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GIS-BASED SUITABILITY MODELING AND MULTI-CRITERIA DECISION ANALYSIS FOR UTILITY SCALE SOLAR PLANTS IN FOUR STATES IN THE SOUTHEAST US

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GIS-BASED SUITABILITY MODELING AND MULTI-CRITERIA DECISION ANALYSIS FOR UTILITY SCALE SOLAR PLANTS IN FOUR STATES IN THE SOUTHEAST U.S.

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ABSTRACT

Photovoltaic (PV) development shows significantly smaller growth in the Southeast U.S., than in the Southwest; which is mainly due to the low cost of fossil-fuel based energy production in the region and the lack of solar incentives. However, the Southeast has appropriate insolation conditions (4.0-6.0 KWh/m^2/day) for photovoltaic deployment and in the past decade the region has experienced the highest population growth for the entire country. These factors, combined with new renewable energy portfolio policies, could create an opportunity for PV to provide some of the energy that will be required to sustain this growth**.** The goal of the study was to investigate the potential for PV generation in the Southeast region by identifying suitable areas for a utility-scale solar power plant deployment. Four states with currently low solar penetration were studied: Georgia, North Carolina, South Carolina and Tennessee. Feasible areas were assessed with Geographic Information Systems (GIS) software using solar, land use and population growth criteria combined with proximity to transmission lines and roads. After the GIS-based assessment of the areas, technological potential was calculated for each state. Multi-decision analysis model (MCDA) was used to simulate the decision making method for a strategic PV installation. The model accounted for all criteria necessary to consider in case of a PV development and also included economic and policy criteria, which is thought to be a strong influence on the PV market. Three different scenarios were established, representing decision makers' theoretical preferences. Map layers created in the first part were used as basis for the MCDA and additional technical, economic and political/market criteria were added. A sensitivity analysis was conducted to test the model's robustness. Finally, weighted criteria were assigned to the GIS map layers, so that the different preference systems could be visualized. As a result, lands suitable for a potential industrial-scale PV deployment were assessed. Moreover, a precise calculation for technical potential was conducted, with a capacity factor determined by the actual insolation of the sum of each specific feasible area. The results of the study showed that, for a utility-scale PV utility deployment, significant amount of feasible areas are available, with good electricity generation potential Moreover, a stable MCDA model was established for supporting strategic decision making in a PV deployment. Also, changes of suitable lands for utility-scale PV installations were visualized in GIS for the state of Tennessee.

DEDICATION

"The only things we can keep are the things we freely give to God. What we try to keep for ourselves is just what we are sure to lose."
- C.S. Lewis, Mere Christianity

I would like to dedicate this work to Ferenc Kovacs and his family, who have been the most influential tools of God in my life. Thank you, for sharing your vision.

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LIST OF ACRONYMS

AHP	Analytical Hierarchy Process
DEM	Digital Elevation Model
DM	Decision Making / Decision Maker
DSS	Decision Support System
EPA	Environmental Protection Agency
FIT	Feed In Tariff
GHG	Greenhouse Gas
GHI	Global Horizontal Irradiation
GIS	Geographical Information Systems
Ha	Hectare
NCDL	National Land Cover Database
NREL	National Renewable Energy Laboratory
MCDA	Multi-criteria decision analysis
PV	Photovoltaics
SEIA	Solar Energy Industries Association
SERC	State Electricity Regulatory Commission
Shp	Shape file
TOPSIS	Technique for order preference by similarity to ideal solutions
WHO	World Health Organization

1. INTRODUCTION

Energy is fundamental for today's growing global economies. It is at the core of some of the world's major challenges such as the mitigation of climate change, the promotion of sustainable development and natural resources or ecosystem protection issues [1]. In the past decades, global primary energy consumption has grown rapidly; a trend is which is expected predicted to continue due to population growth and increasing demand from developing countries [2]. Figure 1, taken from an Energy Information Agency (EIA) report, shows the overall energy demand structure from 1980 onwards, including energy demand projections until 2040. The same document forecasts an average of 3.6 % annual growth for the global economy between 2010 and 2040 [2]. According to this scenario, the U.S. will require 12 % more energy in 2040 than it needed in 2012.

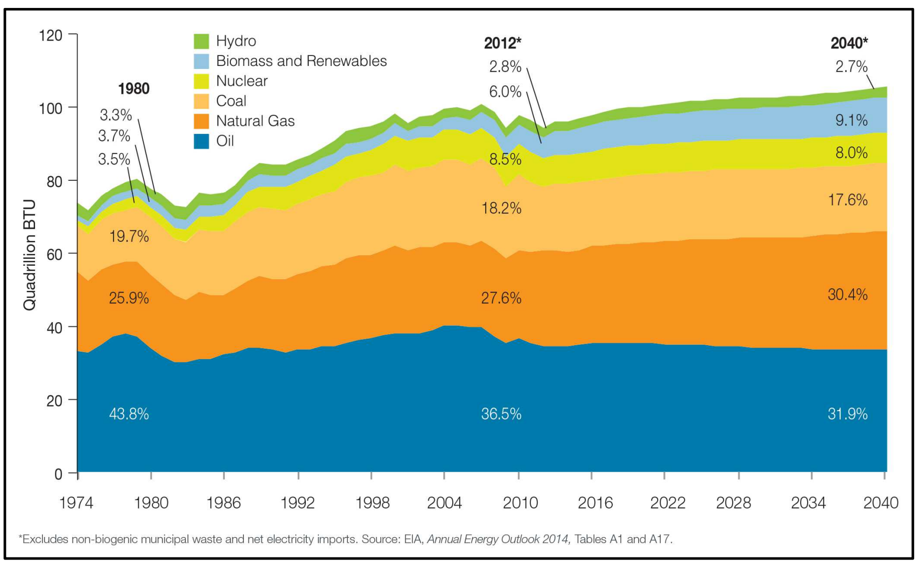


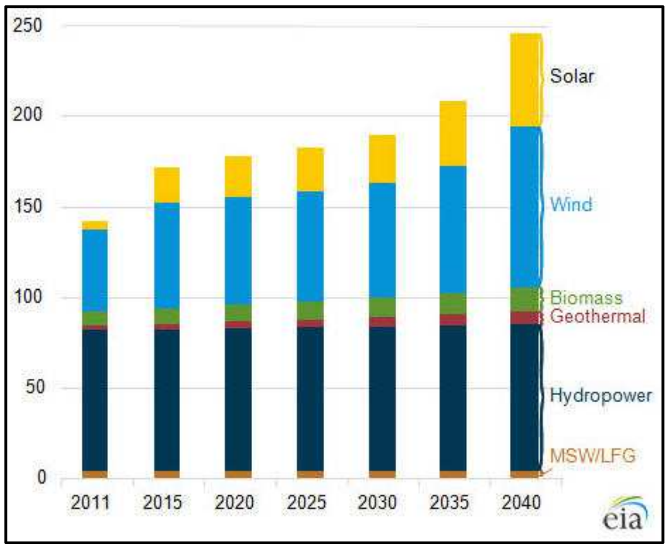
Figure 1: Future U.S. Energy demand according to EIA forecast

The main primary energy consumer in the U.S. is the electric power sector (41%). Most of the electricity is generated from coal (46%), nuclear sources (21%) and natural gas

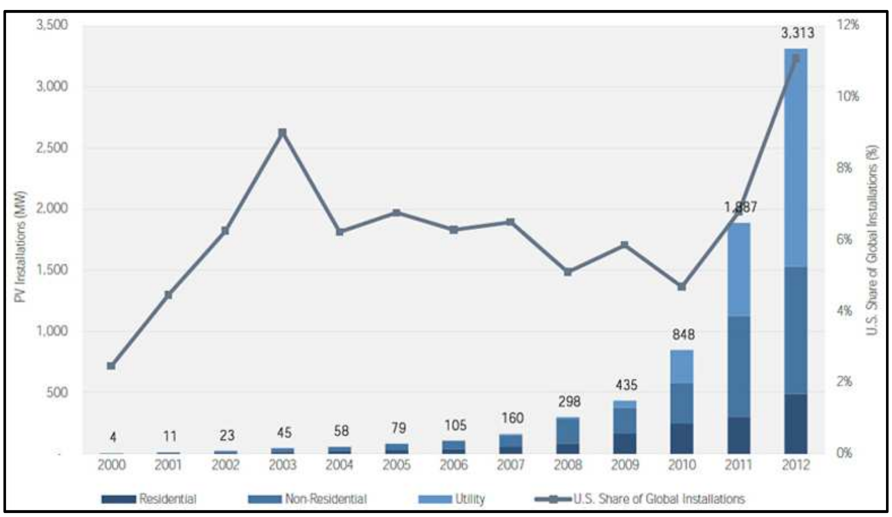
(20%).The electricity production from fossil fuels has a very high environmental impact due to greenhouse gas (GHG) emissions, water and air pollution resulting from the combustion and also because of the extensive land use of the mining process. Emissions during the burning process also produce residual products that present severe health risks. For example, the residual fly ash from the combustion contains heavy metals, such as arsenic or mercury, and is also highly radioactive [3]. According to the World Health Organization (WHO), coal pollution is responsible for about 30 000 deaths annually in the U.S. [4]. Natural gas also contributes to the harmful releases and globally 24.6 % of GHG emissions result from electricity and heat generation and usage can be originated from the usage natural gas [5].

There is an ongoing debate about the status of energy dependency. The depletion of fossil-fuel resources has been a common argument for the research and development of sustainable technologies. Taking a closer look at fossil fuel reserves the situation is twofold. On the one hand, the U.S. is clearly a net oil importer, but on the other hand it seems to have sufficient resources of coal and uranium for the next several decades [6]. According to the Energy Independence and Security Act of 2007 it is desirable to reduce the use of fossil-fuel generated energy, invest into sustainable solutions and thus increase the volume of renewable energy technologies [7]. In October 2013, as a very explicit step towards sustainable energy, the Environmental Protection Agency (EPA) proposed standards on carbon emission limits for both, new and existing power plants. The resulting regulations from this proposal were passed in 2014 and incorporated into the Clean Air Act [8]. These regulations could force the shutdown of several coal-fired power plants and enhance investments into smart grid and renewable energy technologies [9].

In comparison to fossil fuels, renewable energy sources have the potential for zero or near zero emissions of greenhouse gas and other air pollutant [10]. In 2012, the global share of renewables for electricity generation was 20.8 %, and in the U.S. renewable sources accounted for 13 % of the domestic power output [11]. The share of each renewable energy source with an outlook to 2040 is presented in Figure 2 (a).



(a)



(b)

Figure 2: (a) renewable electricity generation capacity by energy source (2011-2040) [2]**and (b) U.S. PV installations and global market share (2005-2016)** [12].

The photovoltaic (PV) energy industry has been experiencing a rapid growth during the last 5 years and is predicted to continue growing at the same rate than shown in Figure 2 (b) [12].

The theoretical energy potential of harnessed solar energy is 600 TW, which is 40 times more than the recent global energy demand (15 TW) [13]. Solar energy has many advantages including being one of the cleanest of all renewable energies, since its operation is silent and does not produce carbon dioxide (CO_2) or other GHG emissions. Photovoltaics is import-independent, and can be easily adapted to various scenarios. For example, utility-scale photovoltaics can be connected to smart grid networks, and PV can also be adapted to small-scale, off-grid applications such as stand-alone PV power systems on rooftops. According to a comprehensive life cycle assessment on PV technologies, emissions from the photovoltaic industry are very small compared to emissions originating from fossil-fuel based plants [14]. PV is also a very safe technology in each life cycle stage (manufacturing, operation, end of life). Safety presents a great advantage, especially in comparison to other sources of energy such as nuclear power, which not only creates radioactive waste, but also has a very high potential for possible deaths in case of a catastrophic accident.

Photovoltaic energy has its limitations including large land use requirements due to the current modules efficiency and their high manufacturing costs. Yet it shows a promising future. Technology prices have been continuously decreasing during the past few years and are forecasted to drop even lower [15]. Also, solar power generation costs are expected to fall to approximately 5 cents/kWh by 2020, which would make PV utilities competitive with coal or gas-fired power plants [16].

In the U.S., photovoltaic installations have been growing in the recent years, with a total installed capacity of 4,751 MW of solar PV in 2013, which is fifteen times the volume installed in 2008 [17]. According to the Solar Energy Industries Association's (SEIA) market report from 2013, solar accounted for 29 % of all sources in electricity generation and was the second largest source of electricity after natural gas. However, the increase in PV installations was unevenly distributed throughout the 50 states. California, Arizona, North Carolina, Massachusetts and New Jersey have been the top five largest markets for PV in 2013, whereas over 30 % of all states have only a very low rate of installed photovoltaic capacity [18]. Although, there is an approximately 970 MW photovoltaic electricity generation in the Mid-Atlantic and Appalachian Highlands regions, the Southwest U.S. still dominates with a 3,500 MW of installed PV capacity. Nevertheless, the U.S. has only addressed a small fraction of its vast potential for PV development [19]. In the next section, the motivation of this work, to assess these PV capacity potential for some of the southeastern states, will be introduced.

1.1. Motivation

The development of solar photovoltaics in the southwest United States first emerged because of the high solar potential and land availability. In the Southeast, the PV market has been growing slower, mainly due to the low cost of the current energy production mix, which is based on fossil fuels and nuclear energy. Another obstacle for PV is the lack of solar incentives, such as feed-in tariffs (FIT), solar portfolio standards for electric utilities, or government loans [20]. In comparison, the Northeast has lower solar irradiation, but has introduced several policies and financial incentives supporting photovoltaic deployment [21]. Additionally, in the Southeast, rough surface terrains and forested areas increase the cost and environmental impact of PV systems due to land transformation. It is likely that these factors have negatively influenced PV development in the Southeast.

Recent statistics indicate that the Southeast has experienced the highest population growth among all U.S. regions (a total change of 14.32 million people; 14.3 % between 2000-2010, versus the average nationwide change; 4.33 million people, around 7 %) [22]; with some of the southeastern states being within the ten most populous in the nation. In 2013, the average monthly electricity consumption was the highest (1,185 kWh) in the East South Central region (TN, KY, AL, MS) and the third highest (1 079 kWh) in the South Atlantic area (WV, DE, DC, MD, VA, DC, NC, SC, GA, FL) [23]. Energy demand has been increasing with 15 % (approximately 15,000,000 MWh) over the 2000-2015 period. Continued population growth will most likely further increase this percentage. This pattern combined with new renewable energy portfolio policies and financial incentives could create an opportunity for PV to provide a portion of the forecasted energy demand.

Solar insolation is an important criterion for a large-scale PV deployment. The southeast U.S. has relatively good insolation conditions, especially compared to the values of Germany, the world leader country in PV installation. Germany has an annual solar irradiation of approximately 3.56 kWh/m^2/year, which equals to the solar energy resources of Seattle or Alaska.[24]. Although solar insolation on the Southeast ranges have an average between 4.5-6.0 kWh/m^2/day [25], this region accounts for only around 10.6 % of the currently operating U.S. installations [26].

To evaluate the potential for PV generation in the Southeast, four adjacent states were selected: Tennessee, North Carolina, South Carolina and Georgia. The main reason of selecting these four states was that they have interconnected transmission networks within the SERC (State Electricity Regulatory Commission) Region [27]. The SERC Reliability

Corporation is a non-profit corporation responsible for improving the reliability, suitability and infrastructure of power supply systems within the central and southeastern states. SERC is divided into five sub-regions. Georgia, North Carolina, South Carolina and Tennessee are the most significant states of the Southeastern, VACAR and Central sub-regions. Another important aspect of the grid-interconnectedness of these states is that the Environmental Protection Agency (EPA) conducts its annual GHG emission output monitoring according to the SERC subdivisions. The Emissions & Generation Resource database (eGRID) is an important source of data on the environmental characteristics of electric power generated in the U.S. [28].

All four states (GA, NC, SC, TN) experienced a rapid population growth from 2000 to 2010. In fact, the population increase in Georgia and North Carolina was 1,501,200 and 1,486,170 persons respectively. This high increase ranks GA and NC within the ten most populous states. Also, these two states have experienced one of the highest population growths in the last decade. The annual solar insolation values for the four southeastern states are good - 5.0 $kWh/m^2/day$ on average- a value similar to the insolation of Florida [25]. Florida has 235 MW of installed PV which is much more compared to the volume of PV Georgia, South Carolina or Tennessee [12]. However, Florida was not included into the current study as it is not a member of the SERC network. From the four studied states, only North Carolina has a significant PV energy generation, although it has lower solar insolation (about 4.5 $kWh/m^2/day$) than Georgia or South Carolina. In 2013, North Carolina was ranked fifth in the nation with respect to utility-scale PV installments [29]. The regulations in NC allow a fast growth in the solar industry. For example, the Renewable Energy Efficiency Portfolio Standard (REPS), allows clean energy companies to compete with utilities [30]. North Carolina has a 557 MW capacity currently installed. The PV deployment pattern of North Carolina shows that solar potential alone is not sufficient to predict solar development and will be useful to understand what factors are the most influential to favor PV investments.

Georgia is another emerging state, experiencing a strong rise of PV installations, resulting in an additional 91 MW of additional PV capacity in 2013. The state showed a 795 % growth compared to the previous year. Recently, the participation in power purchase agreements for state residents has been allowed, which is a principal financial incentive for solar industry support. Georgia also has a performance-based incentive for PV technologies (solar buyback program) [31].

The state of Tennessee currently has 74 MW of installed PV, with significantly less favorable policy environment than North Carolina, the leading state in the region. South Carolina lacks the solar advancing regulatory environment. The main energy source in South Carolina is nuclear power and since the state's utilities are resisting to PV, SC is often ranked in the bottom of the list for states promoting solar energy [32].

A National Renewable Energy Laboratory (NREL) study from 2012 concluded that 70% variation in new PV capacity among the U.S. states is determined by institutional and public approach. Thus, net metering, or public support for a solar PV market (such as Renewable Energy Portfolio Standards) have an important influence on PV deployment. The implementation of low cost policies (e.g. interconnection or net metering) before introducing more expensive regulations may advance the effectiveness of later policies [33]. Thus, a favorable and stable policy environment is desirable to ensure market security and avoid the current uncertainty in this early adoption phase of PV energy deployment [33]. Improving these market and policy conditions would help the PV industry to become more competitive with traditional energy sources and would enable a balanced development for PV throughout the U.S. If solar energy prices could compete with electricity generated from fossil fuels, PV deployment could be accelerated in states with good solar resources but less PV installations, such as South Carolina. The current study was motivated by all of the above factors: increasing electricity demand, growing population, the assumedly good potential of the four states for PV development and the complexity of the solar energy policy environment.

The conducted study was divided into two parts. First section a geographical information system (GIS) was used to perform a site-suitability analysis. Then technical and electricity generation potential of PV for the four states (GA, NC, SC, TN) was calculated. It is not the first study of this sort as NREL conducted a GIS based analysis for renewable energy technical potential in the U.S. in 2012 [25]. However, by narrowing down the scope to only four states; it was possible to improve the analysis using higher resolution data, adding additional constraints which would be used to calculate a more accurate results. The main difference between the two studies was that the NREL report determined solar potential by the sum of feasible areas multiplied with an average insolation, whereas the current work assessed each area with its actual solar irradiation. In this work solar potential was the summary of the actual solar insolation of the feasible lands; resulting in a more accurate value for statewide potential.

As mentioned previously, solar potential is not the only important factor for PV development. The role of other factors being a strong influence in the increase of PV installations is obvious from the example of North Carolina. NC has the highest installed PV capacity, nevertheless it has lower solar irradiation values than Georgia or South Carolina.

To understand the importance of various factors, a multi-criteria decision analysis (MCDA) model was established in the second part of the study.

Multi-criteria decision analysis (MCDA) is a decision support tool, and refers to making choices in the presence of various, often conflicting criteria. Decision support tools, such as MCDA, are an effective component in policy making. MCDA allows for maximizing all benefits over the lifetime of a power plant and is a valuable tool in PV energy deployment. The coupling of GIS-based MCDA analyses has been increasingly applied in the past few years. GIS offers improved data management, storage and visualization for the decision maker. Therefore, after the spatial assessment of feasible areas for utility-scale PV plant installations, an MCDA model was established, to help decision makers account for every important criterion of a large-scale PV installation. Data for the resource and technical criteria was obtained from the site-suitability assessment. Also, new economic and political/market criteria were established. In order to model decision makers' possible weightings, three scenarios were established. The first represented equal importance (equal weighting) of the criteria, attributing more importance (higher weight) to solar insolation and to technical features, respectively. Multi-criteria decision analysis is particularly useful for PV systems assessment, where a compromise solution must be found that minimizes the cost of the structure design and maintenance while optimizes electricity production. The scenario analysis allowed the evaluation of important conditions required for large scale PV penetration on the Southeast. The changes in the amount of desirable areas for the three scenarios were represented for the state of Tennessee on three GIS maps. The goal of representation of the change for desirable areas for PV installation was to demonstrate the impact of decision makers' criteria preference in a PV installation.

The goal of this work was to assess feasible areas for a potential PV deployment for GA, NC, SC and TN, calculate the technical potentials and electricity generation potentials and establish a general MCDA model to aim strategic decision making related to actual PV installations. The goal has been accomplished using the research objectives in the following section.

2. BACKGROUND

2.1. Research objectives

- **Objective 1. (Site Suitability)**
  - A GIS-based site suitability analysis was performed for utility-scale (1 MW) photovoltaic power plants providing area (ha) with incorporating geographical and technical constraints, such as land use, population change, proximity to transmission lines, or road.
  - Technological potential (GW) and electricity production (GWh) were assessed for the states based on the results of the site-suitability analysis. The results were compared to the previous NREL study.
- **Objective 2. (MCDA)**
  - A multi-criteria decision analysis approach using the TOPSIS method was performed to establish an MCDA model able to support to decisions linked to PV power plant installations. The criteria used included solar resource, technology, economy, and policy and market data. Three scenarios with different weightings were investigated with varying weightings. Scenario 1 had equal weights, and Scenario 2 attributed more importance to resource criteria .In Scenario 3 a possible future trend was represented, where the most important criteria would be technical, especially the proximity to the grid factor.
  - The results of the MCDA were displayed on three maps for the state of Tennessee, according to the three scenarios, and showed the change in desirable areas for PV installations.

2.2. GIS and multi-criteria decision modeling

A geographical information system (GIS) enables the user to collect, store, visualize and analyze spatial data and interpret relationships and trends. Computer-based GIS systems have been used since the 1960s and their use have evolved towards three different type of applications. Firstly, the system was used for collection, coordination and access of geographic data. Gradually, GIS has been used more often as an analytical tool, representing mathematical relationships between spatial data, such as map layers with various information [34]. The newest use has been the application of GIS as a decision support system in multi-criteria decision analysis methods (MCDA), through the coupling of GIS and MCDA software.

Multi-criterion decision analysis methods have been developed to support complex decision making when multiple, conflicting factors are involved. The MCDA approach takes account of all criteria in a given issue, helps to structure the problem, provides a model which can be overseen and offers a process that leads to a rational, validated decision. Moreover, MCDA solutions can handle multiple data types, that is, qualitative and quantitative data [35]. GIS is an excellent data source for structuring a multi-criteria problem, The combination of GIS tools with MCDA techniques provides a support for the decision maker in all stages of a decision process, such as design, choice and visualization [36].

The coupling of GIS and MCDA methods can be done on three levels [37]. In a weak coupling, specific software can be used for the different steps of the analysis. While this method has the advantage of low cost, the MCDA system would require manual adjustment of the GIS scheme every time it is coupled with the MCDA system. That is, the results have to be fed into the system manually. This human intervention increases the risk of errors. The second level of coupling is referred to as tight coupling, where the two decision support systems are connected. For this, some MCDA tools are implemented within GIS systems and appear as modules or scripts, executing a specific MCDA task. This is achieved by using the weighted overlay tool in ArcGIS, as it was done in previous studies: [36] [37]. The application allows for the visualization of criteria maps, with pre-set weights manually chosen by the preferences of the user. This coupling ensures a much better communication between GIS and MCDA systems, but it still has some limitations in terms of flexibility and transparency. The most ideal coupling is a fully integrated system, which would offer direct relationships of multi-criteria and spatial analysis functions. However, there is hardly any applications available today, mainly due to data standardization problems [37]. Figure 3 represents the framework concept for a typical GIS-based multi-criteria decision analysis.

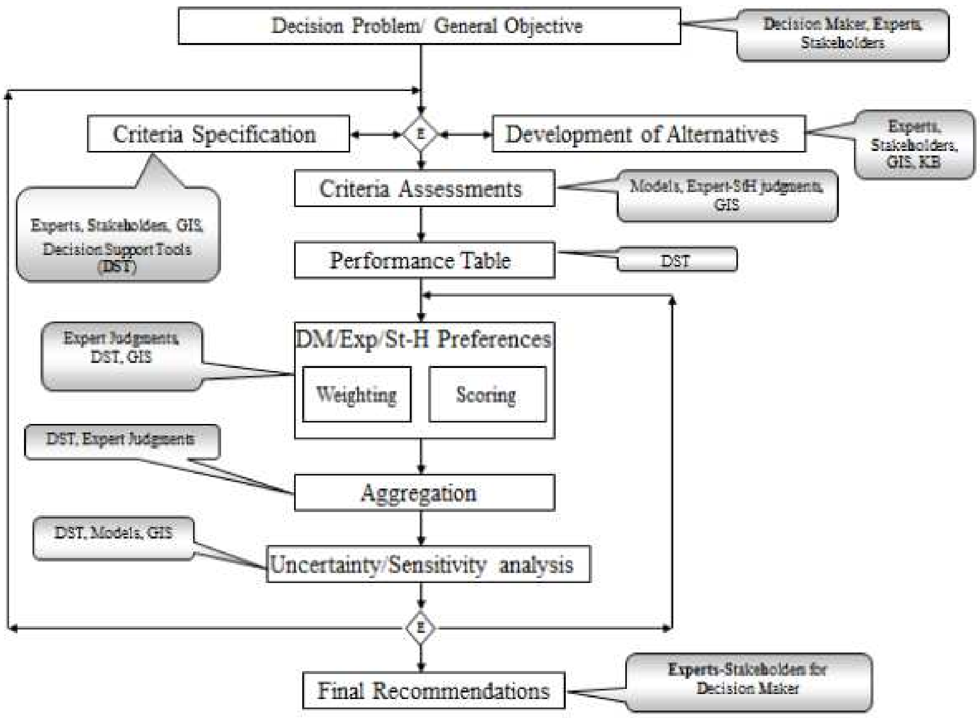


Figure 3: Framework for spatial multi-criteria decision analysis [40]

The white captions show the steps of a general MCDA, whereas the grey squares signify external decision maker input, or the steps completed in the GIS system. Here, a short explanation about MCDA systems has to be provided in order to understand their use for renewable energy analysis problems. The detailed description of MCDA methods was summarized based on Malczewski's substantial book; the "GIS and multi-criteria decision analysis" [41], in "Multi-criteria Decision Analysis" by Ishizaka and Nemery [42] and in different literature reviews [43] [44].

The short description of the most widely used methods for renewable energy studies are listed below:

1. **SAW** – *Simple Additive Weighting / also called WLC – Weighted Linear Combination*

SAW is the most often used and simplest MCDA technology. It is based on the concept of the simple multiplication of the criteria scores with the pre-assigned weights. Overall scores for all alternatives are calculated and the alternative with the highest score is chosen.

2. **AHP** – *Analytical Hierarchy Process*

The method was introduced by Saaty [45] and is constructed of different hierarchy levels. It places the goal on the top, the criteria in the middle and alternatives at the bottom. The input of experts is a pair-wise comparison of the criteria values, which multiplied by the performances of the alternatives will result in the choice of the best scoring solution.

3. **ELECTRE I-IV**. **-** *Elimination and Choice Expressing Reality*

ELECTRE is an outranking method, capable of handling both, qualitative and quantitative discrete criteria. ELECTRE Methods are used to discard some alternatives to the problem, which are unacceptable, and focus on the dominance of the relationships between alternatives. This method avoids compensation for criteria, eliminating the distortion associated with normalization. Such as many outranking method, ELECTRE is based on the prioritization by pair-wise comparison of criteria.

4. **PROMETHEE I. and II**. – *Preference Ranking Organization Method for Enrichment Evaluations*

This method results in the ranking of alternatives based on the decision maker's preference degrees. Its main steps are the calculation of preference degrees for each criteria and the computation of different flows (groups of alternatives). The method is characterized by simplicity and ease of use.

5. **MAUT** – *Multi-attribute Utility Theory*

   One of the most popular methods, MAUT translates the decision maker's preference into a utility function, which is given over a set of attributes. The utility of attributes or criterions does not have to be linear. In this approach, it is anticipated that the decision maker incorporates risk into his consideration.

6. **TOPSIS** - *Technique for Oder Preference by Similarity to the Ideal Solution*

   The idea of TOPSIS is based on measuring the distance of each alternative from a theoretical best and worst solution. This method was chosen for the MCDA part of this study, therefore it is described more in details in Chapter 3.2.

7. **Fuzzy set applications**

   There are two sources of uncertainty in GIS-based multi-criteria decision making; database and decision rule uncertainty [34]. Since fuzzy theory was designed to handle uncertainties, methods derived from the theory are very useful to deal with non-statistical, qualitative or unquantifiable information. In case of an MCDA problem, these data can be linguistic quantifiers, such as categories like "good", "fair", or "poor".

The next chapter focuses on the coupling of GIS and MCDA decision support systems (DSS) related to solar energy.

2.3. GIS-based MCDA decision making for solar energy

GIS-based multi-criteria decision analysis has been widely used for renewable energy analysis problems, involving economic, technical and environmental criteria. The importance of MCDA methods has been constantly growing and the number of studies has approximately tripled since 1995 [43]. Based on literature reviews, it can be concluded that studies were conducted related to several fields, such as renewable energy planning and policy, energy resource allocation, renewable energy evaluation, project selection and environmental hazards. The most commonly used methods are AHP, PROMETHEE, ELECTRE, different Fuzzy set methods and a combination of these [41] [42] [44]. Even though numerous research involved renewable energy solutions, the literature available on GIS-based MCDA studies for solar energy is much more limited. One of the few studies evaluates wind and solar potential on the state level. Janke used the GIS overlay techniques to identify ideal locations for wind and solar farms in Colorado [47]. He established raster layers with a 1500 m resolution for several solar farm criteria including distance to transmission lines, cities and roads, population density, land cover and federal lands. The weights were assigned based on their relative importance to each other. The author used a simple additive weighing to determine relative importance. His work is effective in eliminating non-suitable areas and suggests including additional multi-criteria variables in order to represent the interest of different stakeholders more clearly. The site-suitability analysis used in this study was based on similar methodology, but the MCDA models were improved. In addition, the quality of raster data was improved by using a higher resolution.

Carrion et al. used AHP methodology to establish weights for five criteria, sub-categorized into eighteen factors and more than 30 indicators [48]. The model took into account climate criteria, environmental and legal aspects, orography and location. After validation and consistency check, the module proved to be stable, thus weights were assigned to each variable and normalized. As a result, inappropriate areas were excluded and the four main criteria were ranked in a hierarchical order: climate, orography, environment and location (legal criteria was accounted for in the process, but wasn't assigned to any spatial DSS, and so it did not appear on the final maps). The study area was in the northeast province of Granada, Spain, and consisted of six zones with a surface area of 1,782 km^2. Results showed that the choice of criteria was adequate for result precision, although the study stated that it would be extremely difficult to apply the model to a larger region. The main achievement of the work was that it incorporated the sub-criteria for visual impact and sites of community interest, which could also be considered by social criteria. The significance of this arose from the fact that it was difficult to incorporate economic or social criteria into the combination of GIS and MCDA decision support systems.

In a current study of Sánchez-Lozano et al., AHP and TOPSIS multi-criteria decision analysis technologies were applied to find appropriate solar farm locations in Cartagena, Spain [49]. Criteria weights for climate, location, geomorphology and environment were established according to Saaty's scale, through a literature research and support from an expert of the field of renewable energies. Environment was considered the least important factor. This might be unique for the specific research, as the considered area was very small and thus the impact on the environment was less relevant. After this step, a database was developed from the collected GIS data and combined with the evaluation criteria, resulting in a new layer showing the attributes of each plot, denominated by the factors used in the modeling software.

The latest research of Sanchéz-Lozano et al., focuses on the Region of Murcia in Spain with an ELECTRE evaluation method, using IRIS decision software [50]. Criteria included climate, environmental, location and terrain aspects. Instead of assigning weights to all criteria, they extracted some criterion into a tree structure, to determine their importance and their desired status goal (minimization or maximization). Other restriction criteria were entered into GIS, and expert opinion was used in the decision process. Four iterations resulted in a more stable color-based classification built for the 20 alternatives studied. This methodology might work well for a smaller territory, but it is not appropriate for a large-scale investigation yet.

In summary, the application of GIS-based MCDA decision support systems for solar energy was used to obtain optimal site selection and analysis for photovoltaic power plants or small-scale photovoltaic applications. The criteria specifications included environmental, technical, climate, orographic or locational data and the models did not account for social, economic or political criteria.

To account for additional economic and market/political criteria was the goal of the second objective of the study. Such criteria were established for electricity price and two other related indicators. Also, solar energy favoring incentives and policies were assessed for all four states. The methods for establishing the MCDA model (Objective 2) and for the preceding site-suitability assessment (Objective 1) are described in the next section.

3. METHODS

3.1. Research design for site suitability analysis and the calculation of technical potential

To address Objective 1 (site suitability); a large scale site suitability analysis was conducted for rural areas, fulfilling all pre-set criteria requirements. Criteria were based on a report for developers and investors on site selection recommendations for utility scale solar power plants [51]. In the following list from the report, criteria shown in bold were considered for Objective 1 (site-suitability).

- **Solar resource**
- **Available area**
- **Land use**
- **Topography**
- **Accessibility**
- **Grid connection**
- ***Financial incentives***
- Local climate or
- Geotechnical factors.

Local climate and geotechnical factors and similar location specific information were excluded from this study due to the amount of data that would be required for a state level scale.

The site-suitability analysis was performed using ArcGIS 10.1 [38]. After the raw data acquisition and modification a “negative” layer was created to exclude non-suitable areas such as urban development, water bodies, or environmentally sensitive/protected regions. Reclassified raster layers of slope, road and transmission line infrastructure were combined with the exclusion layer. The resulting final raster displayed all potentially feasible areas for a large-scale solar installation. Figure 4 shows the design and main steps for Objective 1.

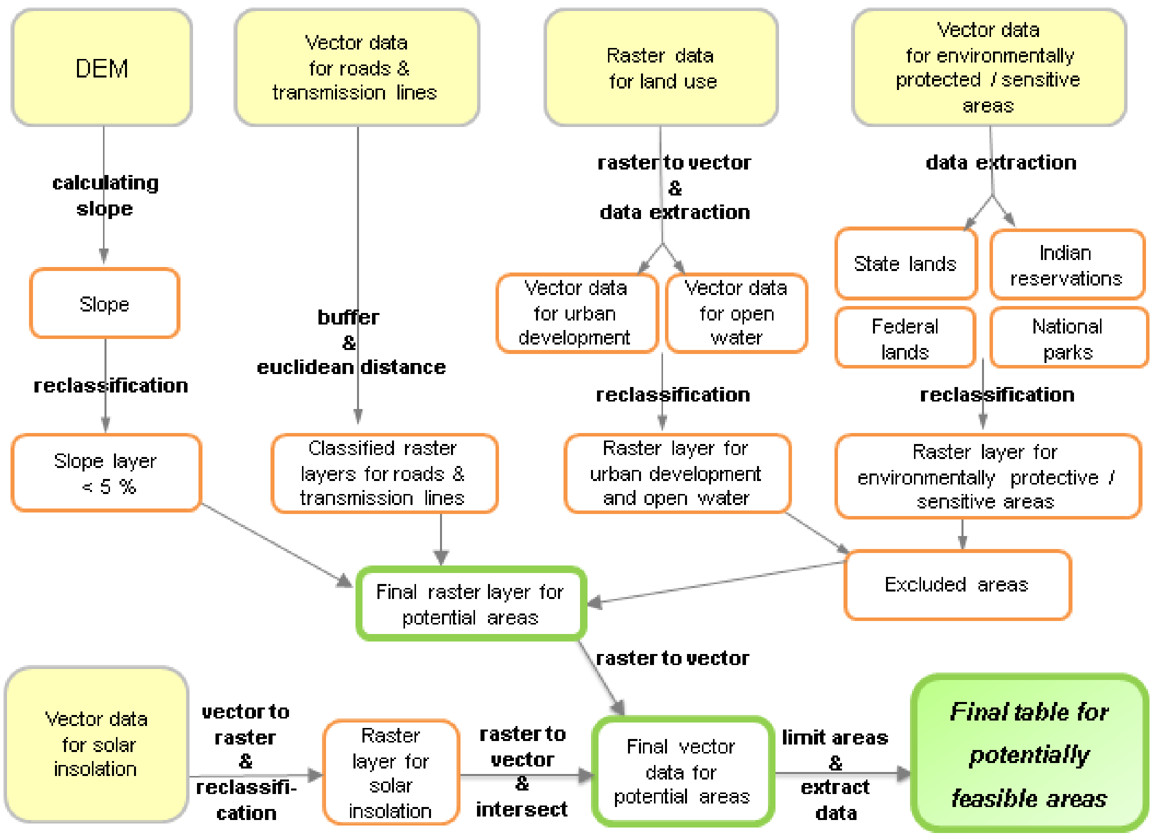


Figure 4: Methodological flow-chart for site-suitability analysis and calculation of technical potential for photovoltaic panel installation

☐ Original data
☐ Intermediate layers
☐ Final layers & data

Raw data, which were obtained from different governmental, non-profit and other free sources, is shown in yellow. The formatting procedures are marked next to the arrows.

After acquiring the raw data, intermediate layers were created. These are shown with an orange frame on Figure 4. The final raster layer (green frame) is a result of applying all criteria and excluding every constraint criteria for all four states. In order to calculate technical potential and electricity generation, the final layer had to be linked to the solar insolation data layer. Performances for PV plants were calculated from the final table (shown in green in the lower right corner of Figure 4).

As part of Objective 1 the technical and electricity generation potential was calculated for the four states. The final raster layer from the site suitability analysis was converted to a polygon and intersected with the previously formatted annual solar insolation data. The Solar insolation data was obtained from the National Renewable Energy Laboratory [52]. This step provided information about the feasible land areas classified according to the particular state's solar insolation values. The database was exported to Excel for better visualization and editing purposes. Total feasible areas per state were calculated and compared with a previous study on renewable energy technical potentials, conducted by NREL [25]. Capacity factors and technical potentials were calculated assuming 15 % panel efficiency and a packing factor of 0.5,. These factors were chosen according to a published review on current installations [53]. There was a significant methodological difference between this study and NREL's work. This difference is described in detail in Chapter 4.1.3.

3.1.2. Raw data acquisition and data formatting

Raw data was available from governmental and other free, public resources but needed to be formatted using various GIS toolsets for specific evaluation criteria. The layers were combined in a final map displaying potentially suitable lands for PV panel installation. Due to hardware constraints, all map layers for the four southeastern states (GA, NC, SC and TN) were created separately, but the same methodology is conducted on all of them. Table 1 summarizes information on the data formatting process used to obtain the raster layers' final resolution for South Carolina.

Table 1: Various criteria used for the study on PV panel installments in South Carolina

Variable	Condition/ constraint	Original file extension	Type	Final data	Final projection for SC	Final resolution (meter x meter)
Elevation (DEM)	< 5 %	TIFF	Grid	Continuous	NAD_1983_UTM_Zone_17	30
Land cover	extraction of certain land use types	Geo TIFF	Grid	Continuous	NAD_1983_UTM_Zone_17	30
Water bodies, Rivers, wetlands	excluded	Shp	Grid	Categorical	NAD_1983_UTM_Zone_17	30
Urban development	excluded	Shp	Grid	Categorical	NAD_1983_UTM_Zone_17	30
Environ-mentally protected/ sensitive areas	excluded	Shp	Grid	Categorical	NAD_1983_UTM_Zone_17	30
Highways, Roads	> 500 m, < 10 000 m	Shp	Grid	Continuous	NAD_1983_UTM_Zone_17	30
Transmission lines	> 500 m, < 10 000 m	Shp	Grid	Continuous	NAD_1983_UTM_Zone_17	30
NREL Solar insolation data	classified	Shp	Grid	Continuous	NAD_1983_UTM_Zone_17	30

The spatial limitations for PV installation were based on the literature; many GIS-based site-suitability analyses for solar energy had identical constraint layers [25] [45] [48] [66]–[69]. In 2012, NREL performed the most relevant assessment on photovoltaic technology potential which included the Southeast [25]. Since the research of NREL was the most applicable to this study; Table 2 compares data sources and constraint criteria from both works.

Table 2: NREL constraint layer exclusions compared to this study

Constraint layer	Source in this study	Source in NREL study (ref)
Water & wetlands	MRLC (NLCD 2006)	MRLC (NLCD 2006)
Urban areas	ESRI 2004 / MRLC	ESRI 2004
Federal lands, national parks and other environmentally sensitive areas	USGS	USGS
Contiguous area requirement	> 1 ha	> 1 km^2
Proximity to power lines	> 500 m < 10,000 m	no data
Proximity to highways	> 500 m < 10,000 m	no data
Slope	< 5 %	< 3 %

The source of the constraint layers was identical; however the restriction on the excluded area was different in the two studies. The contiguous area requirement of greater or equal than 1 hectare (ha) was set according to the latest report on land-use requirements for solar power plants in the U.S., accomplished by NREL [53]. The report suggests a direct land use for PV between 1.6 and 5.8 acres/GWh/year and a generation-weighted average of 3.1 acres/GWh/year. A guide book for utility scale solar developers defines the ideal area for a well-designed solar plant between 1 and 2 hectares [51]. Since an area chosen for a solar power plant can have an irregular shape, the exclusion criterion in this study was set to smaller than 1 ha. Reason for slope criteria and distance selection is further explained on the next few pages.

The same type of raw GIS data and formatting criteria was used for all states. In order to avoid distortions in the map projections, the projected coordinate systems had to be adjusted to the transverse cylindrical (UTM) projection based on North American Datum of 1983.

- NAD_1983_UTM_Zone_17 for South Carolina,
- NAD_1983_StatePlane_Georgia_East_FIPS_1001 for Georgia,
- NAD_1983_StatePlane_North_Carolina_FIPS_3200 for North Carolina and
- NAD_1983_StatePlane_Tennessee_FIPS_4100 for Tennessee.

Horizontal units were given in meters. Similarly, raster layers were standardized to a 30 x 30 meter resolution. Spatial resolution, which is also called cell size, defines the quality of data represented on a map layer. The raster resolution chosen for this study was detailed enough to show sufficient information, but did not necessitate large memory requirements as it is the case for a smaller cell size [58]. The same methodology was used for all four states as shown in sections 3.2.1 to 3.2.4.

Elevation data (DEM) and slope

The Digital Elevation Model (DEM) data represents the surface terrain with continuous elevation values. The data was collected in 2009 by the U.S. Geological Survey and it is the primary elevation information produced by USGS which is available for the entire United States. For this research, the 7.5 minutes DEM tiles were taken from the USGS National Map Viewer and Download Platform [59]. The DEM data is originally in ArcGrid format with a 1/3 arc-second resolution (approx. 10 meters), which was changed to a 1 arc-second resolution (approx. 30 meters) for the blended DEM layer. Elevations for the final raster layer were cross-checked for validation in Google Earth. Figure 5 shows a section of the slope layer for South Carolina.

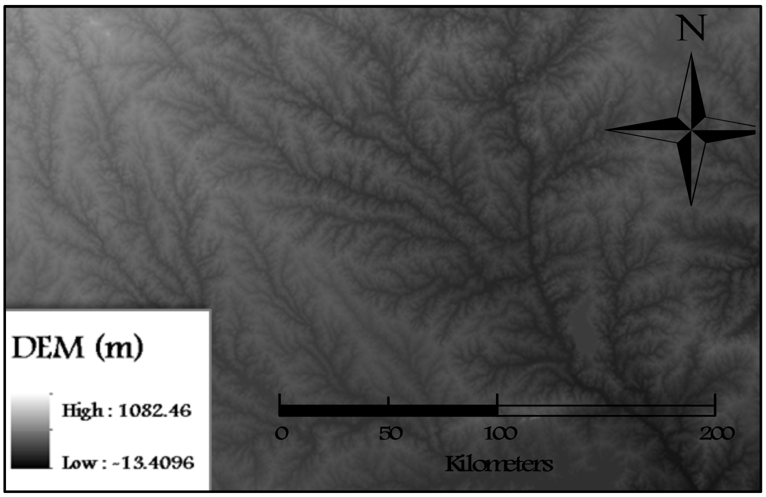
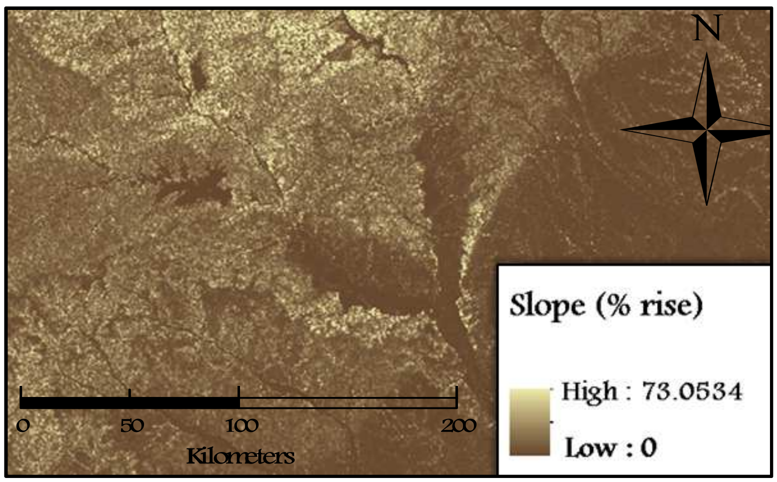


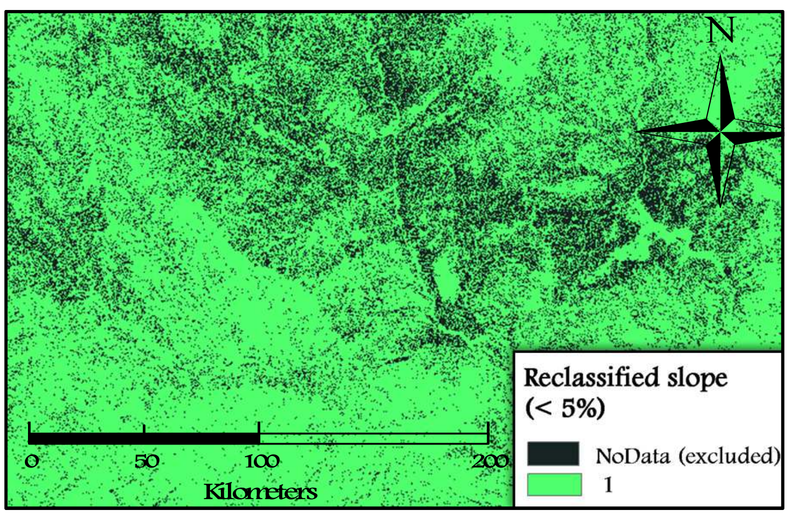
Figure 5: Thumbnail from DEM layer for South Carolina

The tiles were blended together with the Image Analysis tool in the ArcMap toolset to obtain a continuous layer for which the slope can be calculated. The slope was defined as the maximum rate of change between each cell and its neighbors [38] and for this study the slope output measurement was set to percent rise. The value for a flat surface was 0 and for a 45 angle slope the percent rise was 100 %. For industrial-scale PV installations the slope can be a very important economic/technical criterion; the higher the gradient, the more investment is required to flatten the ground. A too high slope, or a disadvantageous orientation could result in the decrease of the PV units' efficiency [60]. For similar PV oriented, GIS-based site-suitability analysis the slope criteria was commonly set to < 3-5 % [26] [46] [69] [70] [74] [75]. In this study the slope constraint was determined to be below

5%. Accordingly, slopes were classified such that for slopes below 5% a 1 value was assigned, and for slopes equal or above 5% a 0 value (NoData) was given. Figure 6 (a) illustrates a section of the slope layer in South Carolina before the reclassification and Figure 6 (b) for the same location after reclassification. The reclassified slope layers were used for the final raster layer creation as exclusion criteria in identifying feasible areas for a PV installation.



(a)



(b)

Figure 6: Sample from slope layer for South Carolina (a) before and (b) after reclassification

Land use data and derived constraint layers

Land use is a very important component of site suitability studies [63]. In the research, different land use values were used for maps created for the site suitability and for the MCDA. For Objective 1 (site-suitability), urban developments and open water bodies had to be excluded due to their non-suitability for an industrial-size PV installation.

The NLCD 2006 Land Cover files, published in 2011, from the U.S. Geological Survey [59] were used for this criterion. Both the original and the final resolutions were set to 30 x 30 meters. The NLCD 2006 classification consists of 16 categories assigned to areas in the conterminous United States based on the satellite data from the Landsat Enhanced Thematic Mapper + (ETM+) from 2006 [64]. Table 3 represents an extract from the original classification containing areas important for the exclusion of urban developments and open water. The complete list is available in Appendix - Table 1.

Table 3: NLCD 2006 Land use classifications [64]

Class / Value	Classification Description
Open water	
11	**Open Water** - areas of open water, generally with less than 25% cover of vegetation or soil.
Developed	
21	**Developed, Open Space** - areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes.
22	**Developed, Low Intensity** - areas with a mixture of constructed materials and

	vegetation. Impervious surfaces account for 20% to 49% percent of total cover. These areas most commonly include single-family housing units.
23	**Developed, Medium Intensity** – areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50% to 79% of the total cover. These areas most commonly include single-family housing units.
24	**Developed High Intensity** -highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses and commercial/industrial. Impervious surfaces account for 80% to 100% of the total cover.

The GeoTIFF files obtained from USGS were blended with the "Image Analysis" toolset, the raster file was converted to a polygon feature class. A feature class can have a polygon, polyline or point geometry and can contain much more values per field compared to a raster layer; the latter is only able to display one specified value type. After creating a land use polygon layer, the land cover categories 21, 22, 23 and 24 were selected and exported to a new polygon layer before conversion back to a raster layer which was to be used as an exclusion criterion. In Figure 7 the excluded urban areas (in red) are displayed. Green fields represent the feasible areas for PV installations.

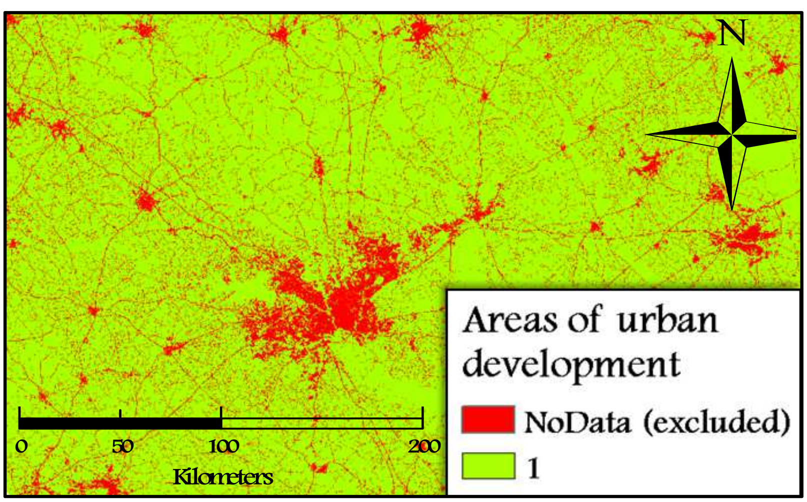


Figure 7: Sample from the urban development raster layer of South Carolina

The same method was used for open water bodies (class 11). While one might assume that it is unlikely that a solar plant will be installed on a wetland, it is actually technically possible and has been done for the South Carolina Electric and Gas (SCE&G) Solar Farm in South Carolina [65] which was built on an area marked as a wetland according to the NLCD 2006 classification (see [64] and Appendix 1. -Figure 1). For this reason, except for the categories listed above, all other land use classes were regarded as potentially suitable areas. For the MCDA, land use classes were aggregated into non-ideal, semi-ideal and ideal land categories (see Chapter 0).

Accessibility: roads and transmission lines

Accessibility proves to be an important factor for potential solar power plant sites; most related site-suitability research incorporates either proximity to roads, or proximity to transmission lines, but most often such research includes both [26] [46] [50] [67] [69] [70]. Road accessibility is important during the whole life cycle of a solar plant, for example, accessibility would be important for construction and installation of the models, maintenance and dismantling at end of life. Its importance could also depend on the technology used; solar plants with tracking systems have typically higher maintenance requirements [51]. Compliance with local fire policies might also require easy accessibility [66].

Data for roads are obtained from the USGS National Map Viewer Download Platform [59]. Interstates, highways and significant roads were selected and extracted to a separate layer. A 500 meter buffer is created around the lines to avoid the slightly negative visual impacts – although this factor greatly depends on the location of the individual plant – and to mitigate the risk of module efficiency decrease or damage from exposure to human impact, such as dust traffic or building activity [51].

The vector file was rasterized and the Euclidean distance tool was applied to obtain potential areas ranging from favorable to less favorable – more distant - locations within the criteria limits (values > 500 m and < 10 000 m, see Table 1). In Figure 8 the map results after the distance from roads classification is displayed.

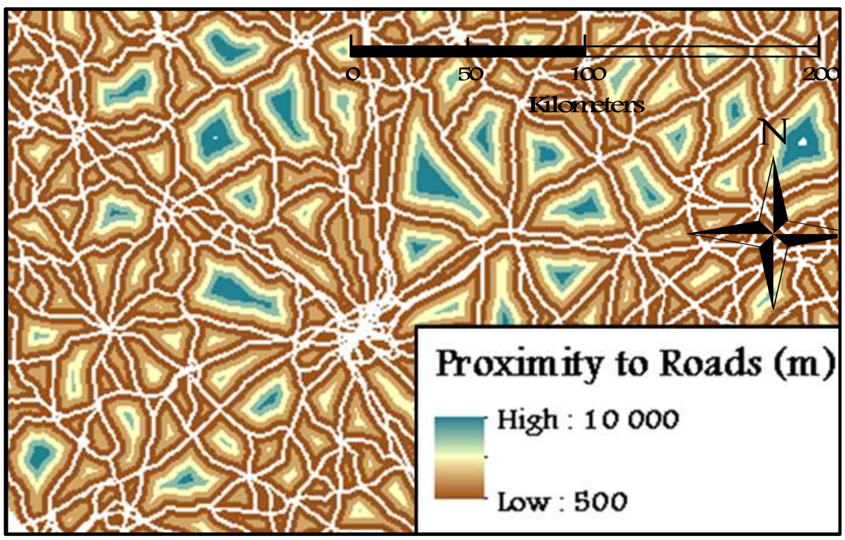


Figure 8: Proximity to roads

Information about transmission lines was obtained from the US Geological Survey and the USGS Earth Explorer website [67] in various Digital Line Graph (DLG) vector file formats, on a 7.5 minute scale. Unfortunately, free transmission line data for the US have neither high quality nor a common data format. Moreover, the data often cover distribution (electricity transferred from substation to the consumer), instead of transmission (electricity transferred from generator to the substation). To compensate for these inconsistencies OpenMap data [68] were used correct the files obtained from the US Geological Survey.

Transmission line data alterations were executed in the same order as the roads. The polylines were assigned a 500 meter buffer, converted to raster files and classified to a range from more to less suitable distances with the help of the Euclidean distance tool. In Figure 9 the distance range from transmission lines are represented for an excerpt of the South Carolina map. The scale is between 500 to 10,000 meters.

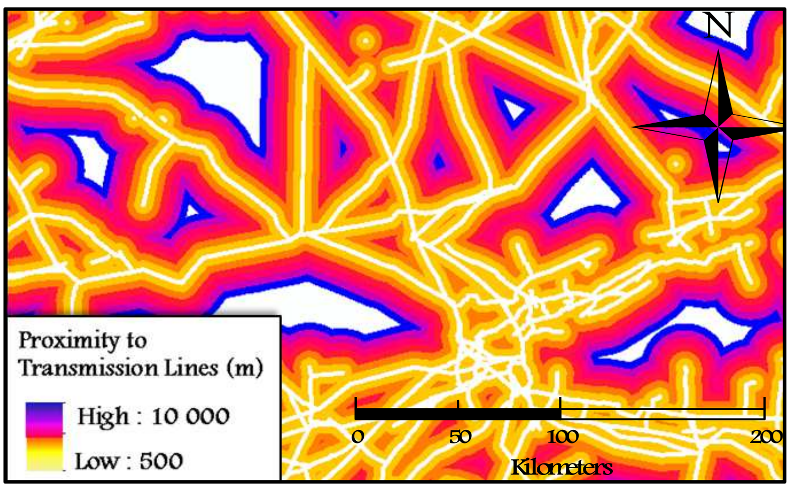


Figure 9: Proximity to transmission lines in meters (m)

Classified raster layers for both, roads and transmission lines were used in the raster calculator tool in addition to other criteria layers and serve as a limiting factor for feasible areas for PV installation. A PV power plant's distance from transmission lines is important for two reasons. Firstly, technical losses during the transmission are proportional to the length of the distribution line, secondly, the construction of new transmission lines can significantly increase the investment costs.

Solar data: annual solar insolation

Solar irradiation is a measure of the energy incident on a unit area of a surface in a given time period, usually a year (kWh/m^2 year). Data for this criterion is taken from the 10 km resolution PV solar radiation map from NREL and is used to obtain information about the annual Global Horizontal Irradiation (GHI) in the southeast US. The NREL GHI data has a 5% uncertainty level.

For a PV development the primary interest is to have a high long term average annual GHI [51]. The GHI values from the NREL database were calculated using the New York/Albany satellite radiation model, taking monthly averages of daily snow cover, atmospheric water vapor and aerosols and trace gases into consideration and validated with ground measurements. Due to incompleteness of the input data the model estimates are accurate to 15% of the true measured solar insolation values, with an increasing uncertainty depending on distances from measurement sources and complexity of the terrain [52]. For this project, the data was modified (re-projected) according to the specific state's coordinate system. Insolation values were reclassified into six different annual solar irradiation categories. In Figure 10 a section from the solar insolation layer of South Carolina is displayed, with a 30 x 30 meter raster resolution before reclassification.

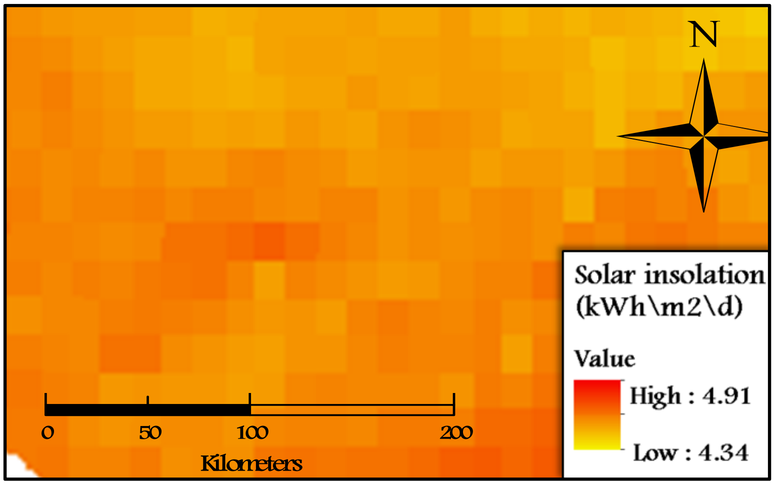


Figure 10: Sample from solar irradiation layer combined with slope (SC)

The solar layer was then vectorized and intersected with the final constraint layer resulting in the irradiation classification of the feasible areas.

It has to be noted that ArcGIS has its own tool for computing solar irradiation; the Area Solar Radiation calculator tool in the Spatial Analyst toolset is able to derive incoming solar insolation from a raster surface, by considering slope, aspect, diffusion, transmittivity and time interval. Including all these factors for measuring solar irradiation was not appropriate for this study since using the tool for large areas is time consuming and accuracy of the results decrease with the increasing size of the studied surface [69].

Additional constraints

Shape files for governmentally managed and/or environmentally sensitive areas, such as national parks, refuges and other federal and Indian lands were taken from the U.S. Geological Survey, converted to raster layers and excluded from the potentially feasible fields for solar development. They were assigned a value of 0 (specified as NoData in the map legends). Although those lands might be theoretically suitable for solar panel installations, building on these areas would be counterproductive to sustainability objectives, namely that primarily less valuable lands should be utilized first for renewable energy development [51]. Therefore, installations in these regions are less preferred [66].

Environmentally hazardous zones

The current work tried to account for environmentally hazardous zones. At the start, hurricane zones were a part of the exclusion layers for the site suitability analysis, however they were not equally available for all four states. A hurricane map layer is shown for the coastal part of South Carolina in Figure 11.

Figure 11: Hurricane zone on the coastal part of South Carolina

A similar pattern was true for other environmentally hazardous zones; these were either not equally available for all four states of the study, or they were not free to obtain.

For example, FEMA flood zone map layers have to be purchased [70]. Furthermore, flood maps are very difficult to apply on the state level, as they are very detailed and come with a high resolution. As having maps for only some states for the environmentally hazardous zones would unevenly reduce feasible areas, these criteria were not considered in the final maps for the site-suitability analysis.

3.2. Research design for the GIS-based multi-criteria decision analysis (MCDA)

Objective three of this research aimed for establishing a robust, replicable Multi-criteria Decision Analysis (MCDA) model, which incorporates environmental, technical, economic and political/market criteria, to be used to prioritize utility-size PV development. The model was structured with the help of DECERNS-DSS software [71] and weights were assigned to the specified criteria according to various scenarios. The results were finally displayed as ArcGIS maps (see Chapter 4.2.4)

From the literature review, most multi-criteria decision methods include similar basic steps [42] [43] [48] [54]–[58] including defining the methods, selection of criteria, generation of alternatives, weighing and validation and/or sensitivity analysis. Following these principles, an eight step method was used for the MCDA part of this study. Map layers created in the first part (GIS based site suitability assessment) – were altered and used as spatial reference for the criteria. The steps of the MCDA process were:

1) Selection of method and criteria,
2) criteria and metrics development,
3) reclassification of existing GIS layers and creation of new layers,
4) alternative generation - determination of reference photovoltaic power plants,
5) choice of criteria weights and alternative scenarios,
6) performance evaluation,
7) weighting – assigning weights to criteria for each alternative and calculation of final scores,

8) validation/Sensitivity analysis, and

9) reasons for the research design, criteria choices and methods are described in detail in the following subsections.

3.2.1. Selection of method and criteria

Selection of method

There has been an increasing interest in using MCDA methodology for renewable energy including solar photovoltaic during the last decade. According to literature reviews, the most commonly used MCDA method is the Analytical Hierarchy Process (AHP), followed by outranking methods, such as the PROMETHEE method or the ELECTRE family [44] [58].

For this project, even though it is not the most common method, the *Technique for order preference by similarity to ideal solutions* (TOPSIS) was chosen due to its unique approach and simplicity.

TOPSIS is a method of outranking that assumes that the utility of every chosen attribute is monotonically increasing or decreasing. The optimality of a certain alternative is determined by its shortest distance from the positive-ideal (best) and longest distance from the negative-ideal (worst) solutions. Therefore TOPSIS incorporates relative weights of criterion importance [78], using a linear relationship between the quantified attribute outcome for an alternative and its preference for benefit attributes [79]. The technique was developed by Huag and Yoon in 1981 as an alternative to another outranking method called ELECTRE (Elimination et Choice Translating Reality) [77].

Modeling software

For the multi-criteria evaluation DECERNS MCDA DE, a sub-application of the DECERNS (Decision Evaluation in Complex Risk Network Systems) desktop Decision Support System family was used [71]. DECERNS MCDA DE is optimal for working with scenarios. The software has been developed upon open source applications and the standalone desktop version was first released in March, 2014.

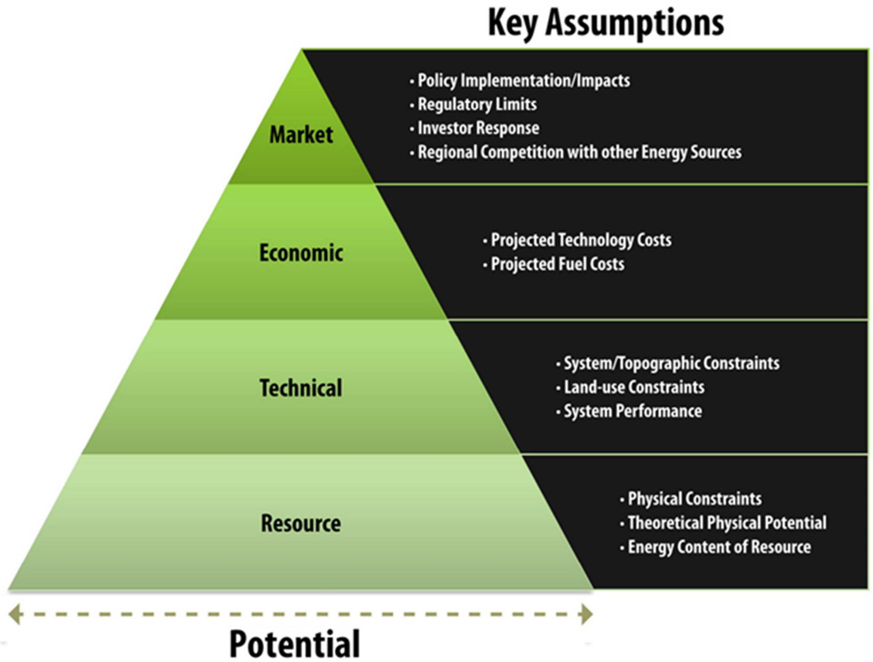
Advantages of using the TOPSIS methods include limited input from the decision maker which reduces the subjective part to defining the weights by which performances will be multiplied. Another relative advantage is that the method can quickly identify the best alternative [80]. According to a simulation study comparing seven MCDA methods, TOPSIS criteria weights typically affect the performance less than the number of alternatives or criteria [81]. The study indicates that TOPSIS was similar to AHP in many regards and is a robust method, especially with a high number of criteria included. In general, TOPSIS fulfills practical considerations expected from an MCDA method, applied for renewable energy related decisions. It is easy to use, it can support decision making, is capable of handling uncertainty and ensures a direct, simple interpretation of the results [82]. However, multi-criteria decision analysis inherently has subjective factors and the choice of method strongly depends of the nature of the problem - all sets of criteria can be accepted or criticized depending on the stakeholder and the situation [83]. Therefore, there is no perfect method.

Selection of criteria

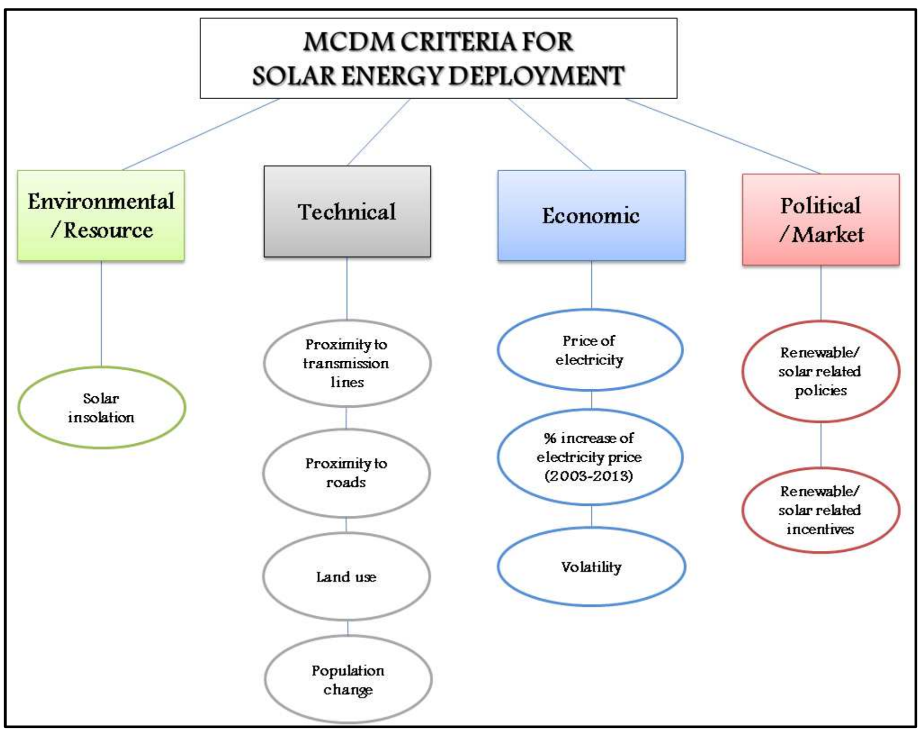
According to a comprehensive literature review conducted in 2011; assessment methods for renewable energy planning and deployment have been an active area of research in the last few decades. Apart from technical and economic criteria other aspects such as environmental, social and political factors have gained importance [46]. However, only a few reviewed papers have tried to incorporate all criteria and even these did only include theoretical planning. Also, only a few papers are related to renewable energy technologies and even less to photovoltaics.

The objective of the current research was to build a robust and replicable model, encompassing all necessary criteria. These factors correspond to the three pillars of sustainability; environmental, economic and social - and thus they are linked together [84]. For example, marketability and the deployment of a certain technology depends not only on its qualities or costs, but also on governmental regulations and social acceptance [46].

The model in this study was based on the preference pyramid used by NREL for defining key criteria for solar installation technical potential. Figure 12 (a) shows the NREL pyramid, with its four levels and Figure 12 (b) illustrates the model established for this study, including four main criteria and ten sub-criteria.



(a)



(b)

Figure 12: (a) NREL pyramid for defining key criteria for solar installation technical potential (b) MCDA decision model for photovoltaic farm deployment with multiple criteria

Criteria and metrics development

After defining the criteria, the correct metrics had to be established for each factor (such as resource, technical, economic and political/market criteria). One of the goals of Objective 2 was final goal to display the results of the MCDA in ArcGIS to show the changes in the areas for the more desirable lands for PV installation. In order to make the MCDA model results compatible with GIS, a consequent classification of all criteria was needed. In Table 4 criteria, sub-criteria with metrics and optimization goal for an ideal solution are represented. All sub-criteria were classified in classes of three or its multiples. Land use had the lowest number of classes (3). In this part of the research a less sensitive aggregation of the land use areas was more suitable to the goals. Therefore, areas were classified into non-ideal, semi-ideal and ideal land types, for a potential PV installation. Solar irradiation had the most class values (12), due to the relatively narrow range of solar insolation data. With the 12 classes, the model was more sensitive in accounting for the differences in solar irradiation.

Table 4: MCDA criteria, metrics and goal for optimization

Crit.	**Technical**				**Resource**	**Economic**			**Political**	
Sub-criteria	Proximity to grid	Proximity to roads	Population change	Land use	Solar irradiation	Price of electricity	Percent rise of price	Price volatility	Policies	Incentives
Unit	(m)	(m)	person	class	kWh/m²/day	cents / kWh	%	non-dimensional	class	class
Goal	min	min	max	max	max	max	max	max	max	max
1	500 - 2,000	500 - 2,000	-3,615 -10,000	Non-ideal	3.87 - 3.96	8.7 – 9.2	< 0.2	< 0.15	1	1
2					3.96 - 4.05					
3	2,000 -3,500	2,000 -3,500	10,000 - 30,000		4.05 - 4.14	9.2 - 9.7	0.21-2.2	0.151-0.25	2	2
4					4.14 - 4.23					
5	3,500 -5,000	3,500 -5,000	30,000 - 60,000	Semi-ideal	4.23 - 4.32	9.7-10.2	2.21-3.2	0.251-0.35	3	3
6					4.32 - 4.41					
7	5,000 -7,000	5,000 -7,000	60,000 - 120,000		4.41 - 4.50	10.5-10.7	3.21-4.2	0.351-0.45	4	4
8					4.50 - 4.59					
9	7,000 -8,500	7,000 -8,500	120,000 - 200,000	Ideal	4.59 - 4.68	11.2-11.7	4.21-5.2	0.451-0.55	5	5
10					4.68 - 4.77					
11	8,500 - 10,000	8,500 -10,000	200,000 -273,147		4.77 - 4.86	12.2-12.7	> 5.21	> 0.551	6	6
12					4.86 - 4.90					

For the environmental/resource and technical factors, GIS layers were used from the site suitability assessment. However, for the economic and political/market criteria, no such maps had been created, therefore new criteria was established. After the setup of all classes, raster layers were reclassified and new layers were created in ArcMap. In the following sub-chapters detailed information is given about the re-classification of existing and the establishment of new layers.

Reclassification of existing criteria

Resource criteria - solar irradiation

As described in Chapter 3.1.2. solar irradiation data were retrieved from NREL and reclassified in two ways. For the site suitability analysis, reclassification was only necessary for calculating technology potential for a future solar plant deployment, thus specifying categories only aimed to make results more transparent. For Objective 2 (MCDA and visualization of MCDA results in GIS), however, solar irradiation had to be broken down into relatively small ranges to enable a better differentiation of areas. The scale of NREL solar irradiation data for the U.S. varies from 2.33 – 6.78 kWh/m^2/day [52]. In comparison, the studied four southeastern states have a tighter range of solar irradiation; 3.96-4.90 kWh/m^2/day. Solar irradiation data were assigned to 12 categories. Classes 1-3 were obtained for North Carolina and Tennessee and classes 11 and 12 appear only in Georgia. Classes 4-10 were present in all four states. The 12 classes for solar irradiation for all four states are illustrated in Figure 13.

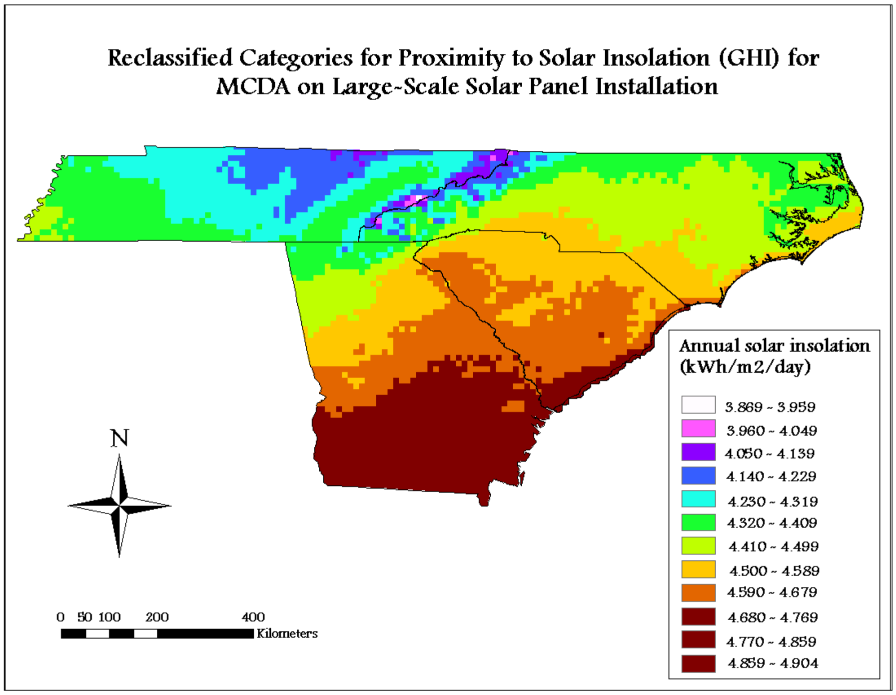


Figure 13: Reclassified solar irradiation categories

Most of the site-suitability multi-criteria decision analyses for solar facility deployment considered solar resource as one of the most important criteria [26] [46] [48] [49] [67] [68] [70] [75] [86]. This is understandable, since climate factors such as solar irradiation and temperature directly influence the power output of solar panels [50] [87]. Temperature data were not included in the current research, but it would be desirable to incorporate it in a future GIS-based MCDA model for PV.

Technical criteria – ideal land

Land cover was chosen as one of the four technical criteria in the MCDA model. When considering a decision about the future deployment of solar power plants, land use can be a limiting factor (such as water or urban developments in this case) and even exclusive for some areas. For example, installing photovoltaic plants on (woody) wetlands can be very expensive.

As was shown in Chapter 3.1.2, land use categorization data were obtained in the latest and most commonly used NLCD classification. In Figure 14an excerpt is presented of the South Carolina land use layer, showing all classifications used for the four states. The map portion indicates Columbia (red and its shades), Lake Murray on the West and a part of Lake Marion on the southeastern part of the state.

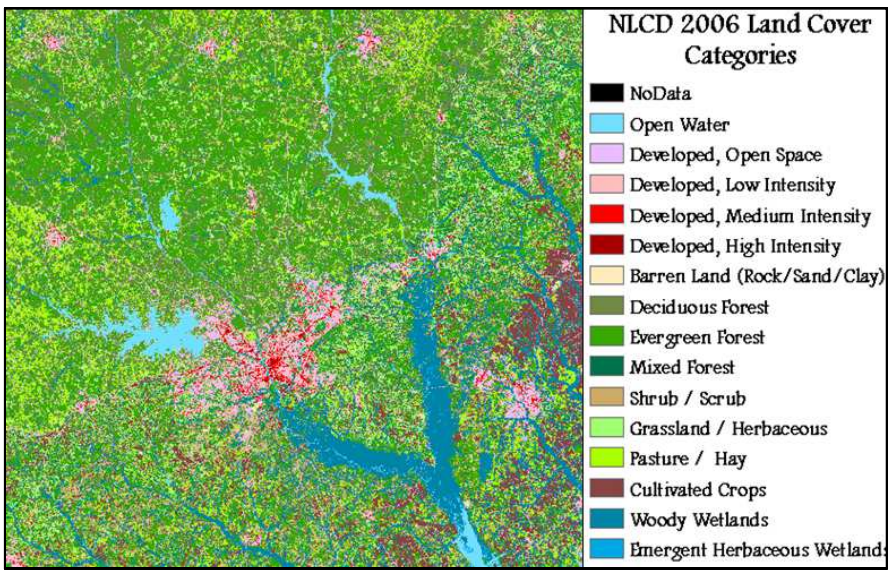


Figure 14: Section of the South Carolina land use map layer with NLCD 2006 classification

For the site-suitability analysis, the land use information was only necessary to create the exclusion layer, however, for the MCDA, land cover mattered more. The significance of land use came from the fact that some areas – such as pastures, grasslands or barren lands - are very suitable for PV utilities, since they need only minimal investment into land preparation or cleaning. Open space, low, medium and high density urban developments and open waters were still excluded, as PV deployment is not possible on these areas. All other land use types were re-classified into three categories. The categories for Objective 2 (MCDA), the specific NLCD 2006 classification numbers and category names can be seen in Table 5.

Table 5: Re-classified land use categories according their NLCD ranking

Land use categories			
Category Nr.	**Category type**	**NCDL 2006 code**	**NLCD class definition**
1	Non-ideal	90	Woody Wetlands
		95	Emergent Herbaceous Wetlands
2	Semi-ideal	41	Deciduous Forest
		42	Evergreen Forest
		43	Mixed Forest
3	Ideal	31	Barren Land (Rock/Sand/Clay)
		52	Shrub/Scrub
		71	Grassland/Herbaceous
		81	Pasture/Hay
		82	Cultivated Crops

Previous classifications found in the literature were taken into consideration for the land use for PV. For example, the literature consdiers shrubs or grasslands an ideal category [46] [70], since none, or only a low amount of investment would be required to clear the area for a photovoltaic installation. In Figure 15 the maps of all four southeastern states are presented, displaying the new scale for land use categories. The class “NoData” stands for the exclusion criteria (urban developments and open water).

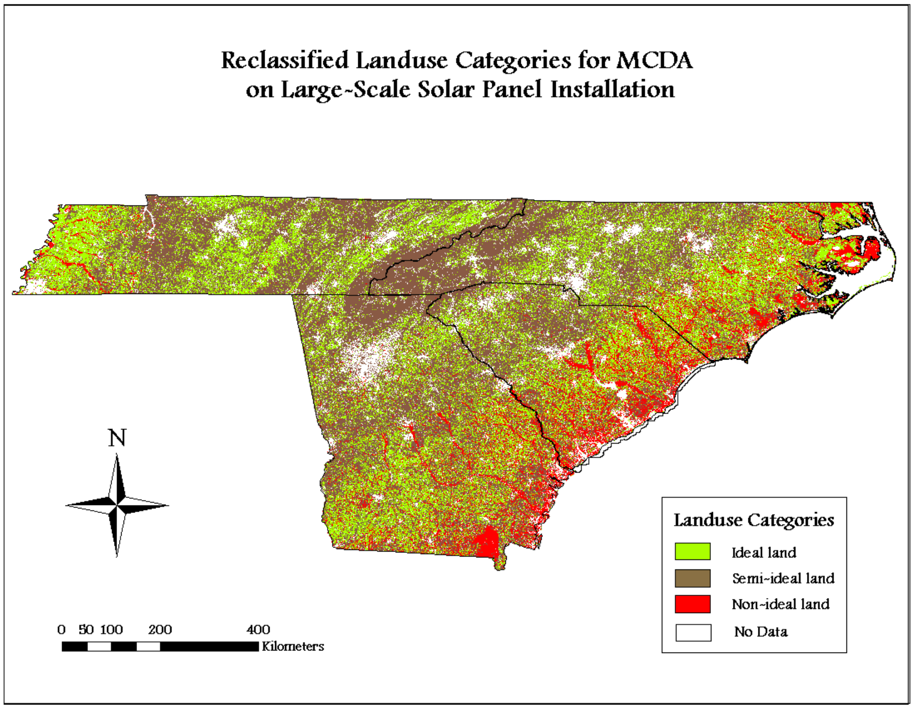
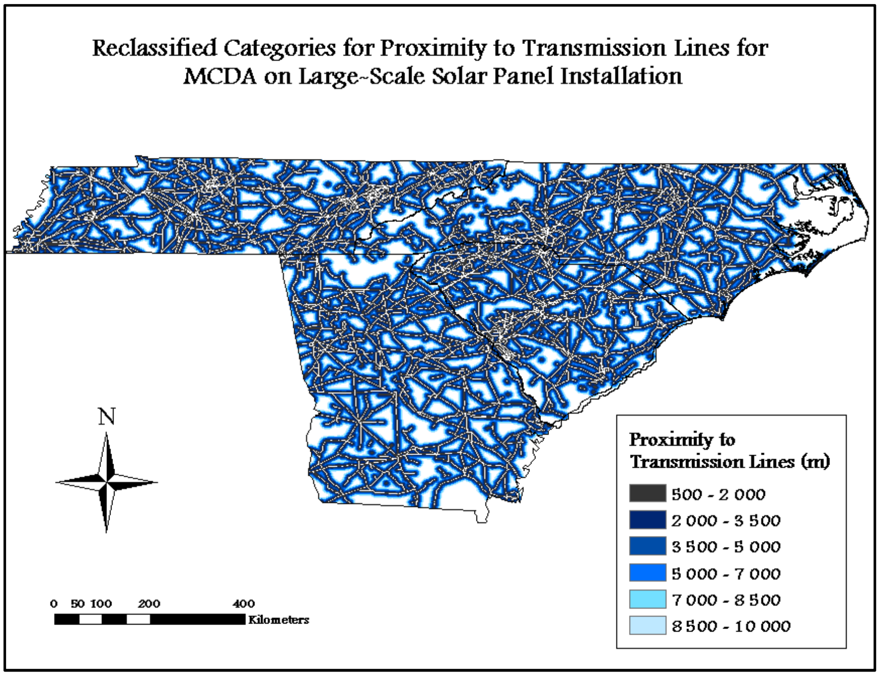


Figure 15: Reclassified land use categories

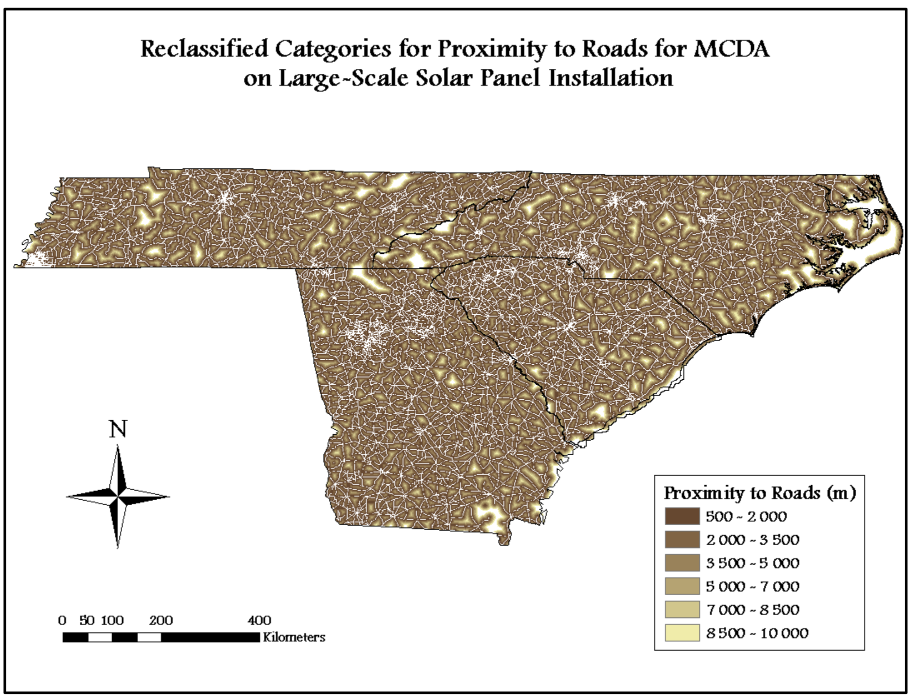
When screening a site for installation on a more local level, other sustainability goals should also be used such as the preference for utilizing contaminated sites, or areas with less valuable natural resources [66]. However, no such accounting for sustainability was included in the present model.

Technical criteria - proximity to transmission lines and to roads

Easy accessibility of infrastructure is a core question for solar plant deployments [87]. Therefore, proximity to the electric grid and to transportation infrastructure is incorporated into the technical criteria for the MCDA model. Similarly to the related layers in Objective 1 (site-suitability assessment), distances are calculated and reclassified into six categories, ranging from 500 to 10,000 meters. The proximity of infrastructure can be a significant factor in investment (road construction, transport of construction material), maintenance costs (security and repairs) and operation (transmission losses), and therefore, should be reduced as much as possible. The cost of building a 345 kV single circuit transmission line, adequate for a utility-scale solar plant connection, would cost $ 1.1 - 2.0 million per mile [88]. Although a recent NREL study indicated that the benefits of establishing a transmission grid for renewable energy development might exceed the investment costs [89], the generally accepted principle is that sustainable energy production and consumption should be as close as possible. Accordingly, the ideal category was set to 500-2,000 meters for both, transmission lines and road infrastructure. In Figure 27(a) and (b) the reclassified maps used for the MCDA model (for the second part of Objective 2) are shown.



(a)



(b)

Figure 16: Reclassified distances for (a) the transmission lines and (b) roads

It can be concluded from Figure 16 that the constraint criteria for the proximity to transmission lines controls the outcome – that is the amount of feasible areas - to a greater degree than the constraint for the road infrastructure. If we compare the high number of transmission lines with the much lower number of road infrastructure it is clear how these lower grid infrastructures can be delimiting.

Developing of new criteria and establishing GIS layers

Technical criteria - population layer

Electricity demand and supply management requires that renewable energy power plants should ideally be planned close to places of demand [51]. Assessing population change is probably the most effective indicator of evaluating future electricity demand, since with the increasing number of households, electricity consumption is also very likely to rise. Population data was obtained from the Census through the Social Explorer web interface [90], which provides an easy access to demographic information and historical census data in the U.S.. The data was downloaded on a per county basis for the two most recent national Censuses in 2000 and 2010 to calculate population change. Population changes range from -3,615 to 273,147 persons and are classified into six categories as illustrated in Figure 17.

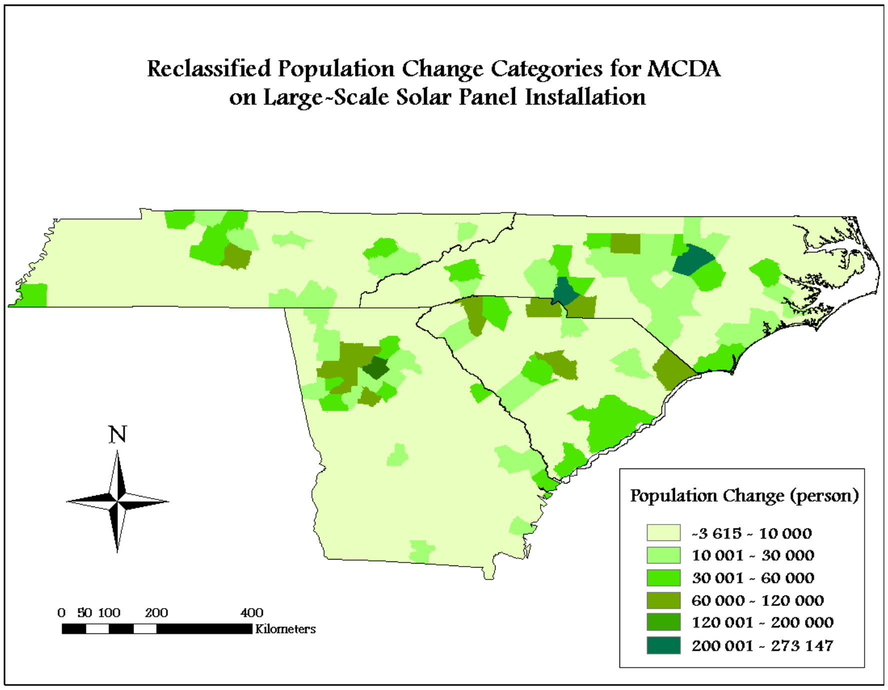


Figure 17: Reclassified layer for population change

According to Figure 17, typical areas for intense population growth were state capitals and major cities. Except for three counties in the highest category, the maximum growth at all other locations was in the 60-120,000 range and the 5Th category level was not present in any of the four states. Given that an average of 164 households can be powered by 1 MW solar photovoltaics [91] settlements with a moderate or low population growth should also be considered with refining the classification. For example, reclassifying groups with one group accounting only for 5,000 persons would give a more sensitive result. Smaller group sizes for the population change would be especially useful for the Southeast, where solar power plant deployment has been slower and smaller in size (typically 1-7 MW) [92]. Obviously, in the second stage of a future planning process, the total number of households powered by 1 MW of electricity needs to be calculated for each state.

Economic criteria - Electricity prices, percent rise and volatility

Recent decreases in technology prices due to technology advancement and the global economic downturn made photovoltaic energy a more prevalent industry. Grid-connected solar projects are still highly depend on electricity prices, grid parity and government incentives to be economic [51] [46]. However, solar energy has a good potential to be competitive with fossil-fuel based energy, as it has the ability to lower the volatility of fossil-fuel market prices and serve as a stable and relatively predictable energy source [93].

In previous MCDA studies, economic criteria have been considered mainly in the form of investment or operational costs, fuel costs, ground study costs, cost of electricity generation or similar costs related mainly to the physical plant [55] [95] [96]. However, after analyzing the relevant literature, it is apparent that electricity prices have not been built into MCDA models; and therefore, have not been combined with a GIS-based analysis.

The goal of introducing a new type of economic criteria was to incorporate a long-term perspective for the solar plant operation, which is greatly independent from the fossil-fuel market. The interest of any potential photovoltaic installer is focused on the highest possible level of electricity prices due to concern for the return on investment as well as the lowest risk for uncertainties such as price volatility. However, other factors must be considered to advance sustainability. For example, renewable energy will also increase energy security and lower the risk of electricity price volatility. Solar energy is abundant and the energy generation of photovoltaic power plants is relatively predictable. Therefore, the frequent change of electricity prices generated from fossil fuels could be avoided. [84] [85]. According to these objectives, three sub-criteria were established;

1) Current price of electricity (an average of the most recent full year, that is 2013)

2) Percent increase within the last 10 years (2003-2013) and

3) Volatility of prices within the last 10 years (2003-2013).

Table 7 displays the three sub-criteria for economic factors and their optimization goal. All three sub-criteria (current price of electricity, percent increase and volatility) had to be maximized in order to have a favorable environment for solar energy. Due to technology prices and installation costs, in the U.S, PV electricity has a higher price than fossil-fuel based electricity. Until the filling of the gap between the two prices and making solar energy competitive, consumers have to pay an averagely 10-15 cents more per Wattage for solar energy [12]. The current electricity price is especially important for the Southeast, where fossil-fuel based electricity is rather cheap compared to the U.S. average [97]. Therefore, if the current price of electricity is high in the region, covered by a specific electricity provider (such as Duke Energy, etc.), people are more willing to pay the higher price of solar energy. The same ideology applies to the percent increase of electricity prices; if fossil-fuel based electricity prices have been raising over the last ten years, customers should be ready to consider alternative electricity sources, such as solar, which will generate more predictable and market independent pricing on the long term. The volatility of electricity prices was included into sub-criteria for the same reason, namely that electricity generated by PV can mitigate volatility and ensure a more secure market environment for consumers in all sectors.

Data for electricity prices are collected from the U.S. Energy Information Administration (EIA) website from the Electric Power Monthly reports, covering the period of 2003-2013 [97].

The current electricity price ('Price of electricity' sub-criteria) is given in cents per kWh and is a simple indicator of price ranges for the given state. For the current research, overall electricity prices were used, which is the average of industrial, commercial and residential sectors. Category limits are determined by the U.S. average electricity price range as a basis for comparison.

For the sub-criteria 'Percent increase of electricity price', a ten year period was considered and the yearly average value for all sectors calculated. Yearly changes were obtained, and the mean computed to obtain the average percent increase of electricity price for the ten-year period, between 2003 and 2013. Here, the basis of comparison was the U.S. average percent electricity increase (3.2 %) over the same period [98].

Prices in the electricity market are a function of time and location and vary according to demand, supply or other system changes. Since electricity generation in the Southeast is mainly based on fossil fuels, it is a subject to the direct influence of gas or coal price changes, and therefore, its volatility can cause market uncertainty. Consequently, price volatility criteria needed to be minimized to support investment in photovoltaic power plants. Figure 18 illustrates the monthly electricity price for the four states from which the annual increase and volatility is calculated.

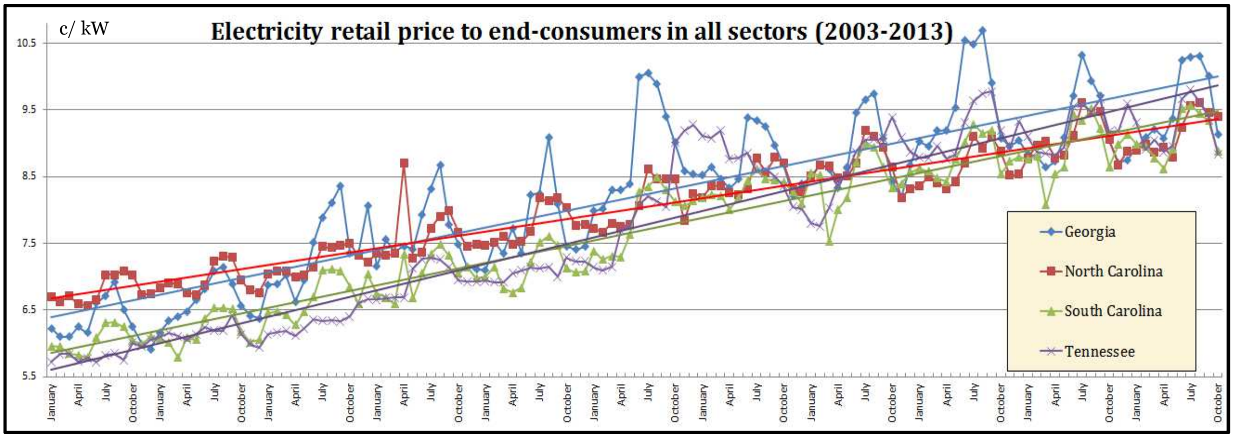


Figure 18: Monthly electricity retail price for all sectors (2003-2013)

A linear regression analysis was conducted using the Excel Analysis ToolPak. The number of data observed was 130, these are the months for the period the data was monitored for (2003-2013). The number of observations is large enough to get precise results with the regression analysis. Important results from the regression are shown in Table 6. Results showed a strong reliability as the consistency stayed below 0.1. The consistency for the linear regression means that the outcomes of the computing procedure showed the same behavior as the number of items in the dataset increased and the results stayed within the statistical margin of error.

Table 6: Results of linear regression for monthly electricity price data (2003-2013)

Regression output data / State	Georgia	North Carolina	South Carolina	Tennessee
R Square	0.7636452	0.8942319	0.9159085	0.8981163
Standard Error	0.5885646	0.2721603	0.3214759	0.4213096
Intercept	6.3714097	6.6510268	5.8306297	5.5753131
X Variable 1	0.0279738	0.0209250	0.0280538	0.0330757
Volatility	**0.44**	**0.31**	**0.48**	**0.59**

Volatility is a dimensionless number, calculated from the ratio of X Variable 1 and the Intercept. The volatility signifies the market price changes of fossil-fuel based electricity prices over the 2003-2013 period. To classify the results, the U.S. average volatility (0.35) was set as a mid- value and classes were set in a reasonable range to enable to discern the differences between states (see Table 7 below).

Table 7: Economic sub-criteria for the GIS –based MCD model

Name of sub-criteria	Price of electricity	Percent rise of electricity price	Volatility of electricity price
Metrics	Cents / kWh	%	non-dimensional
Classes / Optimization goal	max	max	max
1	8.7 – 9.2	< 0.2	< 0.15
2	9.2 - 9.7	0.21-2.2	0.151-0.25
3	9.7-10.2	2.21-3.2	0.251-0.35
4	10.5-10.7	3.21-4.2	0.351-0.45
5	11.2-11.7	4.21-5.2	0.451-0.55
6	12.2-12.7	> 5.21	> 0.551

Policy/market criteria - solar related policies and incentives

Policy criteria can also be a decisive factor in the financial viability of grid-connected solar projects. The legal environment shapes the market and is directly or indirectly responsible for feed-in tariff rates, support initiatives for renewable energy, rebates, solar renewable energy credits (RECs), concessional project funding, and much more [51]. Some efforts have been made to include political criteria into renewable MCDA studies. In a case study for Crete, a criteria according to the EU directive; the 'Implementation of EU and National Environmental Policy' was established, with scores assigned according to potential environmental actions to the main EU and national energy policy priorities [99]. However, in the European Union it is much easier to characterize the renewable energy policy situation, because all countries have the same Renewable Energy Standards to achieve, by 2020 and 2050 [100]. In comparison, there are no overarching goals in the U.S. which would be obligatory for all member states. Moreover, renewable energy development promoting incentives vary widely across the country. Solar energy is also in an early adoption stage, and the policy environment is immature [33]. All in all, measuring policy performance and comparing different U.S. states is difficult as common goals are not clearly set. Nevertheless, it is obvious that incorporating policy criteria into MCDA models is very important, in order to characterize market uncertainty and account for future tendencies. There is a direct correlation between policy measures and small-scale PV adoption [33] that might be even stronger in a utility-scale installation.

Industry related information on solar energy related policies and incentives was taken from the Database of State Incentives for Renewables & Efficiency, DSIRE [21]. DSIRE provides summaries established by the federal, state and local governments and larger electric utilities in the U.S. Data are available in table or map format and have two main categories; "Financial Incentives" and "Rules, Regulations & Policies". Beyond the four states of the Southeast study area, California and New Jersey were also included in the process of establishing new criteria for policies. The reason for the latter is that both states are among the top three solar states in the U.S. therefore they provide a good basis for comparison [29]. Therefore, information was collected for six states (California, New Jersey, Georgia, North Carolina, South Carolina and Tennessee) and is shown in Appendix - Table 2 and Appendix - Table 3. Separate weights were assigned to each policy and incentive, according to their significance for the solar industry. The number of programs was multiplied by the actual program's weight and in this manner a total score was produced for each state. Afterwards, the states were simply ranked in order according to their total scores obtained. Final scores are presented in Table 12, in the next Chapter 4.2.1, under solar policy criteria.

4. RESULTS AND DISCUSSION

4.1. Results of the site-suitability analysis and technical potential

4.1.2. Final raster layer from the site suitability analysis and feasible areas for large scale (> 1 MW) PV installations

Final raster layer for Objective 1 (site-suitability)

After obtaining and formatting the raw data, intermediate constraint layers were created for slope, urban development, water and various environmentally sensitive areas. These layers were combined with classified rasters for roads and transmission lines, excluding all areas over a 10,000 meters distance from the infrastructure. A Map Algebra tool operation was used to combine all the layers to create a final layer containing regions for a potential solar development and excluding all areas not feasible for an industrial-scale PV installation. This layer was converted to a polygon and intersected with the solar insolation layer. The intersection operations used to identify portions of overlapping features and assign them the properties of both input layers. In Figure 19 an excerpt from the polygon layer is shown, indicating the potentially feasible areas in green and the excluded areas in white. Excluded are all roads (white lines) and additional areas, which can be areas for open water, urban development or environmentally sensitive areas.

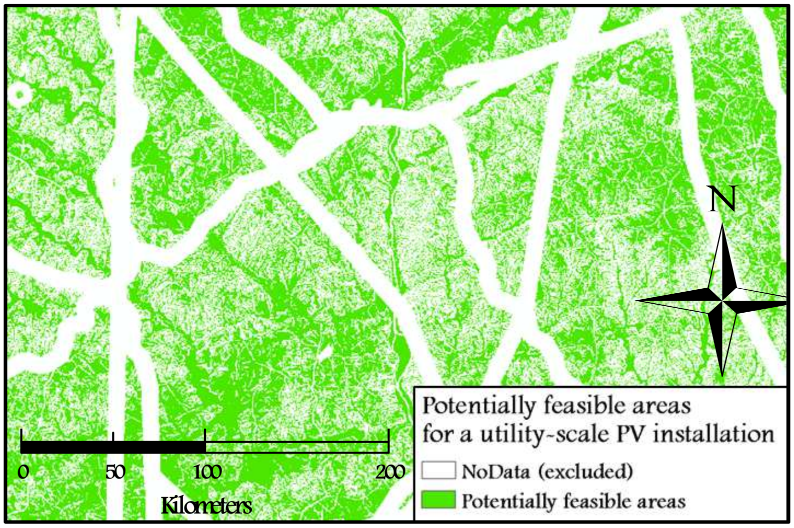


Figure 19: Map excerpt of potentially feasible areas for a utility-scale PV installation (SC)

Feasible areas

Results for the site-suitability analysis consisted of feasible and non-feasible land. Feasible land means that according to the pre-set criteria, those areas are theoretically appropriate for large-scale solar development. In ArcGIS feasible areas were indicated after applying constraint criteria and accounting for all other criteria that did not need to be constrained, such as solar insolation, distance from the grid and distance from roads. In Figure 20 maps for all four states with constraints and feasible land are shown.

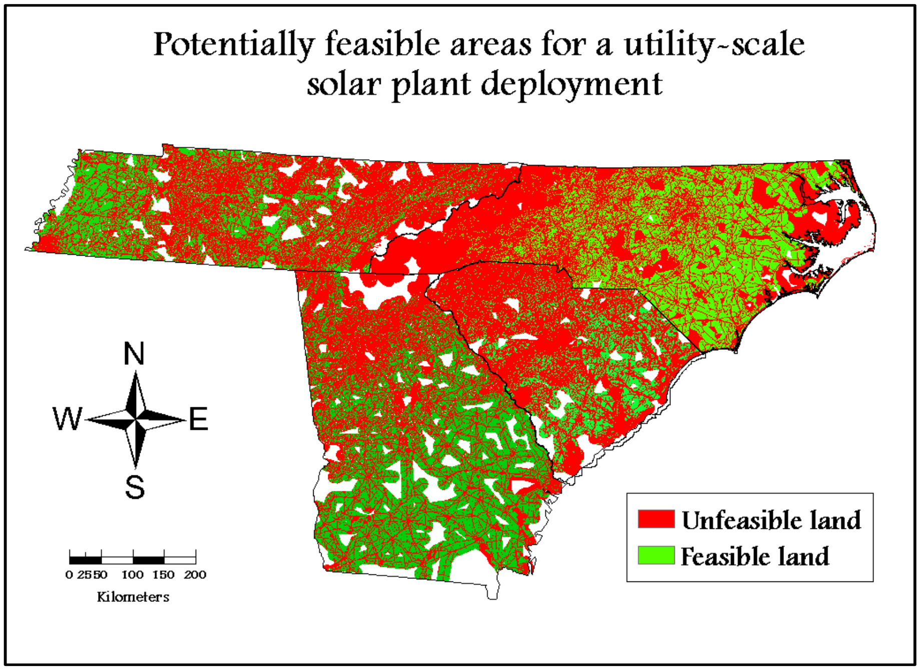


Figure 20: Results for characterizing potentially feasible areas for a large-scale solar plant installation

Zones in red are unfeasible areas and green color is for the feasible lands. Areas in white are over the maximum distance buffer and are also unfeasible. A 1 ha area limit filter is applied as installation sites are desired to be at least around 1-2 hectares [51].

After obtaining feasible areas for each of the four states in ArcGIS, raster layers were converted to polygons and the information was intersected with solar insolation data. The intersection resulted in four tables (one per state), yielding viable areas for a PV installation for each solar insolation class. A summary table of all feasible land areas assigned to the proper solar insolation categories is shown in Table 8. Tables in full details on solar insolation categories are shown in Appendix 1 - Table 1.

Table 8: Summary table for potentially feasible areas for large-scale utility solar installation

STATE	SOLAR IRRADIATION (units)		AREA
Tennessee	**GHI (annual)**		**(km²)**
	min	**max**	
	3.87	4.47	32,722
South Carolina	**GHI (annual)**		**(km²)**
	min	**max**	
	4.34	4.90	74,090
North Carolina	**GHI (annual)**		**(km²)**
	min	**max**	
	3.87	4.83	49,054
Georgia	**GHI (annual)**		**(km²)**
	min	**max**	
	4.20	4.90	123,144
TOTAL FEASIBLE AREAS	**3.87**	**4.90**	**279,011**

4.1.3. Calculation of technical potential, electricity generation potential and capacity factor

As the next step, technical potential and electricity generation potential were calculated. The technical potential here represents the energy generation achieved by the installed PV technology, depending on the resource and technical criteria [52]. The electricity generation potential is the actual power generated by the PV system. Table 5 shows the equations for calculating the annual electric generation potential and the technical potential, respectively.

Table 9: Equations for Annual Electric Generation Potential, Capacity Factor and Technical Potential

Acronyms	Full name of term	Unit	Value	Equation
AEGP	*Annual Electricity Generation Potential*	GWh/year		$AEGP = \frac{\frac{FA}{PF}}{ASI*10^7} * PE$ *(1)*
ASI	*Annual Solar Insolation*	kWh/m²/year		
CF	*Capacity Factor*	- (non-dimensional)		$CF = \frac{AEGP}{TP*8670h/y}$ (2)
FA	*Feasible Area*	m²		
PF	*Packing Factor*	- (non-dimensional)	0.5	
PE	*Panel Efficiency*	%	15	
TP	*Technical Potential*	GW		$TP = \frac{AEGP}{8670h/y}$ (3)

Technical potential is the achievable energy generation of a specific technology, including all constraint criteria, such as resource, land-use, environmental and system performance limitations [25]. By calculating the technical potential, the upper limits of the development potential of the actual state can be estimated. The average technical potential in the four states was 13 GW.

Electricity generation potential is calculated from the sum of the feasible areas, after applying the packing factor. The packing factor is the fraction of the real useful area which absorbs solar irradiation and thus is covered by the solar cell. The packing factor in the current research was 0.5, which halved the feasible areas for PV installation. The reduced area volume was divided by the annual solar insolation and the annual electricity generation potential was calculated, adjusted to 15 % panel efficiency (Equation (1)). The amount of electricity generated by a PV system depends highly on the annual solar irradiation values of the given area. Therefore, in this work, it was very important to account for each area with its specific solar irradiation value. This provided a precise estimate about the electricity generation potential. According to this study's calculation, the power generation potential for the four states was averagely 7,925 GWh/ha.

The capacity factor is a measure of the amount of energy produced by a plant compared to its maximum possible output, expressed as a percentage [53]. The capacity factor (CF) used by NREL was obtained from the National Solar Radiation Database Typical Meteorological Year 3 (TMY3) data set and the SAM (System Advisor Model) and accounts for the whole state. The equation used by NREL for calculating the technical potential is seen in Equation 4 below[25]:

$$\text{State MWh} = \text{State} \sum \left[\text{available land } (km^2) * \text{power density } 48 \left(\frac{MW}{km^2}\right) * \text{state capacity factor } (\%) * 8760 \text{ (hours per year)}\right] \tag{4}$$

As it is apparent from Equation (4), NREL multiplied the average solar insolation with the sum of the feasible areas per state. In the current research, capacity factor was the total of all feasible areas and their specific solar insolation. Therefore, this research had a lower, but a more precise capacity factor for the studied four states than the NREL study. The results, calculated using the equations (1), (2) and (3) are presented in Table 10.

Table 10: Results for electric generation potential (GWh) and technical potential (GW) for this study, in comparison with results obtained by NREL [25].

State	Electric Generation potential for rural utility scale PV (GWh)		Technical potential for rural utility-scale PV (GW)		Potentially feasible areas for rural utility-scale PV (km^2)		Capacity factor	
	This study	NREL study	This study	NREL study	This study	NREL study	This study	NREL study
Georgia	16,097,544	5,492,783.00	9,491	3,088	123,144	64,343	0.194	0.203
North Carolina	6,006,234	4,232,789.93	3,679	2,347	49,054	48,892	0.186	0.206
South Carolina	9,233,225	2,754,973.30	5,493	1,555	74,090	32,399	0.192	0.202
Tennessee	3,867,253	2,225,989.93	2,454	1,267	32,722	26,396	0.180	0.201
TOTAL	**35,204,256**	**14,706,536**	**21,117**	**8,257**	**279,011**	**172,030**	-	-

There were some other differences in the methodologies of the two studies, however, they were less important. For this study on the four southeastern states, a packing factor of 0.5 was assumed. The packing factor (PF) is a non-dimensional term, which was defined earlier in this chapter. Packing factors in the literature range between 13 and 97 %, most of them within 20 and 67 % [53]. NREL did not use a packing factor in its report on the renewable energy potential in the U.S.

Also, a panel efficiency (PE) of 15 % was assumed, which is an average value for C-Si solar panels [101]. In its research, NREL only accounted for rooftop PV module efficiency (13.5 %). It is not clear, if module efficiency was used or not for the calculation of rural utility-scale PV installations. However, because of the rapid development of PV technologies, it was justified to account for an averagely 15% module efficiency, in the current study.

Additionally, the averagely required area required for 1 MW output of a utility scale PV power plant was calculated and shown in Table 11 which is a function of module efficiency and packing factor.

Table 11: Average area requirement for 1 MW output for a PV power plant

Average area requirement for 1 MW PV power plant	**hectares (ha)**	**acres (acs)**
	1.34	**3.31**

The average area requirement for 1 MW output were 1.34 ha in all four states and this value is congruent with some of the literature [53] [86]. However, the area requirement is dependent on the solar irradiation factor and thus it can have a bigger variation if regions on a wider geographical range are investigated.

4.1.4. Discussion and recommendations

The current work aimed to calculate suitable sites and technical potential for photovoltaic deployment on the Southeast. A previous study done by NREL was a comprehensive evaluation of renewable energy technical potential in the entire U.S. [25]. In the NREL report the area limitations were stricter (>1 km^2), although the literature research shows that the minimum area requirement for PV plants is between 1 and 2 ha. The constraints in this study were defined to meet the minimum conditions to be able to account for all possibly feasible areas for PV installation. It also has to be noted, that the significantly higher volume of the obtained feasible areas can partially be attributed to the lowered area constraints in the current study, compared to the previous NREL report (1 ha, instead of 1 km^2). Also, a lower slope factor (< 5 %, instead of < 3 %) did probably contribute to the area increase. However, the increased amount of available land does not contribute to the capacity calculations, since a packing factor of 0.5 was accounted for. Multiplying the available areas with the packing factor resulted in a lower availability (139,506 km^2) than the feasible areas in the NREL study (172,030 km^2).

As can be seen, all four states had over 30,000 km^2 (11,583 square miles) of potentially feasible land, which altogether makes almost 280,000 km^2 (ca. 108,110 square miles). This sum is a considerable quantity of land, and should lead to further research on utility-scale PV installations. The present work was a preliminary characterization to obtain feasible areas more exactly, the assessment has to be conducted on a smaller scale.

Another component that should be compared to the NREL report was the capacity factor. NREL used an average capacity factor for each state, that did not account for the spatial variation of solar insolation. The present work calculated the capacity factor according to Equation (2) in Table 9, considering solar insolation values for each cell of the feasible areas. Concludingly, capacity factors for this study were lower than in the NREL report, because of the spatial variation of the solar irradiation. Thus, capacity factors in the current research are very precise, giving a more exact value than the average state-wide capacity factors in the NREL report.

In a site-suitability analysis for a small area, more criteria should be taken into consideration. For example, aspect for a small area could be calculated with a high level of confidence using built-in ArcMap tools. In contrast, a similar calculation for a large area – such as a whole state –will result in distorted values [102].

On a small scale, getting more exact information about land ownership is also possible. Land ownership is very important when it comes to planning for a specific site location or smaller region, because it can influence investment costs.

To have a better understanding about areas exposed to risk, FEMA flood risk maps or other areas with environmental hazard data should be integrated – however, in the current work this integration of hazardous data was not an option, since the information needed to either be purchased or were not equally available for all four states.

Inclusion of further constraints in the site suitability analysis was also considered, such as areas with a risk of environmental hazard (frequent tornado, hail occurrence, flood zones, etc.). However, these were either not accessible for all four states or free GIS data were not available.

Excluding military lands from the potentially feasible areas should be considered in future studies, as solar arrays can be distracting for military operations [51].

4.2. Results of the multi-criteria decision analysis

4.2.1. Alternative generation – existing PV plants

TOPSIS was chosen as the multi-criteria decision model used in this research. The method is very useful in obtaining alternatives in terms of their closeness to the ideal solution. To better validate the operation of the multi-criteria decision model, a set of alternatives was established. The set consisted of eight existing PV power plants, which were either under construction or already operating. The goal by including them in the model was to obtain information about the decision maker(s) current priorities.

To acquire data about existing plants, an online map and database from SEIA was used as source [92], which contained all major PV projects equal to, or above 1 MW. For South Carolina, both of the PV plants were still in the construction phase. Therefore, information sources were mainly newspaper or magazine articles [67] [92].

Google Earth is applied as a tool for validation of the actual location; place marks and polygons are created and saved according to the available aerial photographs and imported into ArcGIS as kmz files. Figure 21 shows the place marks in ArcGIS.

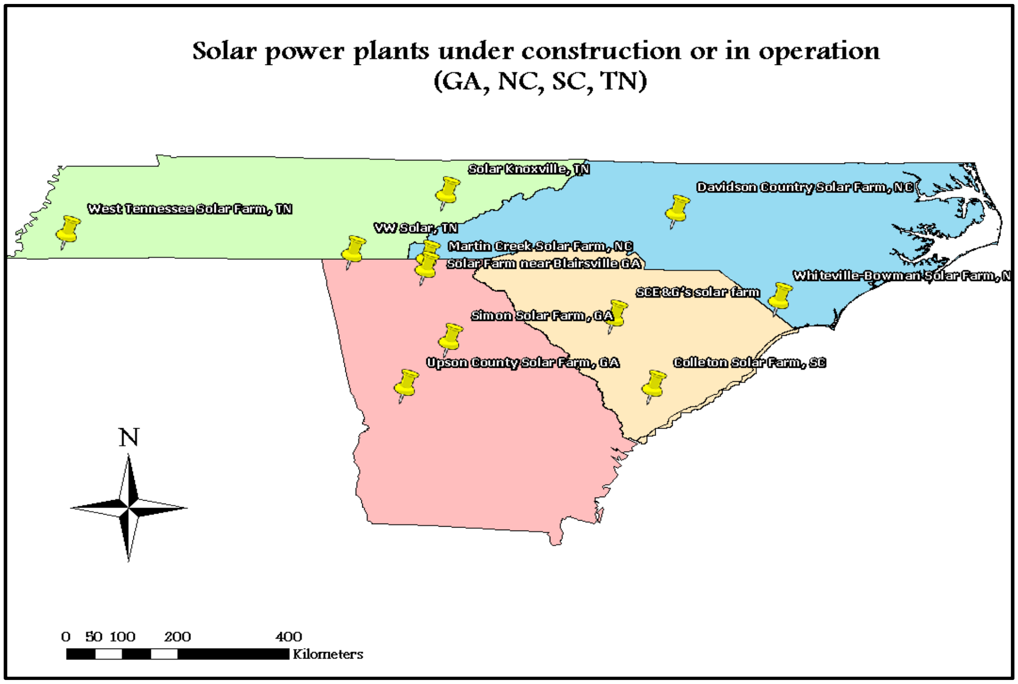


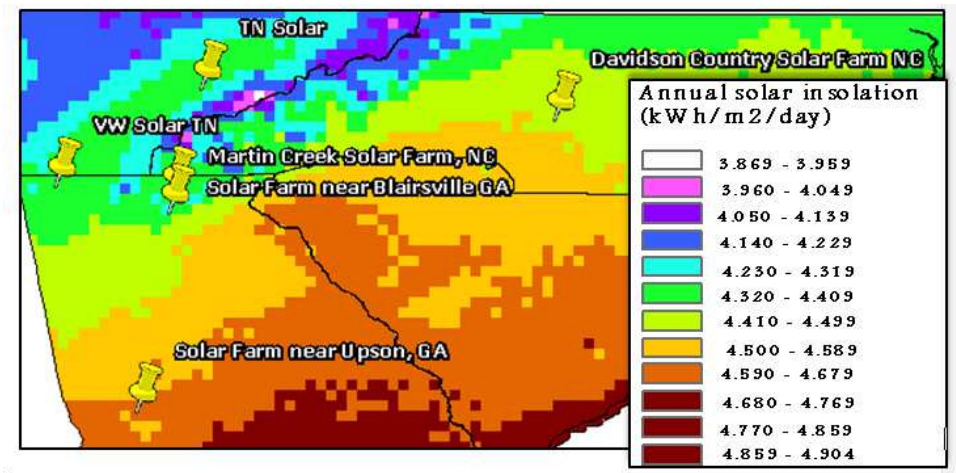
Figure 21: Active PV power plant locations used as alternatives for the MCDA model

After the points were imported in ArcMap, they were displayed on all map layers to determine which category they belong regarding each MCDA criteria. Table 12 shows a summary about the power plants' scores, with general and GIS specific, normalized data for the existing PV plants.

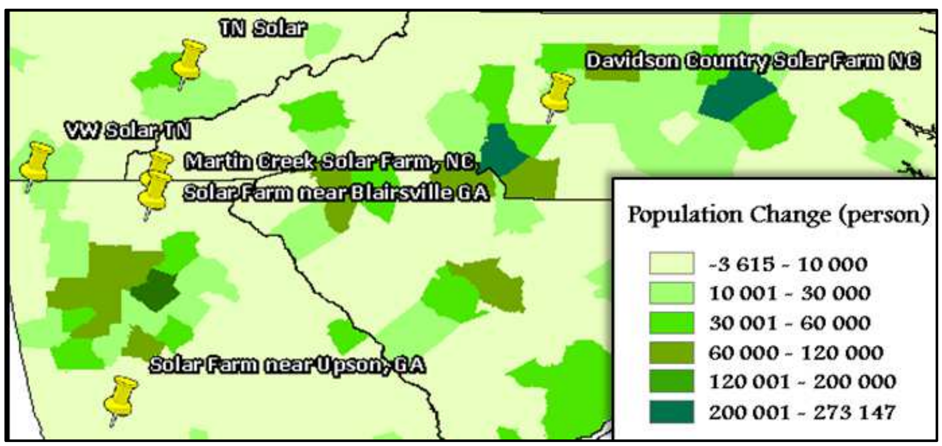
Table 12: Eight currently existing PV plant in the Southeast from various locations in GA, NC, SC and TN – scores for MDCM criteria and status of operation

GENERAL INFORMATION				GIS PERFORMANCE SCORES FOR EXISTING PV PLANTS										STATUS	SPATIAL REFERENCE
#	State	Name of Plant	Size (MW)	RESOURCE	TECHNICAL				ECONOMIC			POLITICAL / MARKET			
				Solar ins.	Land use	Proximity to grid	Proximity to roads	Population change	Price of electricity	Volatility (2003-2013)	Percent increase (2003-2013)	Solar policy	Solar incentives		Latitude (X) Longitude (Y)
1	GA	Upson County Solar Farm	1	8	3	5	6	1	2	4	4	3	1	operating	32°55'13.82"N 84°20'36.58"W
2	GA	Simon Solar Farm	30	8	3	6	4	3	2	4	4	3	1	under construction	33°40'30.78"N 83°40'34.48"W
3	NC	Martin Creek Solar Farm	1	6	2	5	6	1	1	5	3	4	3	operating	35° 1'12.84"N 84° 0'55.82"W
4	NC	Whiteville-Bowman Solar Farm	7	8	3	5	6	1	1	5	3	4	3	operating	34°19'39.75"N 78°45'46.66"W
5	SC	Colleton Solar Farm, SC	3	9	3	5	6	1	1	3	4	2	2	operating	32°54'43.83"N 80°38'56.68"W
6	SC	SCE&G's solar farm	2	8	3	6	6	3	1	3	4	2	2	under constr.	34° 3'20.94"N 81°12'59.89"W
7	TN	Solar Knoxville	1	6	3	6	5	3	3	2	5	1	4	operating	36° 2'41.38"N 83°42'51.40"W
8	TN	West Tennessee Solar Farm	5	6	3	6	6	1	3	2	5	1	4	operating	35°24'34.24"N 89°23'13.40"W

As an example, Figure 22 shows a map portion with a few of the operating PV plants displayed on the solar irradiation and the population map layers in ArcGIS.



(a)



(b)

Figure 22: (a) Map excerpt of solar irradiation map for all four states displaying PV farm locations and (b) Map excerpt for population change map for the same area showing the PV farms

In the following section the performances of the PV power plants will be measured and weighted according to different importance levels of three scenarios. The establishment of the scenarios is introduced in the following chapter (Chapter 4.2.2).

4.2.2. Determining criteria weights and scenarios

The goal of multi-criteria decision making was to find the best alternatives for a finite set of possible solution choices. To find the best option was possible after obtaining the performance of each alternative on a commensurate performance scale. Numerical values, called weights, had to be assigned to each criterion according to the stakeholder's preference system. Every alternative was then multiplied with these weighted criterion values. The assigned weights, were critical in determining the final score and the ranking of the solution alternatives and can strongly influence the results [104].

To achieve commensurability, criteria with different metrics were transformed to match a non-dimensional scale on which the absolute distance from the most-ideal solution was measured. These scales are shown in Table 12 for the existing PV plants.

Based on current patterns and predictions in the literature, three scenarios were chosen, each with different weighting according to three actual or hypothetical perspectives. In Scenario 1, equal importance for all criteria was assumed, in order to calibrate the model and understand the importance of criteria weights. Equal importance would mean that decision makers regard every criterion as identically essential at choosing a location for utility-scale PV facility installation. Results for Scenario 1 are shown in Table 15**.**

For a second scenario (Scenario 2), weights assigned for the criteria were obtained from the literature. Multi-criteria analyses vary in their criteria for the different types of renewable resources, therefore, only the most relevant papers were chosen. Table 13 demonstrates the criteria weights from the literature.

Table 13: Review of criteria weights used in previous work on renewable energy

Topic of paper	EDSS for grid connected PV		Wind and solar farms in Colorado		Solar farm locations SE Spain		PV site-suitability In Oman		Suitability for PV in the SW U.S.
Reference	[48]		[47]		[49]		[62]		[56]
Technical criteria	**OW**[1]	**NW**[2]	**OW**	**NW**	**OW**	**NW**	**OW**	**NW**	**OW**
Solar irradiation	0.5764	*54.9 %*	3	*37.5 %*	23.802	*23.8 %*	0.545	*54.5 %*	30 %
Slope	0.2556	*24.3 %*	-	-	11.203	*11.2 %*	-		40 %
Distance to grid	0.0507	*4.8 %*	2	*25 %*	32.539	*32.5 %*	-		20 %
Distance to roads	0.0507	*4.8 %*	1	*12.5 %*	4.291	*4.3 %*	0.168	*16.8 %*	10 %
Land use / Land ownership	0.1172	*11.2 %*	1	*12.5 %*	5.553*	*5.6 %*	0.287	*28.7 %*	-
Population	-		1	*12.5 %*	2.849**	*2.8 %*	-	*54.5 %*	-
Total	1.05	*100 %*	8	*100 %*	80.237 ***	*100 %*	1	*100 %*	100

[1] Original weight
[2] Normalized weights
*The criteria are called * agrological capacity and ** distance to villages in the paper, but in the meaning it is similar to the criteria other researches are using.*
**** The research consists of more criteria, which were not included here.*

Criteria in the above studies were similar with the ones chosen for the current research. Some of the researchers used further types of criteria, but their weights were typically less significant and economic or market factors were not found among them. It has to be noted, that the solar criterion is often combined with the temperature, the slope and the aspect criteria – the lack of these in the current study is accounted for in the discussion, Chapter 4.2.5.

The literature research can be regarded as a bottom-up investigation of present tendencies. To account for the top-down approach, studies from strategic organizations (such as NREL or EPA) were scrutinized. According to NREL's key assumptions, when accounting for PV deployment potential the most important criterion is (natural) resources, followed by technical, economic and finally market factors [25]. The NREL ranking was already presented in Chapter 3.1, Figure 12.

Another strategic document, used in this research for further information on the criteria preference of strategic institutions, an EPA/NREL report on screening feasible sites for PV potential was studied [105]. The Solar Decision Tree, applied as a guideline in solar energy installations is presented in Figure 23**.**

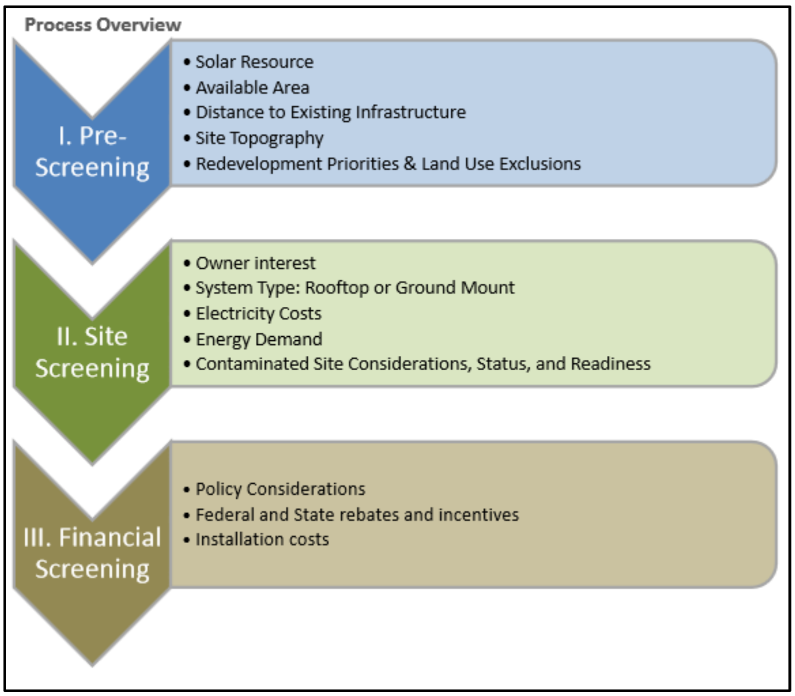


Figure 23: US EPA & NREL 'solar decision tree'

As is evident, with either a bottom-up or a top-down approach, the most valued criterion is (solar) resource. This importance can be explained with the relatively low efficiency of solar panels and high investment and technology costs. Therefore, as technology improves and prices decrease – due to various external factors, such as market demand or policy support - it is very likely that in the future the significance of solar resource will decrease and land availability will become of main importance [34] [75] [95] [96]. The future scenario (Scenario 3) with changed criteria priorities is shown in Figure 24.

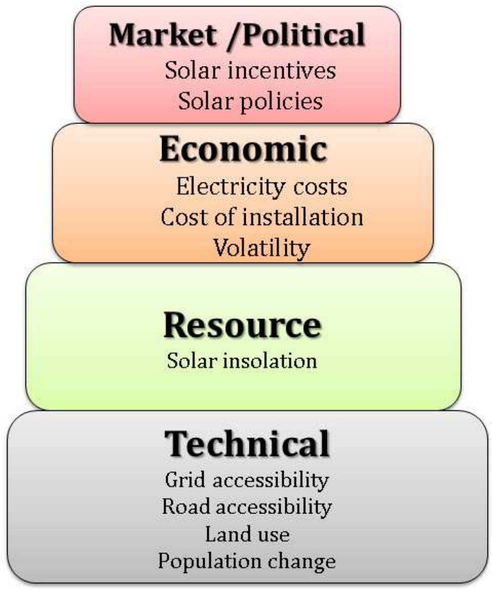


Figure 24: Scenario 3 - future scenario with a high importance on land availability criteria

Economic and policy/market criteria stayed unchanged in both, Scenario 2 and Scenario 3 (technology potential and MCDA). In further research on MCDM criteria for PV related decisions in the U.S., however, economic and market criteria weighting needs to be changed to have a better understanding of the influence of those factors.

4.2.3. MCDA modeling

MCDA models are usually designed as decision making matrices. In Table 14 the DM matrix for the existing photovoltaic plants is presented, with two levels of criteria and the performances of alternatives (that is PV plants). The same structure had to be established in the DECERNS MCDA DE software, in the form of a so-called "value tree"; which is the basic component of any multi-criteria decision support system [40]. The value tree for the eight studied PV farms is presented in Figure 25 below.

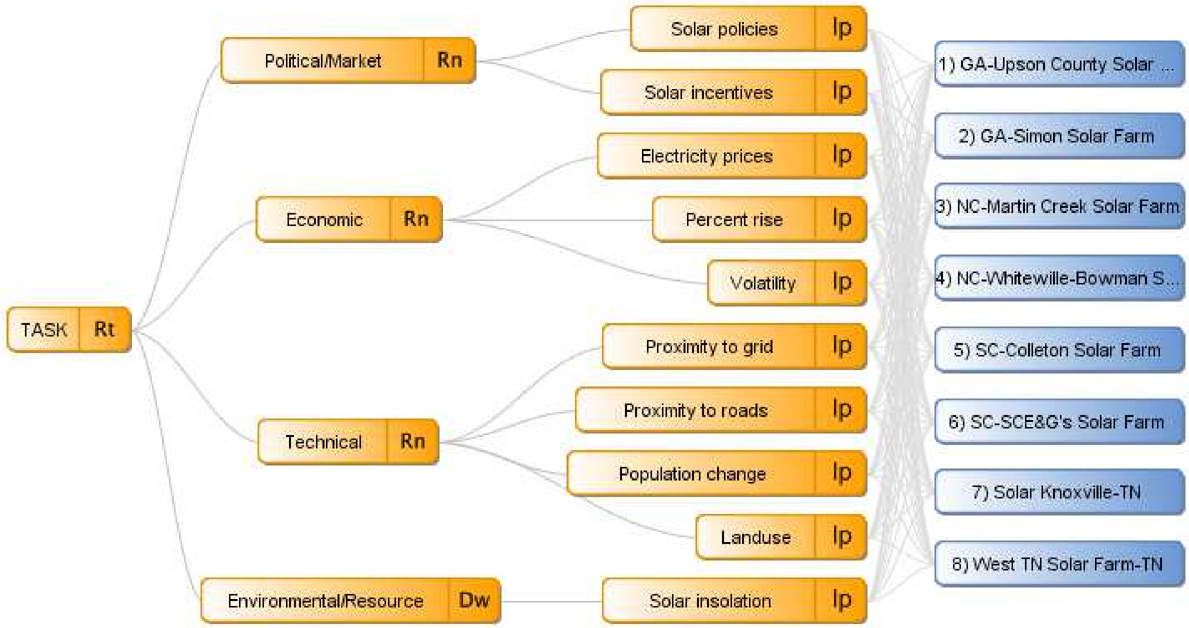


Figure 25: Value tree for TOPSIS method (software: DECERNS DE MCDA)

As seen in Table 14 the criteria used for ordering performances was measured on multiple scales (such as solar irradiation on a scale from 1-12, proximity to the grid from 1-6, etc.). Therefore, scores were normalized before feeding the data into the value tree. There are two types of normalization commonly used for TOPSIS, the ideal and the distributive normalization. The ideal normalization requires the dividing of each performance with the lowest or highest value in each criteria column, depending on whether its condition is set as the minimum or maximum. In the current study it was not necessary to normalize for minimum or maximum values, as DECERNS DE software can be pre-set to meet this requirement. Therefore, distributive normalization was used to obtain commensurable performance scores which were calculated as follows [42].

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} x^2_{ij}}} \qquad \text{where } j = 1,2,3....n \text{ and } i = 1,2,3......m, \qquad (3)$$

where x_{ij} is part of the decision matrix X and is the performance of j alternative with respect of i criterion.

The DECERNS software calculated the performance matrix with normalized weights for each alternative. Table 14 presents the scores of existing PV plants after the distributive normalization:

Table 14: Performance matrix for the studied eight PV plants

Existing PV Plants			Resource	Technical				Economic			Policy/Market		Total Scores
#	State	Name of Plant	Solar irradiation	Land use	Proximity to grid	Proximity to roads	Population change	Price of electricity	Volatility	Percent increase of price	Policies	Incentives	
1	GA	Upson County Solar Farm	0.38	0.37	0.32	0.37	0.18	0.37	0.38	0.35	0.39	0.13	3.23
2	GA	Simon Solar Farm	0.38	0.37	0.38	0.25	0.53	0.37	0.38	0.35	0.39	0.13	3.52
3	NC	Martin Creek Solar Farm	0.28	0.24	0.32	0.37	0.18	0.18	0.48	0.26	0.52	0.39	3.23
4	NC	Whiteville-Bowman Solar Farm	0.38	0.37	0.32	0.37	0.18	0.18	0.48	0.26	0.52	0.39	3.45
5	SC	Colleton Solar Farm	0.43	0.37	0.32	0.37	0.18	0.18	0.29	0.35	0.26	0.26	3.00
6	SC	SCE&G's Solar Farm	0.38	0.37	0.38	0.37	0.53	0.18	0.29	0.35	0.26	0.26	3.37
7	TN	Solar Knoxville	0.28	0.37	0.38	0.31	0.53	0.55	0.19	0.44	0.13	0.52	3.70
8	TN	West Tennessee Solar Farm	0.28	0.37	0.38	0.37	0.18	0.55	0.19	0.44	0.13	0.52	3.41

Weighting

After the normalization, pre-determined weights were assigned to the scores and the two values were multiplied. Determination of the weights usually is set by decision makers or other involved stakeholders, who are qualified for judging the importance of the criteria. In the current study, weights were established according to Chapter 4.2.2**.,** mainly based on the literature and present trends communicated by important regulatory organizations. Three scenarios were established, for equal weighting, with an emphasis on solar irradiation and on accessibility, respectively. The weights for the three scenarios in our study are presented in Table 15.

Table 15: Summary table for weights for the three proposed scenarios

Scenario 1 (equal weighting)										
Criteria	**Resource**	**Technical**				**Economic**			**Political**	
Weight for criteria	**0.25**	**0.25**				**0.25**			**0.25**	
Sub-criteria	**Solar insolation**	**Land use**	**Proximity to grid**	**Proximty to roads**	**Population change**	**Price of electricity**	**Volatility**	**Percent increase of price**	**Policies**	**Incentives**
Percent ratio for sub-criteria	25%	6%	6%	6%	6%	8%	8%	8%	13%	13%
Total weight	0.25	0.0625	0.0625	0.0625	0.0625	0.083	0.083	0.08333	0.125	0.125
Scenario 2 (current preference - solar insolation)										
Criteria	**Resource**	**Technical**				**Economic**			**Political**	
Weight for criteria	**0.45**	**0.35**				**0.15**			**0.05**	
Sub-criteria	**Solar insolation**	**Land use**	**Proximity to grid**	**Proximty to roads**	**Population change**	**Price of electricity**	**Volatility**	**Percent increase of price**	**Policies**	**Incentives**
Percent ratio for sub-criteria	100%	20%	40%	30%	10%	50%	20%	30%	33%	67%
Total weight	0.45	0.07	0.14	0.105	0.035	0.075	0.03	0.045	0.0165	0.0335
Scenario 3 (future preference - accessibility)										
Criteria	**Resource**	**Technical**				**Economic**			**Political**	
Weight for criteria	**0.2**	**0.6**				**0.15**			**0.05**	
Sub-criteria	**Solar insolation**	**Land use**	**Proximity to grid**	**Proximty to roads**	**Population change**	**Price of electricity**	**Volatility**	**Percent increase of price**	**Policies**	**Incentives**
Percent ratio for sub-criteria	100%	20%	40%	30%	10%	50%	20%	30%	33%	67%
Total weight	0.2	0.12	0.24	0.18	0.06	0.075	0.03	0.045	0.0165	0.0335

As a next step, a weighted normalized matrix was constructed. The equation for weighting the matrix is:

$$w_{ij} = x_{ij} * r_{ij}$$ where j=1,2,3……n and i=1,2,3…..m. (4)

Similarity index

The results with final weights for the alternatives were displayed as two dimensional column diagrams as shown in Figure 26. Each alternative (in this case existing PV power plants) was compared to the ideal solution and the negative-ideal solution although these are not displayed on the graph. An example for the ideal and non-ideal solution can be seen in Table 16.

Table 16: Example for 'Best ideal' and 'Worst ideal' alternatives – Scenario 2

Ideal points

	Solar insolation	Proximity to grid	Land use	opulation change	roximity to roads	Volatility	rice of electricity	Policies	cent increas of pr	Incentives
Best ideal	0.43	0.32	0.37	0.53	0.25	0.19	0.55	0.52	0.44	0.52
Worst ideal	0.28	0.38	0.24	0.18	0.37	0.48	0.18	0.13	0.26	0.13

According to the alternative's distance to ideal point; each alternative had a so-called similarity index. The term 'Similarity Index' means how similar the scores of a specific alternative are to the ideal solution. As it is seen in Figure 26, the highest similarity was 0.65 and the lowest is 0.15.

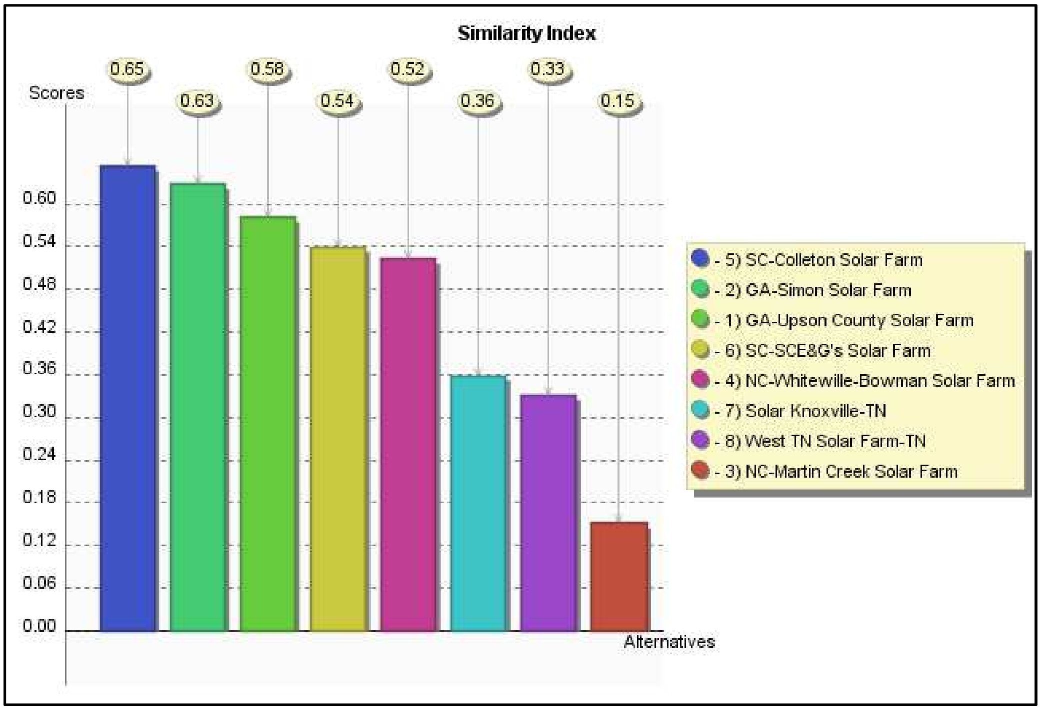


Figure 26: Ranking of the PV plants according their final score in Scenario 2

The similarity index scores and final rankings for the three scenarios are summarized in Table 17.

Table 17: TOPSIS similarity index scores and ranks for the three studied Scenarios (S1='equal weighting', S2='current preference – solar irradiation' and S3='future preference – accessibility')

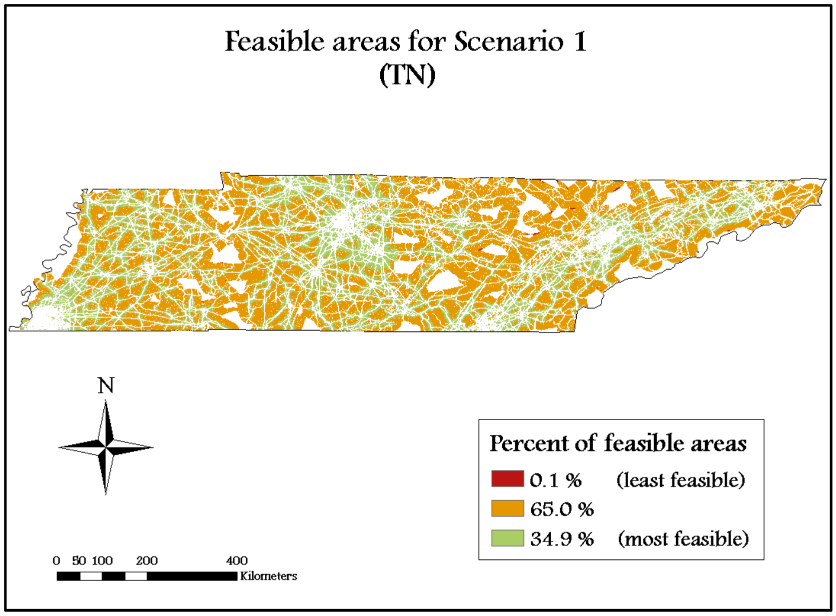
Existing Solar Plants			Scores and Ranks in Scenarios					
#	State	Name of Plant	Score S 1	Rank S 1	Score S 2	Rank S 2	Score S 3	Rank S 3
1	GA	Upson County Solar Farm	0.47	3	0.58	3	0.47	3
2	GA	Simon Solar Farm	0.62	1	0.63	2	0.62	1
3	NC	Martin Creek Solar Farm	0.25	7	0.15	8	0.25	8
4	NC	Whiteville-Bowman Solar Farm	0.41	6	0,52	5	0.41	7
5	SC	Colleton Solar Farm	0.46	4	0.65	1	0.46	4
6	SC	SCE&G's Solar Farm	0.45	5	0.54	4	0.45	6
7	TN	Solar Knoxville	0.55	2	0.36	6	0.55	2
8	TN	West Tennessee Solar Farm	0.45	5	0.33	7	0.45	5

Both, the highest (0.62) and the lowest (0.15) scores were obtained in Scenario 2, which represents the current decision making approach. The wide scoring could be a consequence of the weight distribution in Scenario 2. Solar irradiation was given a weight of 0.45 which resulted in a strong preference for PV plants with high GHI values, even if the scores for other criteria were lower or equal to those of other alternatives. Therefore, PV plant No. 1 (Upson County Solar Farm in GA) and No. 3 (Martin Creek Solar Farm in NC) had a high ranking in all scenarios because of their good solar irradiation values. Both of the farms had the same total scores before the weighting process (Table 14); however, Upson County Solar Farm was constantly ranked as 3rd, whereas Martin Creek Solar Farm was ranked on the 7th or 8th place. Economic factors and land use criteria also differed between the two, but the difference per se was not an explanation for the distance of the two rankings.

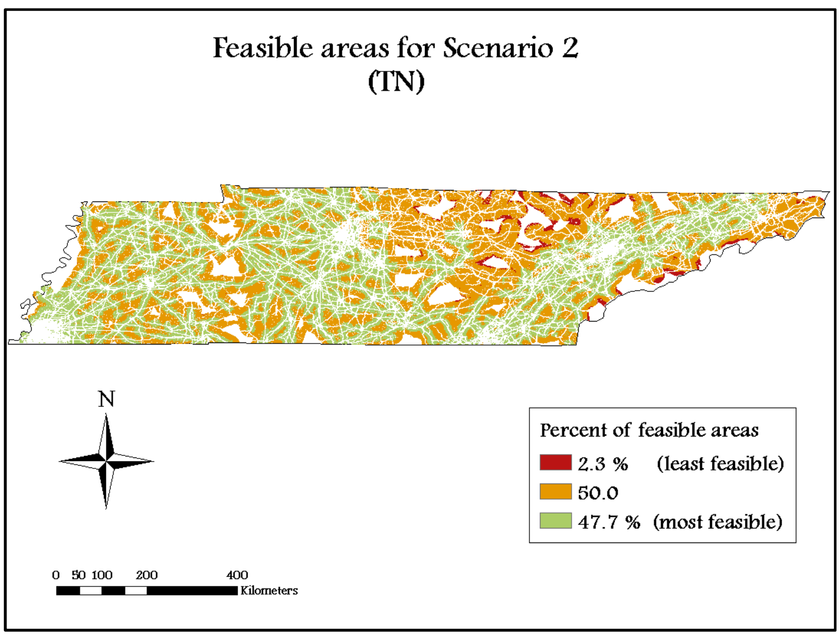
Solar Farm Knoxville (No. 7) showed the highest total score before weighting (3.70) and was ranked 2nd and 6th place, according to the actual scenario's solar irradiation preference. The relatively low ranking was possible, because the alternative had a balanced distribution of relatively high scores in most of the criteria, except for solar irradiation. The opposite was true for Colleton Solar Farm in SC (No. 5), which was ranked 1st in Scenario 2 (with a score of 0.65), due to its solar features – the highest (0.47) among the eight alternative -, but was ranked in the mid-range in the other scenarios (0.46 score in both, Scenario 1 and 2). All three scenarios ranked high PV farm No. 2 (Simon Solar farm, GA). The PV farm had the second highest overall scores (0.62, 0.63 and 0.62 respectively).

4.2.4. Final GIS maps with weighted layers

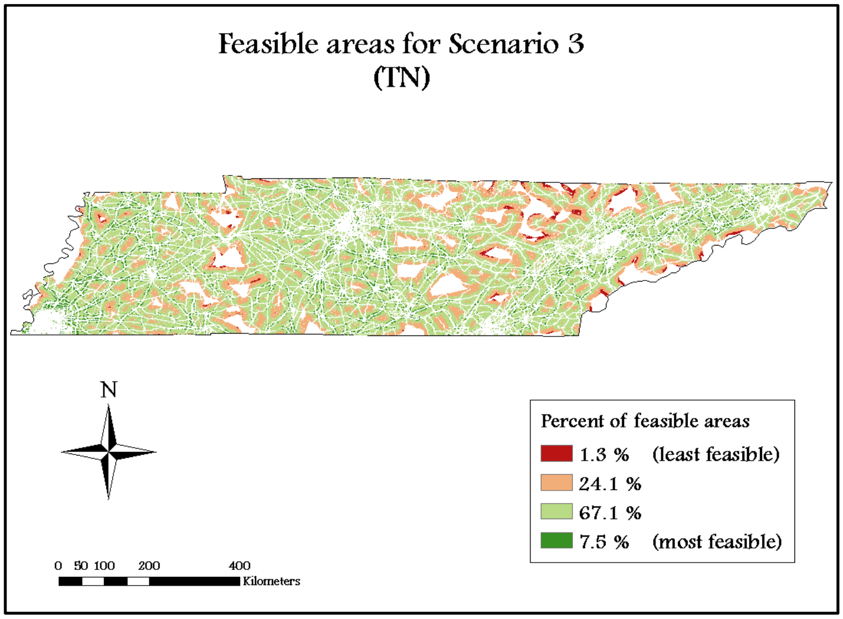
According to the three scenarios in the MCDA model, final maps were created. The map layers presented only resource and technical criteria, however for economic and market/policy factors data were not varying in space on the state level. Figure 27 (a), (b) and (c) provide insight about the effects of changing the criteria weights on the feasible areas. By looking at all three figures, an increase in the most desirable areas can be observed. For a better visibility, the results are represented only on the state of Tennessee; however, similar results could be expected from the three other states as well. As the MCDA and the GIS system were not fully coupled, every change in criteria weights had to be altered manually.


Feasible areas for Scenario 1
(TN)
N
Percent of feasible areas
0.1 % (least feasible)
65.0 %
34.9 % (most feasible)
0 50 100 200 400
Kilometers

(a)


Feasible areas for Scenario 2
(TN)
N
Percent of feasible areas
2.3 % (least feasible)
50.0
47.7 % (most feasible)
0 50 100 200 400
Kilometers

(b)



(c)

Figure 27: Final map layers with (a) Scenario 1 - equal weighting (b) Scenario 2 –emphasis on solar resource criteria (c) Scenario 3 – emphasis on land accessibility

The changes in the percentage of areas are summarized in Table 18. The classification for areas happened according to the software's algorithm, using the weighted sum tool.

Table 18: Summary table for the percent ratio change of areas weighted according to the three scenarios in the MCDA

Class / Scenario	Scenario 1	Scenario 2	Scenario 3
Least desirable for PV installation	0.1 %	2.3 %	**1.3 %**
	65 %	50 %	**24.1 %**
	34.9 %	47.7 %	**67.1 %**
Most desirable for PV installation	-	-	**7.5 %**

From the results of Table 18 it follows, that the best option was Scenario 3, where all criteria weights were the most balanced. The number of classes was previously set to six; however, areas weren't assigned to all classes . For a simple understanding, these classes are not listed in Table 18, and classes with a value are not numbered, but have linguistic classification. As it is presented in the summary table (Table 18), only Scenario 3 had 7.5 % of the areas in the most desirable category for PV installation.

4.2.5. Sensitivity analysis for the MCDA model

To gain a better understanding about the influence of the weights in the different scenarios, the sensitivity analysis tool was used. The tool is built into the DECERNS MCDA DE software. Sensitivity analysis was to test the robustness of the model and determine the effects of changing single inputs on the final results. Figure 28 shows the criterion analysis window from DECERNS MCDA DE. The weightings from 0 to 1 are shown on the x-axis. A slider (shown as the vertical red line) is positioned at a selected weight (0.45 as shown in Figure 28), and can be manually moved to represent changes in the criterion's weighting. The model is the more sensitive the earlier the slider reaches any crossing of the attribute lines (shown in different colors, each for a specific PV power plant). A crossing of the attribute lines means a change in the ranking.

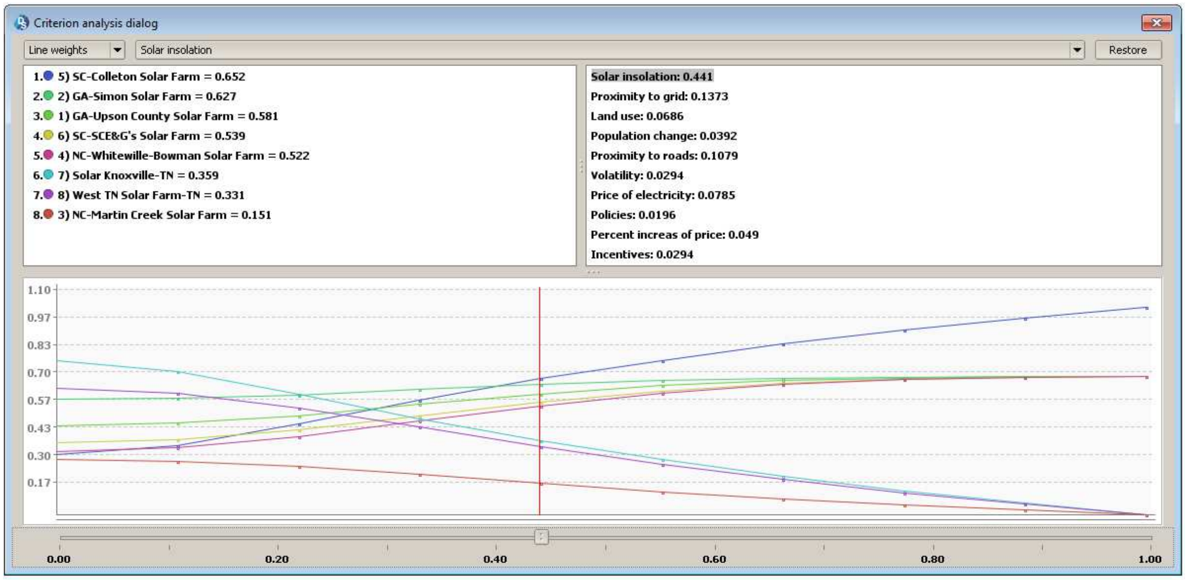


Figure 28: Sensitivity analysis tool displaying line weights for TOPSIS in DECERNS MCDA DE

The robustness of the three models (that is the three scenarios) was tested, by comparing the values of change for each criterion. The change in minimum of two rankings was counted as a threshold for sensitivity significance. The two directions are marked as (-) and (+), although the values obviously signify the absolute change. Table 19 summarizes the resulting value differences for each criterion in the models.

Table 19: Results for sensitivity analysis – the change of values resulting in two or more alterations of alternative rankings

Criteria / Sensitivity	Solar insolation	Land use	Proximity to grid	Proximity to roads	Population change	Price of electricity	Volatility	Percent increase of price	Policies	Incentives
SCENARIO 1										
Very sensitive	(+) 0.024 (-) 0.013				(-) 0.011		(+) 0.014 (-) 0.029	(-) 0.02	(+) 0.014 (-) no significant change	(+) 0.015 (-) 0.009
Relatively sensitive			(+) 0.083 (-) 0.076		(+) 0.064	(+) 0.032		(+) 0.05		
Insensitive		(+) 0.213 (-) no change		(+) 0.134 (-) no significant change						
SCENARIO 2										
Very sensitive	-	-	-	-	-	-	-	-	-	-
Relatively sensitive					(+) 0.046 (-) 0.039	(+) 0.045 (-) 0.078	(+) 0.095 (-) no change			
Insensitive	(+) no change (-) 0.111	(+) 0.56 (-) no change	(+) 0.118 (-) no change	(+) 0.246 (-) no change				(+) 0.151 (-) no change	(+) 0.056 (-) no change	(+) 0.021 (-) no change
SCENARIO 3										
Very sensitive	(-) 0.013				(-) 0.011	(-) 0.011	(+) 0.011 (-) 0.029		(+) 0.011 (-) no significant change	(+) 0.016 (-) 0.016
Relatively sensitive	(+) 0.035		(+) 0.078 (-) 0.074		(+) 0.069	(+) 0.032		(+) 0.046 (-) no significant change		
Insensitive	-	(+) 0.211 (-) no change	-	(+) 0.132 (-) no significant change	-	-	-	-	-	-

Different categories for measuring the sensitivity were established as follows:

1) Very sensitive: 0 – 0.03
2) Relatively sensitive: 0.03 – 0.1
3) Insensitive: > 0.1

The Incentives criterion in Scenario 1 was the weakest with a score of -0.009 and the land use criterion under Scenario 2 was the most robust (that is the least sensitive) with a score of +0.56. However, values generally ranged between 0.011 and 0.213. As the results showed, Scenario 1 and Scenario 3 had a weaker sensitivity, with Scenario 3 having no criteria in the insensitive category. Scenario 2 was the most robust model, displaying only moderate to very low sensitivity. Scenario 1 (equal weighting) was a very sensitive model, which is not surprising, knowing that the weights in that scenario are equally important. Therefore, the ranking is more likely to change if one of the weights is altered. However, Scenario 3 is almost as weak as Scenario 1 (with slightly lower or higher weights for all criteria. This should imply a change in the weighting of Scenario 3, such as it is described in the discussion section (Chapter 4.2.6).

4.2.6. Discussion and recommendations

A definite advantage of the current work is that it excludes areas from any constraint criteria. Such areas are called no-conflict regions and assessing only those will minimize the chance of a miss-allocation. For example, only areas with a slope under a 5% were included, whereas some studies had a generally inclusive approach on slope criteria and categorized slopes according their steepness, but did not exclude areas with steep slopes [46] [108]. Excluding slopes above a 5 % rise was found to be more reasonable in the current work, as areas above this value would probably not be considered for a potential utility-scale installation, due to the significant amount of available land with lower steepness.

Incorporating further technical and environmental criteria

Although, mounting of the solar panels can be designed for various surfaces, the most cost-effective and simplest constructed PV plant would stand on almost flat land (ideally 1 or 2 % slope [47] [106]), with slight south facing slope [51]. Therefore, aspect could be taken into consideration in future research. Aspect could have been considered in both, the suite-suitability and the MCDA part of the study.

By now, GIS-based MCDA studies on solar energy only accounted for the proximity of urban developments or population density. Population growth criterion has not been incorporated into DM models; although, it can be a better indicator for increased electricity demand.

Incorporating further economic criteria

Additional economic criteria could be established, such as cost of investment, land costs, labor costs, etc. A spatial relationship for these criteria would be recommended and would enable a better visualization in GIS systems. Alternatively, criteria could be established on the state-level and thus it would vary once multiple states are considered. Coupling economic and political/market criteria to GIS has not been done earlier, and it could be a very unique GIS-based MCDA application suitable for conditions in the U.S.

Also, further spatial criteria could be included into the MCDA study part. Such as aspect, also temperature should be incorporated and modelled in further studies (see climate factor in some of the studies), as in c-Si modules every degree rise in Celsius temperature above 25 °C reduces efficiency around 0.5 % [51]. Therefore, temperature criteria is important to maximize the capacity of the solar panels [38] [46].This would have another advantage, namely that TOPSIS outcomes are more precise with the increasing number of criteria [49] [98].

When a solar plant deployment plan proceeds from preliminary assessment to the actual planning phase, models predicting future energy prices or impacts of certain policy measures (such as introducing tax reductions, or Renewable Energy Portfolio Standards) should be incorporated into the decision making process. With integrating those into an early step of the multi-criteria decision analysis it will be possible to account for more precise future installation or operation costs at a certain location.

For characterizing land accessibility and land use, three categories were chosen as described in Chapter 3.2.1. These categories are important because of investment and land clearing costs can rise significantly by choosing one over the other. However, other categorization could also be acceptable if the objective was to include additional sustainability aspects. For example, another category could be added that considers low quality agricultural or contaminated areas (such as brown sites) for use as PV sites. Therefore, these areas could be grouped into a separate category.

Most of the solar farms are rather small on an industrial scale, with a 1-7 MW capacity. Therefore, it is possible that the decision making process for those solar farms' geographical locations was rather simple, without involving too many stakeholders. However, Simon Solar Farm in GA (No. 2) is a 30 MW photovoltaic plant, which is considered large, the largest among the recently operating photovoltaic utilities within the four states. The facility scores high in all the three scenarios (its rankings are S1 = 1, S2 = 2, S3 = 1); therefore it can be assumed that for this plant a more foresighted DM process was prepared. This assumption about a more circumspect decision can be validated by observing the plant's performance for the four strongest criteria; solar irradiation (0.38), proximity to grid (0.38), land use (0.37) and population change (0.53). This strong performance ensures the plant's high ranking in all three scenarios. Also, it seems that for this plant, a Scenario 3 approach was preferred, that is, the PV plant scores the highest for the proximity to grid criteria. The highest priority given to technical features over solar resources would be a fact supporting literature references about future criteria weighting changes [38] [76] [96] [99]. However, observing values of the eight existing solar plants it is obvious that accessibility of infrastructure is the factor which influences their ranking the most.

The key to accuracy in TOPSIS depends on how weights are established [80]. In conclusion, the results of the current study will be less suitable for a photovoltaic farm with simple equal weighting, since there is no distinction in the importance between the criteria. The sensitivity analysis for Scenario 1 (equal weighting) proves this statement displaying only two complete criteria with a strong sensitivity. This result is as expected, as equal weighting is the simplest decision making method, mostly used for avoiding risk [110]. However, Scenario 3 has similarly low sensitivity to Scenario 1. As mentioned earlier, in Chapter 4.2.5 (Sensitivity analysis), this should lead to further changes on the weights of Scenario 3. The similarly low sensitivity and the similar ratings in Scenario 1 and Scenario 3 could be a limitation of the model. Namely, economic and market/political criteria has not been changed in these scenarios. In conclusion, a future recommendation could be to vary the weightings of economic and political/market criteria.

Sensitivity analysis is a necessary part of MCDA problems, first to better understand the change in the model results when input criteria are changed. Secondly, sensitivity analysis in MCDA models is also important, because criteria are not constant and will change over time. Therefore, a sensitivity analysis can be conducted to predict how a model would change in the future.

Scenario 2 represents a current DM approach, putting a strong emphasis on solar irradiation. The structure of Scenario 3 proves to be the most robust of all three scenario models. According to this model, photovoltaic farms in states with a high solar irradiation (GA and SC) occupy the first four ranks, even if they score lower for other criteria.

Scenario 3 does not present a robust model structure. The lowest (worst) sensitivity values, are attributed to solar irradiation. From this, we can assume that future MCDA techniques should account more for the natural resources than this scenario does. As stated earlier in the discussion, weights for Scenario 3 should be altered and the sensitivity monitored in order to know when the model becomes more stable.

It has to be noted that uncertainty in modeling a solar plant can occur in more aspects. For instance, the inter-annual variation in solar resource or other errors in specifications of the module characteristics, or even operating the plant can involve uncertainties. Further uncertainty can originate from yield or revenue predictions of a PV plant, or from the uncertainties of the solar irradiation, as mentioned in Chapter 3.1.2. [52]. Total uncertainty is a sum of all improbabilities in the mentioned factors and is expected to add up to approximately 10 % in a modelling process [51].

5. CONCLUSIONS

This current research intended to draw attention to a region in the southeast of the U.S., where due to its positive conditions, deployment of PV power plants may be beneficial. The study was divided into two parts. In the first part (Objective 1), a GIS based site-suitability analysis was performed, and then technical potential and electricity generation potential was calculated. In the second part (Objective 2), an MCDA model was built for a better understanding on how to make decisions in the strategic planning phase of a photovoltaic deployment. Lastly – as a part of Objective 2 -, MCDA results were displayed in ArcGIS for a better visualization of the three considered scenarios.

To the knowledge of the author, GIS-based MCDA modeling for photovoltaic power plant deployment has not been conducted on this scale yet – the largest study considered to date was at the state level. Neither economic nor political criteria have yet been incorporated into GIS-based MCDA models related to photovoltaic plant installation. In addition, new technical criteria, this is, population growth was integrated into the presented work, because it was found to be a better indicator for an increased electricity demand than population density, which is commonly used in the literature [45] [48] [61].

The current study had balanced criteria (no redundant criteria, no duplicates), however, adding aspect and slope factor would be desirable, because it would represent a model which accounts for every important factor considered in the literature. However,, social criteria could be integrated into both, the GIS and the MCDA models, depending on the nature of decision making process.. For the current analysis, social criteria was less relevant, but it should be measured when residential income is accounted for, or when different renewable technologies are compared [46].

For future models, it should be strongly considered that as technology improves and prices drop, climate criteria might become less and less important (of course, over a certain solar insolation level; it might not be very economical to install large-scale photovoltaic power plants in Alaska, for example), and the significance of land use and location (that is land accessibility) will very likely increase[48]. Therefore, decision makers should have at least the same level of preference for land accessibility (especially grid proximity) criteria as for solar resources.

Building scenarios in MCDA with a goal to coupling the results with GIS should imply spatial variability for the criteria. The U.S. has the advantage to plan renewable energy development for multiple states and this should be used to incorporate economic, social and political/market criteria into GIS-based multi criteria decision support models. The inclusion of these factors is very important as the U.S. has a vast potential for PV development and its success is strongly related to not only the solar resource, but also the market and political situation (such as the presence of financial incentives or policy environment).

The specification of computer that was used to conduct the research was suitable to run the ArcGIS software, however, hardware problems occurred when trying to create maps for all four states at once. Therefore, statewide data is obtained for each state separately, and the GIS operations were conducted individually as well. Assuming that appropriate hardware is accessible, it would be possible to represent economic and political criteria for all states simultaneously. Therefore spatial variations could be better accounted for when handling multiple states as one map in GIS (see reference study on utility-scale PV installation for the Southwest U.S. [56].

APPENDICES

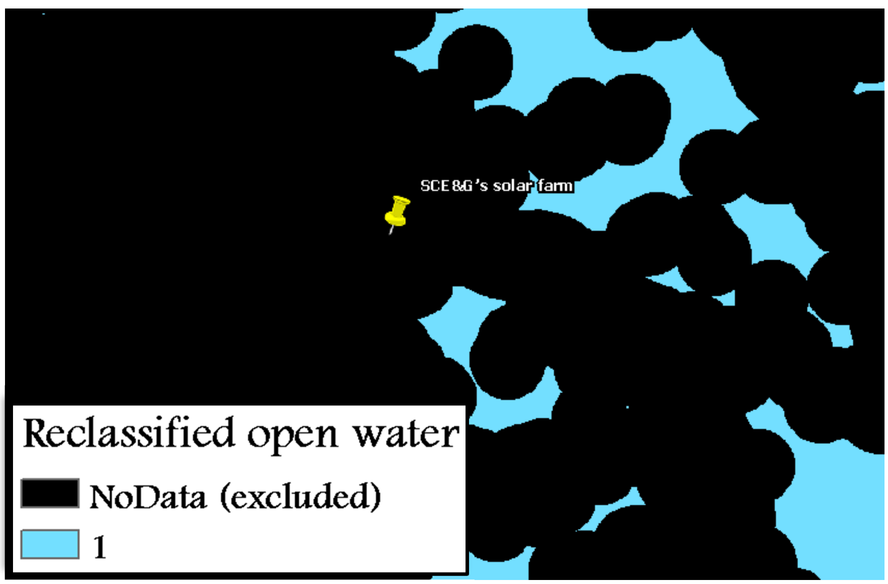
Appendix I

Appendix - Table 1: NLCD 2006 Land use classifications – full classification

Class / Value	Classification Description
Open water	
11	**Open Water** - areas of open water, generally with less than 25% cover of vegetation or soil.
Developed	
21	**Developed, Open Space** - areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes.
22	**Developed, Low Intensity** - areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20% to 49% percent of total cover. These areas most commonly include single-family housing units.
23	**Developed, Medium Intensity** – areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50% to 79% of the total cover. These areas most commonly include single-family housing units.
24	**Developed High Intensity** -highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses and commercial/industrial. Impervious surfaces account for 80% to 100% of the total cover.
Barren	
31	**Barren Land (Rock/Sand/Clay)** - areas of bedrock, desert pavement, scarps, talus, slides, volcanic material, glacial debris, sand dunes, strip mines, gravel pits and other accumulations of earthen material. Generally, vegetation accounts for less than 15% of total cover.
Forest	
41	**Deciduous Forest** - areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species shed foliage simultaneously in response to seasonal change.
42	**Evergreen Forest** - areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species maintain their leaves all year. Canopy is never without green foliage.
43	**Mixed Forest** - areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. Neither deciduous nor evergreen species are greater than 75% of total tree cover.
Shrubland	
52	**Shrub/Scrub** - areas dominated by shrubs; less than 5 meters tall with shrub

	canopy typically greater than 20% of total vegetation. This class includes true shrubs, young trees in an early successional stage or trees stunted from environmental conditions.
Herbaceous	
71	**Grassland/Herbaceous** - areas dominated by gramanoid or herbaceous vegetation, generally greater than 80% of total vegetation. These areas are not subject to intensive management such as tilling, but can be utilized for grazing.
Planted/Cultivated	
81	**Pasture/Hay** – areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing or the production of seed or hay crops, typically on a perennial cycle. Pasture/hay vegetation accounts for greater than 20% of total vegetation.
82	**Cultivated Crops** – areas used for the production of annual crops, such as corn, soybeans, vegetables, tobacco, and cotton, and also perennial woody crops such as orchards and vineyards. Crop vegetation accounts for greater than 20% of total vegetation. This class also includes all land being actively tilled.
Wetlands	
90	**Woody Wetlands** - areas where forest or shrubland vegetation accounts for greater than 20% of vegetative cover and the soil or substrate is periodically saturated with or covered with water.
95	**Emergent Herbaceous Wetlands** - Areas where perennial herbaceous vegetation accounts for greater than 80% of vegetative cover and the soil or substrate is periodically saturated with or covered with water.

(a)



(b)

Appendix 1. -Figure 1 (a) showing SCE&G Solar Farm in South Carolina which is on a wetland (exclusion) field, according to the NLCD 2006 land cover classification. (b) the same area is shown on the exclusion layer of this map

Appendix - Table 2: DSIRE - Financial Incentives for Renewable Energy

Type / Name of incentive		Georgia	Tennessee	North Carolina	South Carolina	California	New Jersey	Weight
1.	**Public Benefit Funds (PBF)**					PBF for Renewables, Energy Efficieny and R&D 2008-2011: $65.5 million annually* Efficiency: $228 million annually RD&D: $62.5 million annually	Societal Benefits Charge $2.635 billion (2001-June 2013) Per-kWh surcharge (varies annually by funding target)	2
2.	**Renewable Portfolio Standards (RPS)**			Yes Electric cooperatives municipalities utilities: 10 % 2018 Solar: 0.2 % by 2018 Credit trading: Yes		• 20% of retail sales by Decembe 31, 2013 • 25% of retails sales by December 31, 2016 • 33% of retails sales by December 31, 2020	Solar 2.450% by 2015 as Class I renewable and 4.1% solar electricity by energy year 2027-2028	3
3.	**Interconnection for PV**	Interconnection Standards (up to 100 kW)		Interconnection Standards (no upper limits)	Interconnection Standards (up to 100 kW)	Interconnection standards (no limits)	Interconnection Standards (no limits)	1
4.	**Access laws / Solar,Wind Access Policy for Renewables**	Solar Easements (doesn't seem too important)		Solar Access Law (not too important)		Solar Easement and the Solar Shade Control Act & Solar Rights Act • Santa Cruz County - Solar Access Protection • Sebastopol - Solar Access • Santa Cruz - Solar Access Ordinance • Sacramento - Zoning and Subdivision Regulations	Solar Easements (doesn't seem to important)	1
5.	**Constr. & Design**			Solar Permitting Standards – Template Solar Energy Development Ordinance		Solar Construction Permitting Standards (minimalizes charges for solar system building permits) Commercial: $1,000 up to 50 kW, plus $7 for every kW between 51 kW and 250 kW, plus $5 for every kW over 250 kW	Solar Permitting Laws - Use of solar in industrial-zoned parcel(s) of 20 contiguous acres or more	3

Score	**2**	**0**	**8**	**1**	**10.8**	**10**	

☐ state incentive

☐ local

Scores:

+ 0.2 for local policy for single cities/areas within state

+ 0.5 for policy for the entire state

Appendix - Table 3: Financial Incentives for Renewable Energy

Type / Name of incentive			Georgia	Tennessee	North Carolina	South Carolina	California	New Jersey	WEIGHT
Financial Incentives for Renewable Energy	1.	Corporate tax credit			Renewable Energy Tax Credit 35 % Max. $ 2.5 million per installation (no capacity limits)				2
	2.	Sales tax		Sales Tax Credit for Clean Energy Technology 100% of sales and use tax			Partial Sales and Use Tax Exemption for Agricultural Solar Power Facilities 100% of the taxes levied by the State. Local and district sales taxes will still apply At least half of the electricity produced by the system must be used to power agricultural equipment.	Solar Energy Sales Tax Exemption 100% exemption No max. incentive	3
	3.	Property tax		Green Energy Property Tax Assessment Solar property assessed value may not exceed 12.5% of total installed costs	Property Tax Abatement for Solar Electric Systems 80% of the appraised value		Property Tax Exclusion for Solar Energy Systems 100% of system value; 75% of system value exemption for dual-use equipment	Property Tax Exemption for Renewable Energy Systems 100% of value added by renewable system	2
	4.	Rebates					California Solar Initiative - PV Incentives Systems must be installed by appropriately licensed California solar contractors or self-installed by the system owner. PV modules must be UL 1703-certified $1.95 billion over 10 years Lodi Electric Utility - PV Rebate Program 2013 Program Year: $1.94/W Max: Non-residential: $40,000 Budget: Approximately $6 million over 10 years. Pacific Power - PV Rebate Program Amount: *adjusted based on expected performance* Commercial: $0.36/W Tax-exempt Entities: $1.11/W Maximum system size: 5 MW		2

							SMUD - Non-Residential PV Incentive Program Expected Performance Based Incentive (for systems up to 1 MW): $0.65/watt AC Performance Based Incentive: $0.10/kWh for 5 years or $0.06/kWh for 10 years Incentives are decreased for systems > 1 MW $650,000 for up-front incentives at current $0.65/W incentive level.		
							City of San Francisco - <u>Solar Energy Incentive Program</u> Non-residential (Industrial): $1,500 per kW Non-residential (Industrial):: $10,000		
Financial Incentives for Renewable Energy	**7.**	**Loans**		<u>Commercial Energy Efficiency Loan Program</u> $20,000 - $5 million Shared Savings Option: retain up to 50% of monthly energy savings, pay loan with remainder. Max. incentive: $5 million 100% of cost Interest Rate: 2% fixed up to 5 yr. term; 5% fixed for 5-10 yr. terms Repayment up to 10 yrs.					3

	5.	**Industry Recruit-ment/Sup-port for Renew-able Energy**		Green Energy Tax Credit $1,500,000/tax year for $250 million in capital investment Terms: The investment must equal at least $250 million within three years Sales and Use Tax Credit for Emerging Clean Energy Industry Tax rate reduced to 0.5% Terms: Taxpayer must make $100 million investment (minimum) and create 50 full-time jobs at 150% rate of Tennessee's average occupational wage.	Renewable Energy Equipment Manufacturer Tax Credit Amount: 25 % (no limit) Credit taken in equal installments over 5 years	Renewable Energy Manufacturing Tax Credit 10 % $500,000 for any year and $5 million total for all years (2010-2015)	Sales and Use Tax Exclusion for Advanced Transportation and Alternative Energy Manufacturing Program 100% exemption $100,000,000 per year	Edison Innovation Clean Energy Manufacturing Fund - Grants and Loans Total (grants and loans): $3.3 million Grants: $300,000 Loans: $3 million 50% cost share required; Loans at 2% interest for up to 10 years with three year deferral of principal repayment Edison Innovation Green Growth Fund Loans Varies; loans from $250,000 - $2 million available Maximum Loan: $2 million (1:1 cash match required from non-state grants, deeply subordinated debt or equity) Performance Grant Conversion (end of loan term): up to 50% of loan amount Fixed five-year term; interest rates of 2%	2
	6.	**Performance-Based Incentive for PV**	Georgia Power Solar Buyback Program $0.17/kWh Up to 25 or 100 kW		NC GreenPower Production Incentive Varies by technology and system size PV up to 5 kW: $0.06/kWh PV larger than 5 kW: must enter bid process System limits: Solar PV: 5 kW maximum for expedited process	Palmetto Clean Energy (PaCE) Program Varies by technology and customer demand for Palmetto Clean Energy (PaCE) Varies by technology and customer	Feed-In Tariff Tariff is based on the "Renewable Market Adjusting Tariff" Tariff is based on the "Renewable Market Adjusting Tariff" Up to 3 MW	Solar Renewable Energy Certificates (SRECs) Varies; average prices ranged from $225 - $390 per MWh during 2012 with significant variations for individual trades 2012-2013 compliance year: ~$641 per MWh (~$0.641 per kWh) (no limits)	3

						demand for Palmetto Clean Energy (PaCE)			
			TVA - Mid-Sized Renewable Standard Offer Program Typical pricing for 2013: Varying between $0.029/kWh - $0.082/kWh with an average of $0.037/kWh (up to 20 MW) Up to 20 year contract with a 5% increase in base rates per year	TVA - Mid-Sized Renewable Standard Offer Program Seasonal and time-of-day prices are set at the date of execution of the contract agreement. Typical pricing for 2013: Varying between $0.029/kWh-$0.082/kWh with an average of $0.037/kWh Up to 20 year contract with a 5% increase in base rates per year System limits: 50 kW-20 MW	TVA - Mid-Sized Renewable Standard Offer Program Seasonal and time-of-day prices are set at the date of execution of the contract agreement. Typical pricing for 2013: Varying between $0.029/kWh-$0.082/kWh with an average of $0.037/kWh Up to 20 year contract with a 5% increase in base rates per year (system limits 50 kW-20MW)		LADWP - Feed-in Tariff (FiT) Program $0.17/kWh adjusted by a time of delivery multiplier Base price will step down over time as certain MW goals are met Max. incentive: $0.3825/kWh 30 kW - 3 MW DC Up to 20 years Project size: 100 MW of Projects		
				Established in 2010, this voluntary FIT program sets a 20-year contract rate for PV, wind, biomass, and anaerobic projects ranging from 50	Established in 2010, this voluntary FIT program sets a 20-year contract rate for PV, wind, biomass, and anaerobic projects ranging from 50 kW to 20 MW. The total program		City of Palo Alto Utilities - Palo Alto CLEAN (Clean Local Energy Accessible Now) $0.165/kWh 20 years No minimum or maximum project size Up to 2 MW of projects for 2013		

				kW to 20 MW. The total program goal is 100 MW. Tariffs vary by time of day and season, and range from \$0.03/kWh to \$0.082/kWh in 2013. TVA gets renewable energy credits (RECs) associated with generation.	goal is 100 MW. Tariffs vary by time of day and season, and range from \$0.03/kWh to \$0.082/kWh in 2013. TVA gets renewable energy credits (RECs) associated with generation. ***		Marin Clean Energy - Feed-In Tariff ** Varies by technology and position in program capacity queue 1 MW or smaller Budget: 10 MW of projects (separate table of energy prices in different periods)		
Score			3.5	14	10.2	5	14.4	10.5	

☐ state incentive
☐ utility
☐ local
☐ non-profit

<u>Scores:</u>

+ 0.2 for local/non-profit/utility incentive within state

+ 0.5 for state level/utility incentive for the entire state

⇨ Discounts, rebates, reductions and support is higher level for the entire state

Appendix 1 - Table 1: Solar insolation categories in the four states

GEORGIA	GHI (annual)		Area (km^2)
	min	max	
Class 1	4.20	4.41	6,645.89
Class 2	4.41	4.51	14,013.20
Class 3	4.51	4.58	17,606.70
Class 4	4.58	4.65	20,170.93
Class 5	4.65	4.72	31,398.48
Class 6	4.72	4.90	36,711.09
GEORGIA TOTAL AREA			**126,546.29**

NORTH CAROLINA	GHI (annual)		Area (km^2)
	min	max	
Class 1	3.87	4.19	26.64
Class 2	4.19	4.31	154.91
Class 3	4.31	4.40	4,223.27
Class 4	4.40	4.45	17,108.15
Class 5	4.45	4.51	18,909.65
Class 6	4.51	4.73	8631.525196
NORTH CAROLINA TOTAL AREA			**49,054.14**

SOUTH CAROLINA	GHI (annual)		Area (km^2)
	min	max	
Class 1	4.34	4.4	0.59
Class 2	4.41	4.5	870.69
Class 3	4.51	4.6	39,383.98
Class 4	4.61	4.7	31,398.83
Class 5	4.71	4.8	1,873.76
Class 6	4.81	4.9	562.48
SOUTH CAROLINA TOTAL AREA			**74,090**

TENNESSEE	**GHI (annual)**		**Area (km²)**
	min	**max**	
Class 1	3.87	4.13	46.59
Class 2	4.13	4.21	1798.04
Class 3	4.21	4.26	6334.95
Class 4	4.26	4.32	7179.60
Class 5	4.32	4.37	10672.69
Class 6	4.37	4.47	6689.94
TENESSEE TOTAL AREA			**32,721.82**

Description of operating solar farms

1. Upson County Solar Farm (GA)

- Developer: Solar Design & Development
- Electricity Purchaser: Georgia Power
- City/County: Upson County
- Technology: PV / Crystalline silicon
- Status: Operating
- Capacity (MW): 1.00
- Online Date: Jul-12
- Located on 10 acres

Georgia aims to develop 50 MW capacity by 2015. The location for the Upson County Solar Farm was chosen partly because it is next to a Georgia Power substation and also close to a residential area with electricity demand. Also a southern facing slope was chosen for the utility. The same company is making a 60 million investment in a 20 MW solar plant [111].

2. Simon Solar Farm (GA)

- Developer: Silicon Ranch
- Electricity Purchaser: Georgia Power
- City/County: Social Circle
- Technology: PV / Crystalline silicon
- Status: Under Construction
- Capacity (MW): 30.00
- Date Announced: January 2013

The solar farm is under construction – it is supposed to be one of the biggest solar farms on the Southeast. Its area is 200 acres (ca. 81 ha) and is 50 miles east of Atlanta.

The farm's subsidiary; called Silicon Ranch has a 20 year Power Purchase Agreement with Georgia Power [112].

3. Martin Creek Solar Farm (NC)

- Developer: SunEdison
- Electricity Purchaser: Duke Energy
- City/County: Davidson County
- Technology: PV / Crystalline silicon
- Status: Operating
- Capacity (MW): 16.00
- Online Date: January 2011

Photo: Flickr - Duke Energy

The solar farm's production is about 1.3 million kWh of electricity each year, which powers ca. 150 average-sized household, according to the article's author. The farm was built on the property of the Martins Creek Elementary School in Murphy, N.C. and has a 10 year purchase agreement for the electricity [113].

4. **Whiteville-Bowman Solar Farm (NC)**

- Developer: Strata Solar
- Electricity Purchaser: Progress Energy Carolinas
- City/County: Whiteville
- Technology: PV / Crystalline silicon
- Status: Operating
- Capacity (MW): 7.00
- Online Date: November 2012
- Number of Modules: 24,354

The solar farm produces ca. 11 000 MWh of electricity annually. It provides enough electricity to about 800 households and was a 20 million dollars investment. The farm offsets 4620 tons of CO2 each year, which equals to 8.8 million miles travelled by car [114].

5. **Colleton Solar Farm (SC)**

- Developer: TIG Sun Energy I LLC
- Electricity Purchaser: South Carolina Electric Cooperatives and Santee Cooper
- City/County: Colleton
- Technology: PV / Crystalline silicon
- Status: Operating
- Capacity (MW): 3.00
- Online Date: December 2013

When operating at its peak, the farm is capable of generating 3 MW of power. This capacity doubles the amount of solar in the state and enough to supply ca. 300 households with power. The project area is 14 acres and the investment costs are about the 6 million dollars [103].

6. **SCE&G's solar farm**

The SCE&G solar farm is under construction and will have the biggest capacity in the state (20 MW) once it is ready. It will power about 20 000 homes. The construction is supposed to be finished by the end of 2014. It is built near to the McMeekin power station, which was a coal power plant in the 1950s and is closed by now [65].

7. Solar Knoxville

- Developer: Efficient Energy of Tennessee
- Electricity Purchaser: Tennessee Valley Authority
- City/County: Knox
- Technology: PV / Crystalline silicon
- Status: Operating
- Capacity (MW): 1.00
- Online Date: 2013

According to a report, the construction of the solar farm created approximately 765 jobs. The project area is 5.5 acres and the array is expected to produce an annual 1.2 MWh energy, which powers 120 households annually [115].

9. West Tennessee Solar Farm

West Tennessee Solar Farm is a 5 MW facility, which constructed by the University of Tennessee. The university was contracted by the Tennessee Department of Economic and Community Development and is responsible for the power plant's operation. The farm started its operation in 2012 and provides electricity for about 500 homes, offsetting 250 tons of coal per month. The project area is more than 25 acres [116]. Although the solar farm was built by a university, it's location is not pre-determined (it is several miles from campus, on an area with low slope and relatively good solar insolation (for the state Tennessee).

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