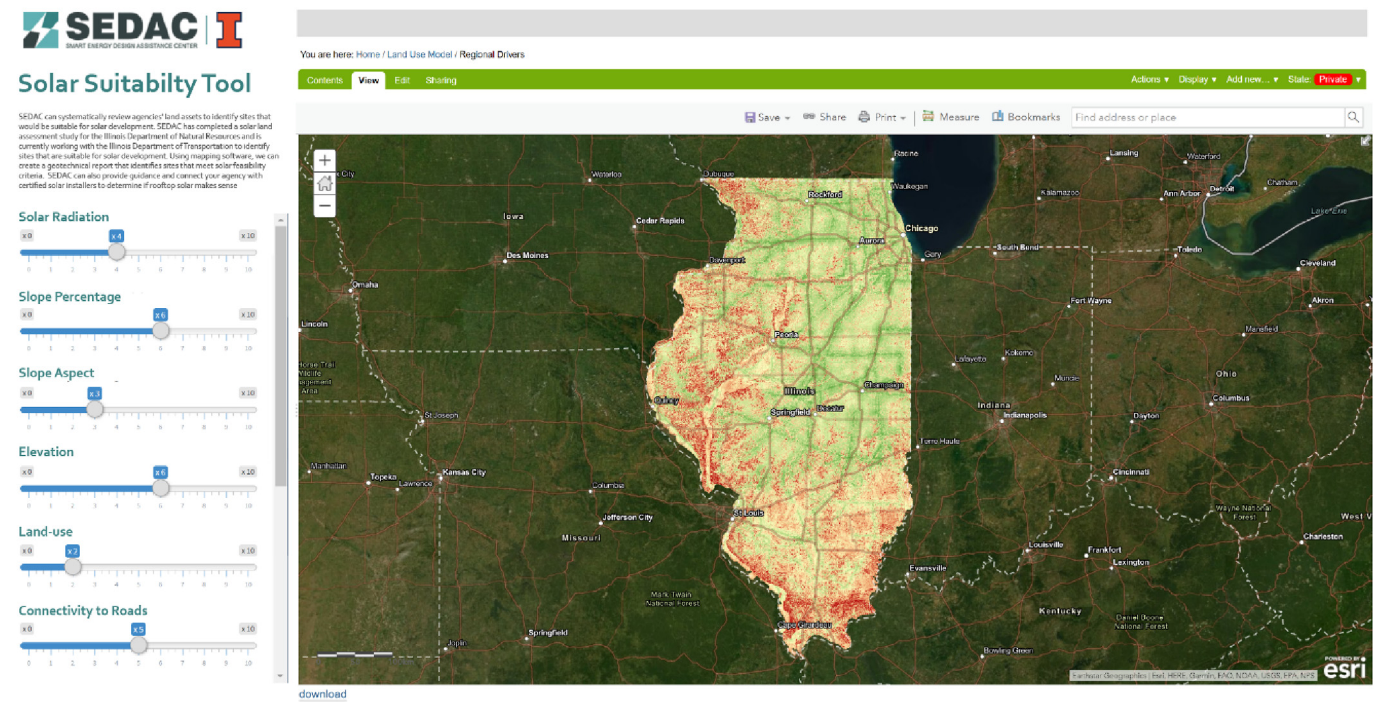


**Fig. 7.** A screenshot of the web-based interactive platform for Solar Suitability Analysis available at (https://smartenergy.illinois.edu/solar/). Variables are adjusted and weighted on the left with a google API based interactive viewer for visualizing output on the right.

In conclusion, this paper attempts to offer planning and decision support to a government agency as an aid to promote more sustainable solar development. The approaches proposed examines solar energy potential at a large scale using fine-grained data and analysis techniques. We suggest considerations for *in situ* details for real-world actions. Criteria selection and their relative importance will differ from region to region. Therefore, we emphasize that this research does not provide a standard or mandatory protocol but provides guidance with an optimized, responsive and scalable approach. The approach is incorporated with a logical and readily understandable method (MCDA) and communicates resulting information in a way that facilitates collaboration and strategic decision-making (PSS). We believe that this work is a valuable contribution to the improvement of the renewable energy profile for Illinois and can be adapted for solar development planning in other places.

## CRediT authorship contribution statement

**Yoonshin Kwak:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Brian Deal:** Writing – review & editing, Supervision, Funding acquisition. **Tom Heavisides:** Supervision.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.renene.2021.05.165.

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