Analyzing Solar Photovoltaic Farm Suitability for Properties in North & South Carolina

by

Brian Durham

A capstone submitted to Johns Hopkins University in conformity with the requirements for the degree of Master of Science in Energy Policy & Climate

Baltimore, Maryland

May 7, 2019

Table of Contents

Executive Summary

As we witness the impacts of the climate crisis continue to become more severe, it is essential for the public and private sectors of the United States to begin rapidly transitioning to clean energy sources to meet its commitments of the Paris Climate Accord ("USA | Climate Action Tracker," 2019). This study uses Multi-Criteria Decision Making (MCDM) with the Analytical Hierarchy Process (AHP) and Geographic Information Systems (GIS) to locate land and property owners within North and South Carolina most suitable for solar photovoltaic (PV) farm development. A geoprocessing model was built using ESRI's ArcGIS software to assign levels of importance to various GIS layers of the natural and built environment. The model successfully identifies existing solar PV farms as ideal sites for development while locating thousands of additional acres suitable for solar PV farm development throughout both states. This suitability dataset should help solar development teams works more efficiently. Ideally, more efficient solar development teams will be able to complete more projects, leading to more clean energy on the grid and a faster reduction of our greenhouse gas emissions.

Introduction

On December 12, 2015, in Paris, France, the 195 countries participating in the United Nations Framework Convention on Climate Change agreed to begin the process of reducing greenhouse gas emissions to keep the global temperature increase below 2.0 degrees Celsius. Cost estimates vary widely according to various studies; however, all agree that massive investments will be needed to avoid catastrophic climate change. The longer society takes to transition to clean energy, the larger the cost (Rogelj et al., 2013).

Since Donald Trump became the President of the United States, the outlook for keeping warming below 2.0 degrees Celsius is doubtful at best. When Syria signed the historic agreement in November 2017, the United States became the only one of 195 countries in the world not taking part in the Paris Climate Accord. Climate change deniers and those that willfully ignore the problem for financial gain, with long histories in the fossil fuel industry, have received important cabinet positions and political appointments (Forrest, 2019). While President Trump's promises of re-opening coal plants are unlikely due to market conditions, the prospects of a carbon tax or restrictions on methane released into the atmosphere are far-fetched. Without federal regulations, the United States will not reach its emissions targets set by the Paris Agreement in 2050 ("USA | Climate Action Tracker," 2019). Now more than ever, it is imperative for private citizens and organizations to play a role in reducing greenhouse gas emissions.

Geographic Information Systems (GIS) gives users the power to visualize, manipulate, and analyze the spatial properties and relationships of data. Effective data analysis leads to smarter, more informed decision making. This report used GIS to combine several datasets to determine suitable properties for solar photovoltaic (PV) farm development. The resulting GIS dataset will help developers target properties and help landowners identify potential development. The suitability dataset will save time and money by avoiding unnecessary due diligence on sites that are poorly suited for solar PV developments. Ideally, the final dataset will be utilized by third parties searching for land to build new solar farms, leading to new clean energy on the grid and reduced greenhouse gas emissions.

Multi-Criteria Decision Making (MCDM) is a technique regularly used in the site selection process. This technique pairs well with GIS due to the ease of combining multiple layers, or criteria, together and analyzes results (Sánchez-Lozano, Teruel-Solano, Soto-Elvira, & Socorro García-Cascales, 2013). Pohekar & Ramachandran (2004) reviewed 90 scientific papers and found the Analytical Hierarchy Process to be the most frequently used technique for siting sustainable energy projects. The Analytical Hierarchy Process (AHP) allows a researcher to apply different levels of importance to various criteria (Watson & Hudson, 2015). For example, when determining suitability for solar PV locations, this study places high importance on land use and distance to transmission lines but lower importance to tree canopy and soils type. All are criteria worthy of consideration, but some are more important than others.

Determining site suitability for renewable energy projects using the MCDM/AHP/GIS approach has been applied many times successfully in studies around the globe. Watson & Hudson (2015) used the technique in Southern England and compared the suitability of wind farm to the suitability of solar PV farms. The study found Southern England to be significantly more suitable for large solar development than wind, with 294 km^2 'very suitable' for solar PV farms. Sánchez-Lozano, Teruel-Solano, Soto-Elvira, & Socorro García-Cascales (2013) MCDM/AHP/GIS to determine solar farm suitability for Cartagena in Southeastern Spain. Noorollahi, Fadai, Akbarpour Shirazi, & Hassan Ghodsipour (2016) applied the technique to study the entire nation of Iran and found 237,920 km^2 to have excellent solar farm suitability. Farthing et al. (2016) performed an excellent solar PV farm suitability analysis for the State of South Carolina and found 11,143 km^2 suitable for solar PV farms. Farthing et al. (2016) utilized land use, slope, and aspect data for the suitability analysis with additional datasets used to eliminate areas from consideration.

Similar to Farthing et al. (2016) this report will study South Carolina's solar farm PV suitability. The study area will also be expanded to include North Carolina. This report will use many additional criteria in the suitability analysis. Twenty-foot cell size LiDAR-Derived topographic datasets will also make this analysis stand out. This report will also use actual property ownership data to establish a database of landowners with the most suitable land for solar PV development.

Background

The cost to install new solar PV has dropped dramatically over several years. Over the last 40 years, the PV module price per watt has dropped from over $100 to under $1 in 2014, higher than two orders of magnitude. Government and privately funded research and development played a significant role in increasing module efficiency from 1980-2012 and was the primary driver of reducing costs. In the early 2000s, improved economies of scale also became a major factor in cost reduction (McNerney, Kavlak, & Trancik, 2018). Since 2009 the cost of levelized solar power purchase agreements has dropped 85% (Bolinger & Seel, 2018).

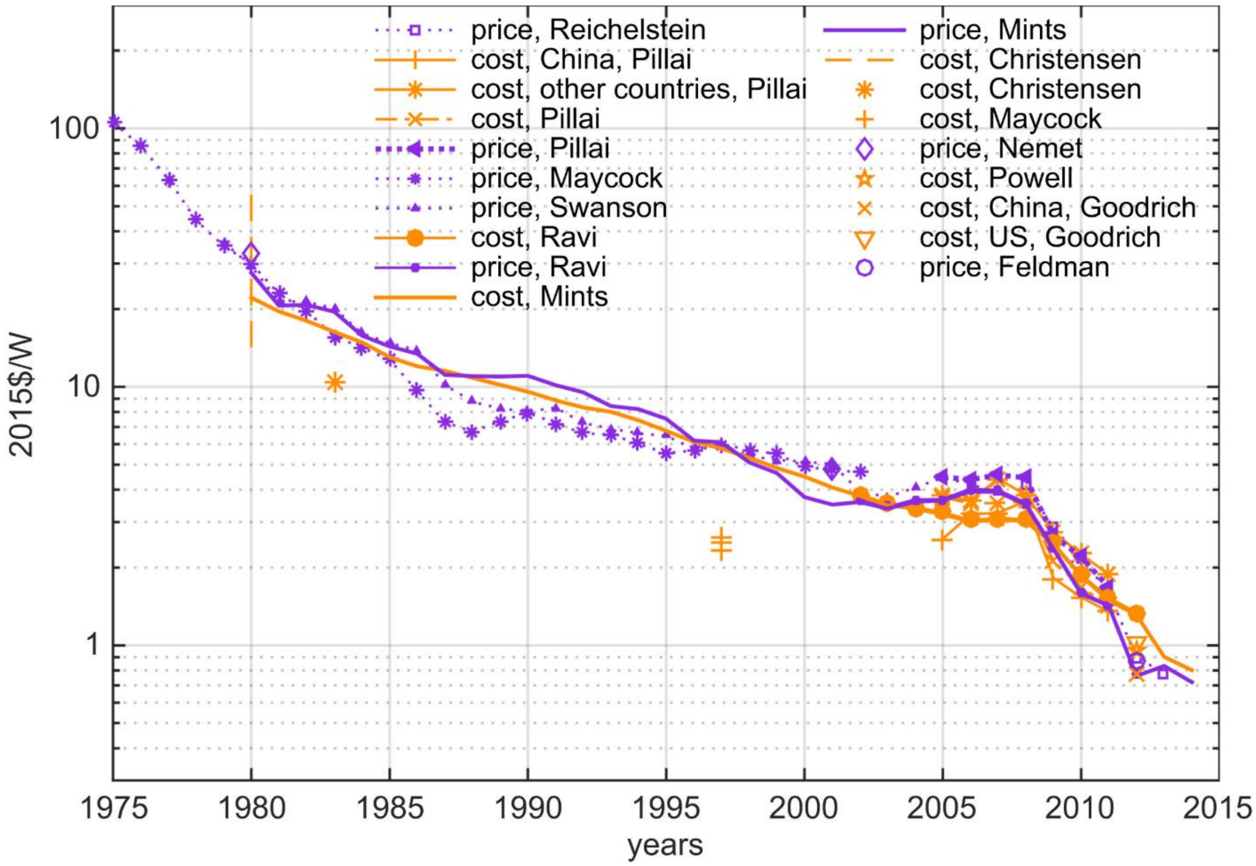

Figure 1 - Solar PV module price per watt change over time. (McNerney, Kavlak, & Trancik, 2018)

Before 2015, a significant amount of solar PV projects had not been completed in the Southeast USA. However, in 2017 the Southeast emerged as the leading market for new solar PV installations. North Carolina alone had 16% of all new installed capacity in the United States (Bolinger & Seel, 2018).

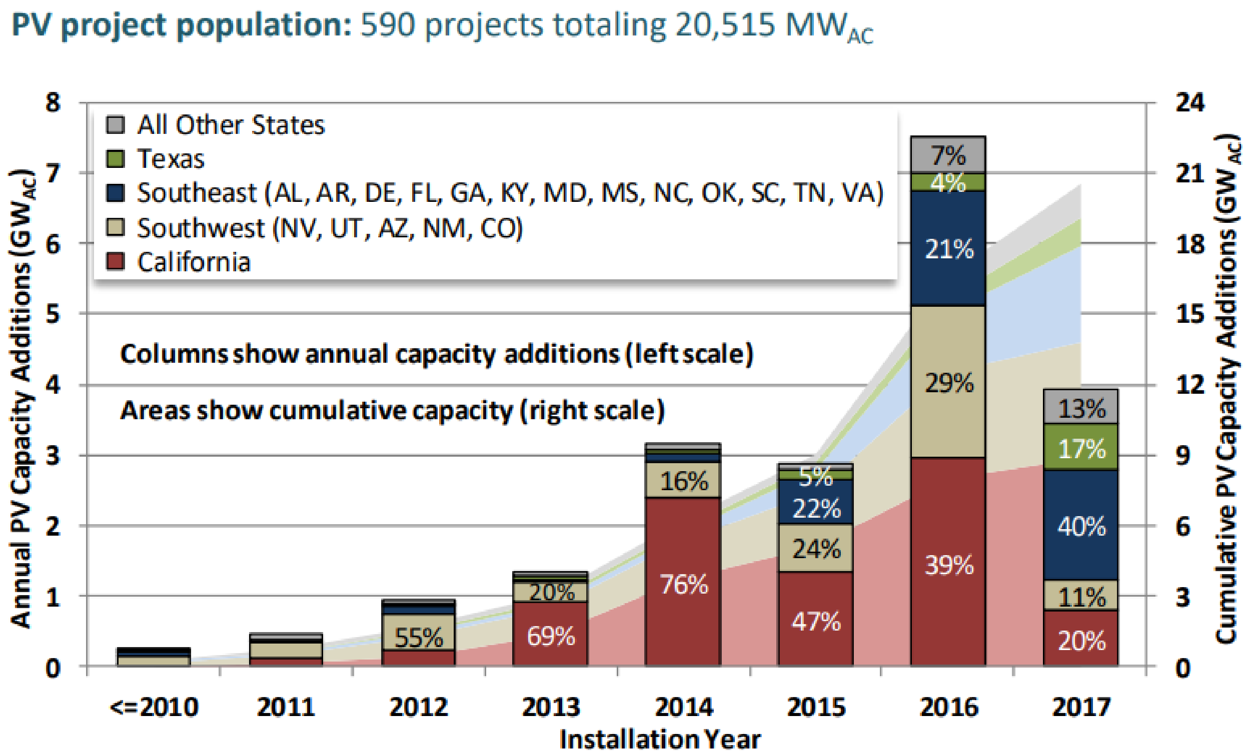

Figure 2 - 40% of newly installed capacity in 2017 was installed in the Southeast. 16% of all capacity was installed in North Carolina. (Bolinger & Seel, 2018)

In 2008, two of the three major utilities in South Carolina announced a joint effort to build the VC Summer Nuclear Plant with Toshiba subsidiary Westinghouse tasked leading the construction of the plant. The project was initially expected to cost $9 billion, fully paid for by ratepayers. After nine years of timeline and budget overruns, Westinghouse filed for Chapter 11 bankruptcy with $9 billion in losses in March 2017. In July 2017 Santee Cooper announced that all work on the VC Summer Plant with Westinghouse unable to complete the work and the new projected cost of the project at over $23 billion (Crees, 2018). Following the collapse of the VC Summer Nuclear power plant project, political conditions within South Carolina's state legislature changed quickly. The bankruptcy of Westinghouse led to the State legislature investigating the project and the release of years of communications of high-level executives of South Carolina's largest utilities. The failed project led to the waste of $7 billion, leaving ratepayers to cover the cost of executive mismanagement and negligence. According to the South Carolina House Judiciary Committee Chair Peter McCoy, the State Legislature is ready for new, innovative energy solutions (Peter McCoy, 2019). This sentiment was supported by the unanimous passage Representative McCoy's Energy Freedom Act through the South Carolina House in 2019. While the policy future for the State is not certain, South Carolina could be only a few policy passages away from a significant solar PV investment.

188.5 GW of potential solar projects are in queues throughout the United States, eight times more than the current solar generation capacity. The Southeast is second only to California for projects waiting to be developed (Bolinger & Seel, 2018). This is yet another signal for solar's bright future in the Southeast. Organizations and individuals who will be building this solar infrastructure will need to understand what land is best suited for solar PV development.

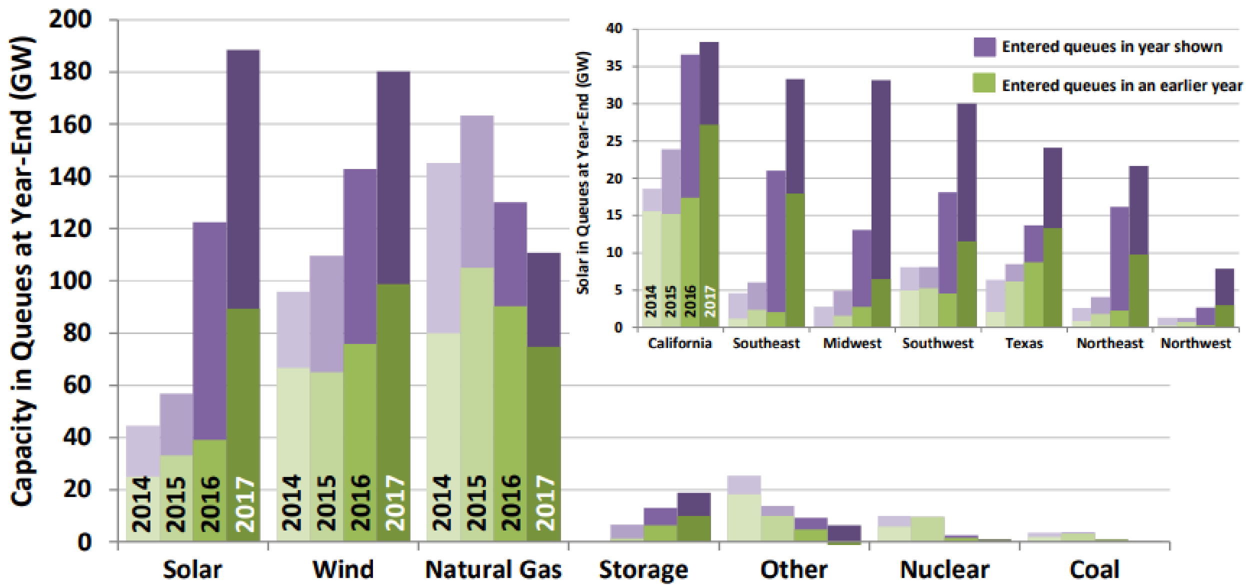

Figure 3 - Solar projects ready to be built by year. 188.5 GW of potential solar projects were waiting to be built at the end of 2017, the highest ever. This was more than eight times the installed capacity at the end of 2017. Important to note that these projects are not guaranteed to be built. (Bolinger & Seel, 2018)

Methodology

The first step in a land analysis is to collect data that allows you to create a digital representation of the land. GIS datasets of the natural and built environment were acquired for criteria essential to solar PV development. Individual datasets can contain an unlimited number of subtypes or categories of data. For example, a land use dataset will contain multiple data types for different land coverages to indicate areas of forest, agricultural land, or areas that have been developed. A flood zone dataset contains polygon boundaries for areas FEMA determines to be vulnerable to different types of flooding. ESRI's ArcGIS software was used to manage and process each dataset. Within ArcGIS, ModelBuilder allowed for the creation of streamlined, repeatable analysis processes.

GIS datasets are treated as layers, all of which were overlaid to determine suitability. A cost-weighted overlay allows layers to be weighted, or assigned importance, differently than others. Each category was reclassified to a value that indicates its suitability for solar farm development. The cost-weighted overlay is advantageous for fine-tuning model results based on user or client preference but also allows for flexibility based on region or project-specific criteria. As an example, this study places high importance on the distance of a property to transmission lines. If an interested party was not concerned with the distance to transmission lines, the analysis could quickly and easily be re-run to ignore the location of a property's proximity to transmission lines. This modification would produce a significantly different final product that would make many properties appear more suitable for development.

Figure 4 - The data processing model to prepare individual datasets to be used in the Cost-Weighted Overlay.

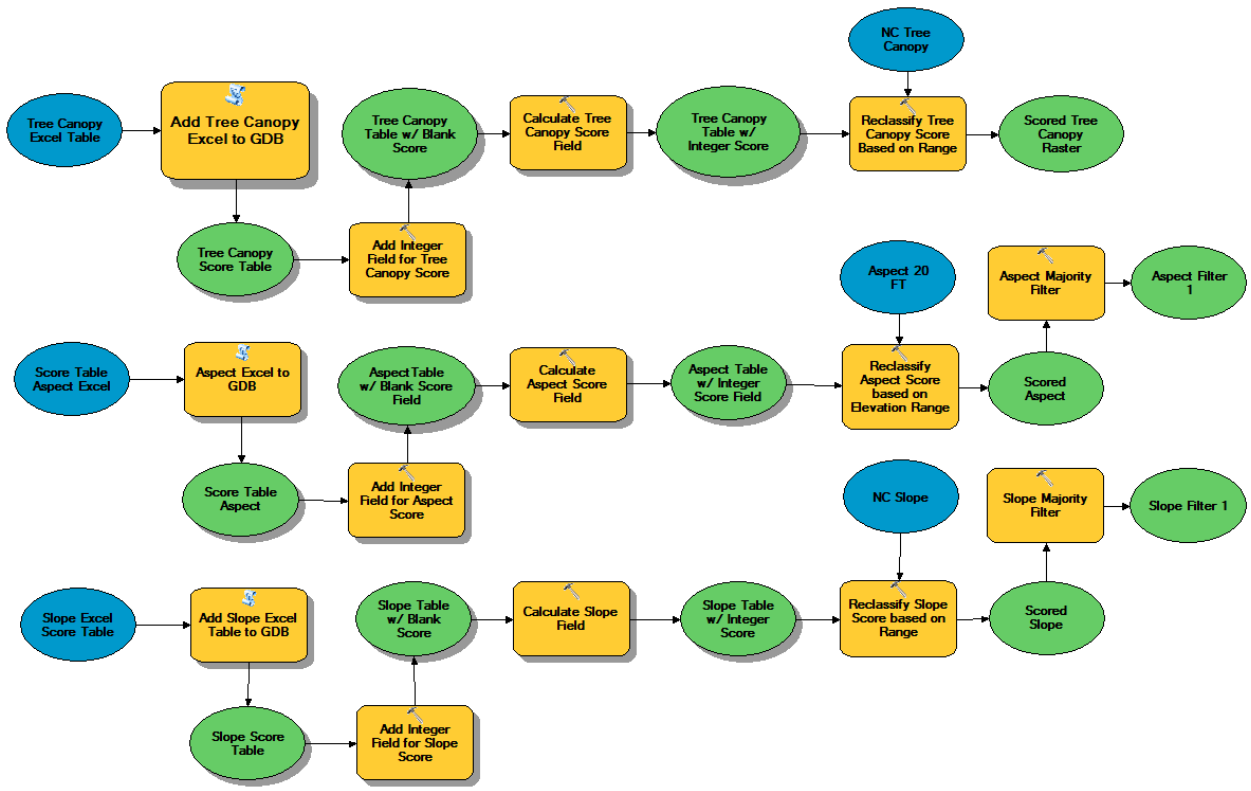

Figure 5 – The data processing model to prepare individual datasets to be used in the Cost-Weighted Overlay (continued from the previous figure).

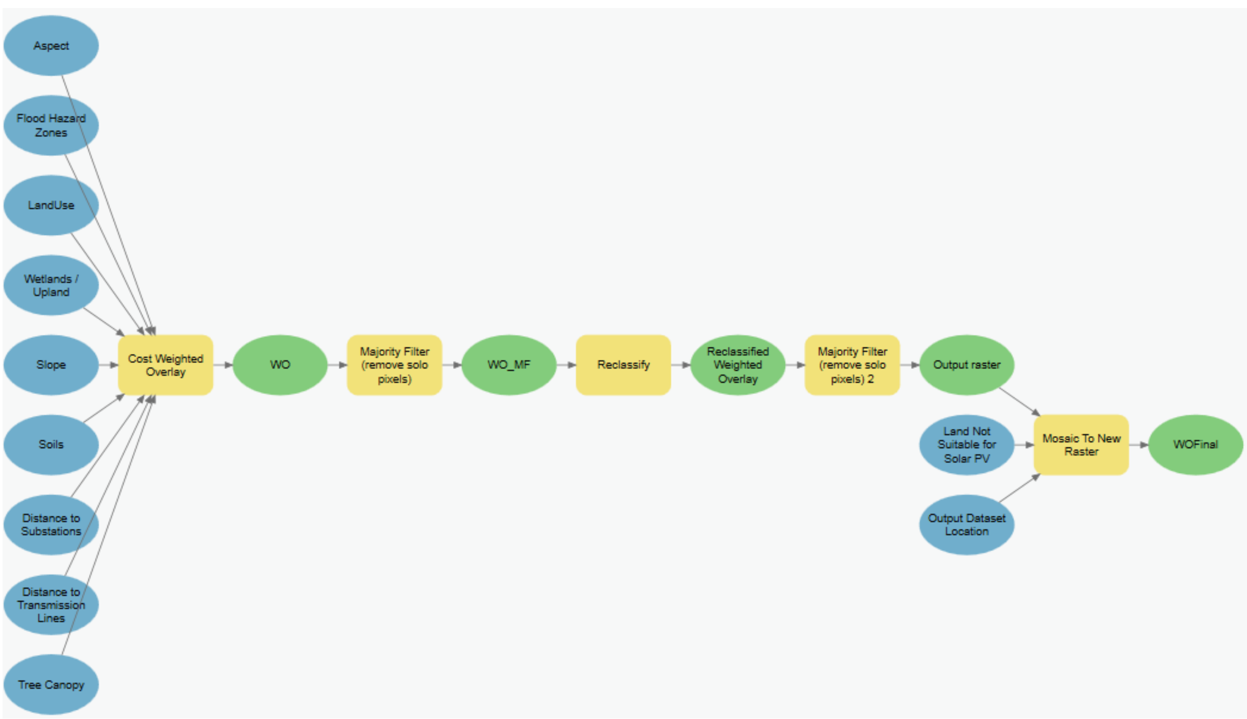

Figure 5 - The processed datasets from the model in Figure 4 are used in the cost-weighted overlay. The majority filter tool is used to remove single pixels or "clean-up" the raster dataset. The weighted overlay is reclassified, then unsuitable land is removed

All datasets are publicly available for download except for transmission lines and substation locations. Table 1 shows each layer used in the cost-weighted overlay, the source of each dataset, the overall dataset's weight, and the suitability value of each sub-type. The resulting cost-weighted overlay dataset was reclassified to assign the most suitable land a value of '100' and the least suitable received a value of '1.' Each dataset is described in detail in the "Cost-weighted Overlay Analysis Datasets" section.

Layer	Weight	Type	Value
National Land	**19%**		
Cover Dataset		Barren Land	100
Source:		Cultivated Crops	70
USGS MRLC		Deciduous Forest	20
		Developed, High Intensity	1
		Developed, Low Intensity	1
		Developed, Medium Intensity	1
		Developed, Open Space	1
		Emergent Herbaceous Wetlands	5
		Evergreen Forest	10
		Hay/Pasture	80
		Herbaceous	10
		Mixed Forest	10
		Open Water	1
		Shrub/Scrub	25
		Unconsolidated Shore	1
		Woody Wetlands	5
Wetlands	**11%**		
Source:		Estuarine and Marine Deepwater	1
US Fish &		Estuarine and Marine Wetland	1
Wildlife Service		Freshwater Emergent Wetland	1
		Freshwater Forested/Shrub Wetland	1
		Freshwater Pond	1
		Lake	1
		Other	1
		Riverine	1
		Upland	100
Tree Canopy	**8%**		
Source:		0	100
USGS MRLC		1-15	75
NLCD		16-50	50
		51-70	25
		71-256	1
Distance to	**7%**		
Substations		0.10 miles away or less	100
Source:		0.11 - 0.25 miles away	75
Platts Map Data Pro		0.26 - 0.50 miles away	50

Layer	Weight	Type	Value
Distance to	**15%**		
Transmission Lines		0.10 miles away or less	100
Source:		0.11 - 0.25 miles away	75
Platts Map Data Pro		0.26 - 0.50 miles away	50
Slope	**15%**		
Source:		0-10%	100
SC DNR/NC OneMap		10% or greater	1
Flood Zones	**11%**		
Source:		A	1
FEMA		AE	1
National Flood		AH	1
Hazard Layer		AO	1
		AREA NOT INCLUDED	75
		D	75
		OPEN WATER	1
		VE	1
		X	100
		Shaded X	75
Aspect	**11%**		
Source:		0-18	1
SC DNR/NC OneMap		19-54	9
		55-90	34
		91-126	65
		127-162	90
		163-198	100
		199-234	90
		235-270	65
		271-306	34
		307-342	9
		343-360	1
Hydrologic	**3%**		
Soils Group		A	100
Source:		A/D	75
USDA NRCS		B	75
gSSURGO		B/D	50
		C	50
		D	25
		Water	1

Table 1: Table of datasets used in the Cost-weighted Overlay. Layer weights are assigned based on importance to site suitability. Each layer type receives its weighted value. A value of '0' means not at all suitable and a value of '100' is ideal.

Some land types are not suitable for solar farm development in most circumstances. This land was removed from consideration in the analysis. A raster 'erase' dataset was created with all areas set to a value of '1'. Airports, open water, flood hazard zones, developed areas, protected areas, parks, and parcels less than 2 acres were all removed. This was performed by using the 'Mosaic to New Raster' tool in ArcGIS to build a complete 'erase' raster dataset. The 'Mosaic to New Raster' tool was used again to overlay the '1' cells on top of the cost-weighted overlay raster dataset to provide the final solar PV farm suitability dataset. Table 2 lists all datasets used to remove land from consideration.

Data Type	**Source**
Protected Areas	IUCN, World Database on Protected Areas
Flood Hazard Zones	FEMA, National Flood Hazard Layer
Open Water/Hydrologic Features	USGS, National Hydrography Dataset
Developed Areas	USGS, National Land Cover Dataset
Local, State, Federal Parks	ESRI
Airport Boundaries	ESRI
Parcels Less Than 2 Acres with 80 Ft Buffer	CoreLogic

Table 2 -These datasets were used to build the 'erase' layer. Features replaced values in the cost weighed overlay with a value of '1.'

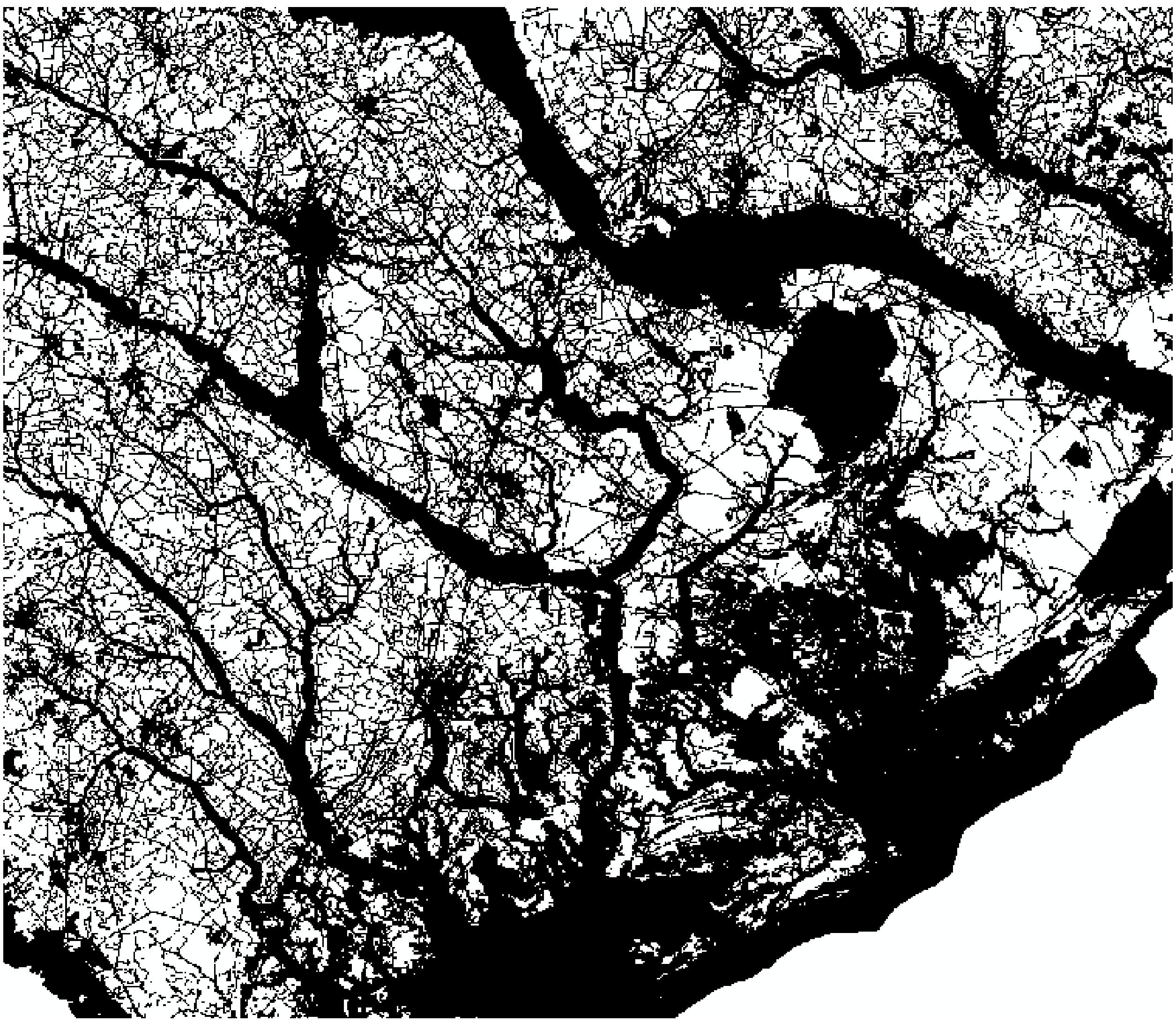

Figure 6 - Zooming in to examine the final 'erase' layer, which resets all suitability values to a score of '1'. At this regional scale, water bodies, floodplains, road networks, and developed areas are noticeable (shown here in black).

The resulting suitability raster grid contained values from 1 to 100 to indicate suitability. Individual grid values were reclassified into suitability categories. The values and classifications are shown in Table 3. The reclassified raster grid was converted to a polygon feature class using the "Raster to Feature" tool in ArcGIS. By converting the dataset to a polygon feature class, this allows acreages to be calculated for each category. The polygon dataset can also be intersected with other datasets, including county boundaries and property parcels.

The "Spatial Join" tool was run on each the polygon dataset to join each suitability polygon to the county boundaries. Then, the dataset was "Dissolved" by the County and Suitability. These steps created a dataset with three polygons for each County, one for Potentially Suitable, Suitable, and Very Suitable land. This table was exported to an Excel spreadsheet to create the statistics for each state shown in the 'Results' section.

Value	Reclassified	Suitability
0-65	65	Not Suitable
66-75	75	Potentially Suitable
76-85	85	Suitable
86-100	100	Very Suitable

Table 3 – The cost-weighted overlay solar suitability dataset was reclassified into four categories shown above.

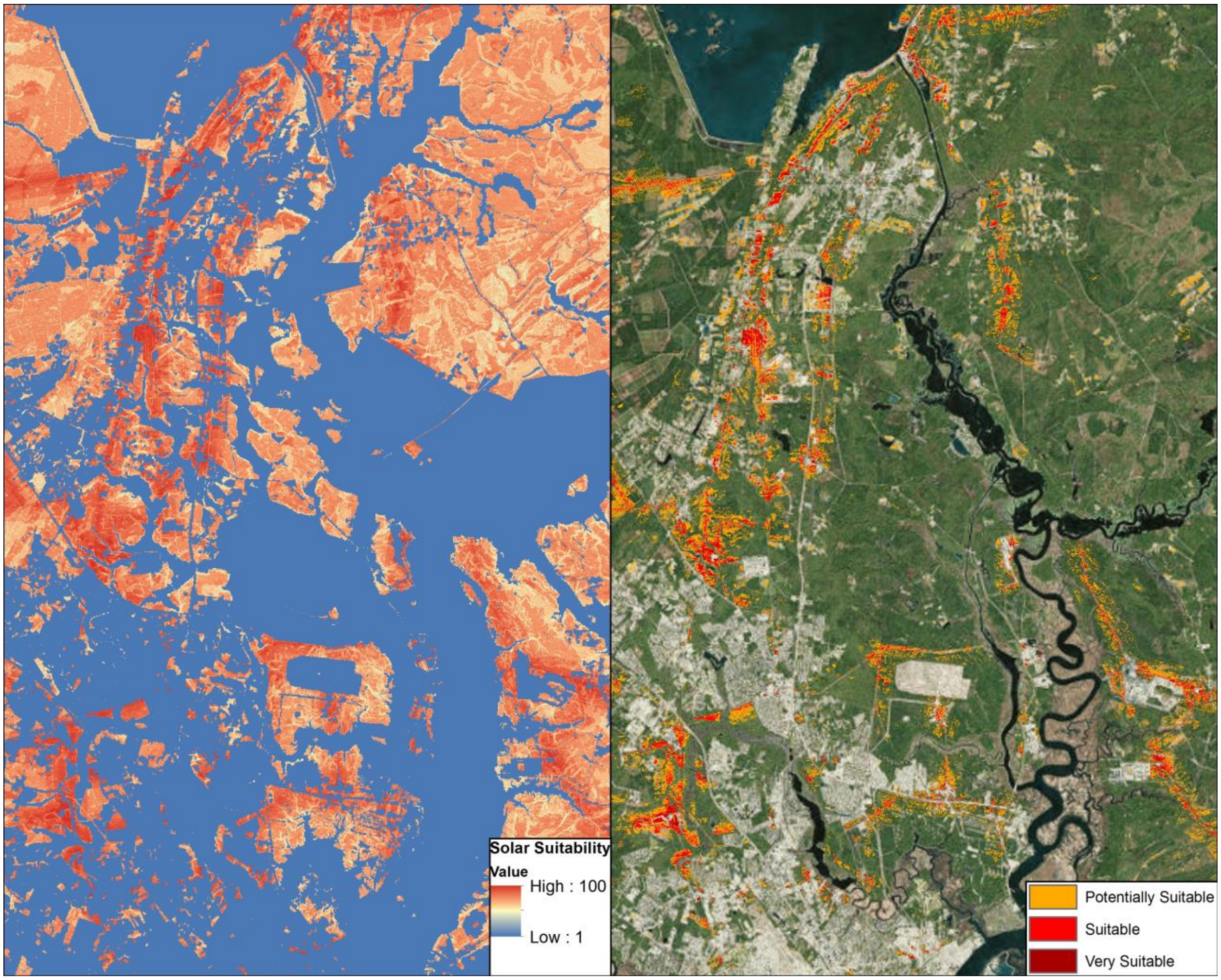

Figure 7 - The final output cost-weighted overlay dataset after unsuitable land has been "erased" with the Mosaic to New Raster tool. The dataset is scored with the most suitable for solar development at a '100' and the least suitable at a '1' (left). These values were reclassified according to the values shown in Table 3 (right).

Cost-weighted Overlay Analysis Datasets

Land Use/Land Cover

The National Land Cover Dataset, derived from LANDSAT satellite imagery, is the definitive land cover dataset for the continental United States. This 30-meter pixel resolution dataset is excellent for analyzing data at regional scales. Each 30x30 meter cell is given a land classification. For example, if the land has been developed for a residential neighborhood, a dense urban center, or an industrial facility, it will be classified as developed. Rivers, ponds, lakes, and oceans will be classified as open water. Different land types have different spectral signatures allowing them to be classified by a mix of algorithms and manual analysis and review. Each land classification type and reclassified value can be seen in Table 1. These values were derived from Koriatov et al., 2013 and Farthing et al. 2016. However, upon reviewing initial model output results, developed areas were reduced to '1' and were removed from development consideration. Land use is very important for potential development. Open water, developed areas, and wetlands are scored lowest to avoid these areas for development. The publicly available NLCD can be downloaded at www.mrlc.gov. This dataset received the highest weighting at 19%.

Tree Canopy

Tree canopy percentage is a dataset derived from the National Land Cover Dataset. This dataset shows which land areas are covered by forest to which areas have been cleared. Density is estimated from Landsat imagery (Huang, Yang, Wylie, Homer, & Itss, 2011). While clearing land to build new solar farms is common, there a cost associated with removing trees. Heavy tree cover should not cause a developer to walk away from a property, but cleared land is preferable. The publicly available tree canopy percentage dataset can be downloaded at www.mrlc.gov. Since cleared land is not essential to development, this dataset was weighted lower at 8%.

Wetlands

The US Fish & Wildlife Service built, maintains, and actively updates the National Wetlands Inventory, the definitive dataset for wetlands throughout the United States. Wetlands provide habitat for plants and wildlife, recharge groundwater, reduce flooding, offer food, and support cultural and recreational activities ("National Wetlands Inventory," 2019). The NWI dataset provides an excellent reference for understanding the approximate extent and type of wetland at a 1:12,000 scale (Dahl, Dick, Swords, & Wilen, 2015). The dataset is not suitable for legal wetland delineation but is sufficient for conveying a general understanding of where wetlands are located. Building in wetland areas involves additional cost and requires going through lengthy permitting hurdles. Avoiding wetland areas provides benefit to the environment and faster project completion time. The publicly available National Wetlands Inventory dataset can be downloaded at www.fws.gov/wetlands. This important dataset was weighted at 11%.

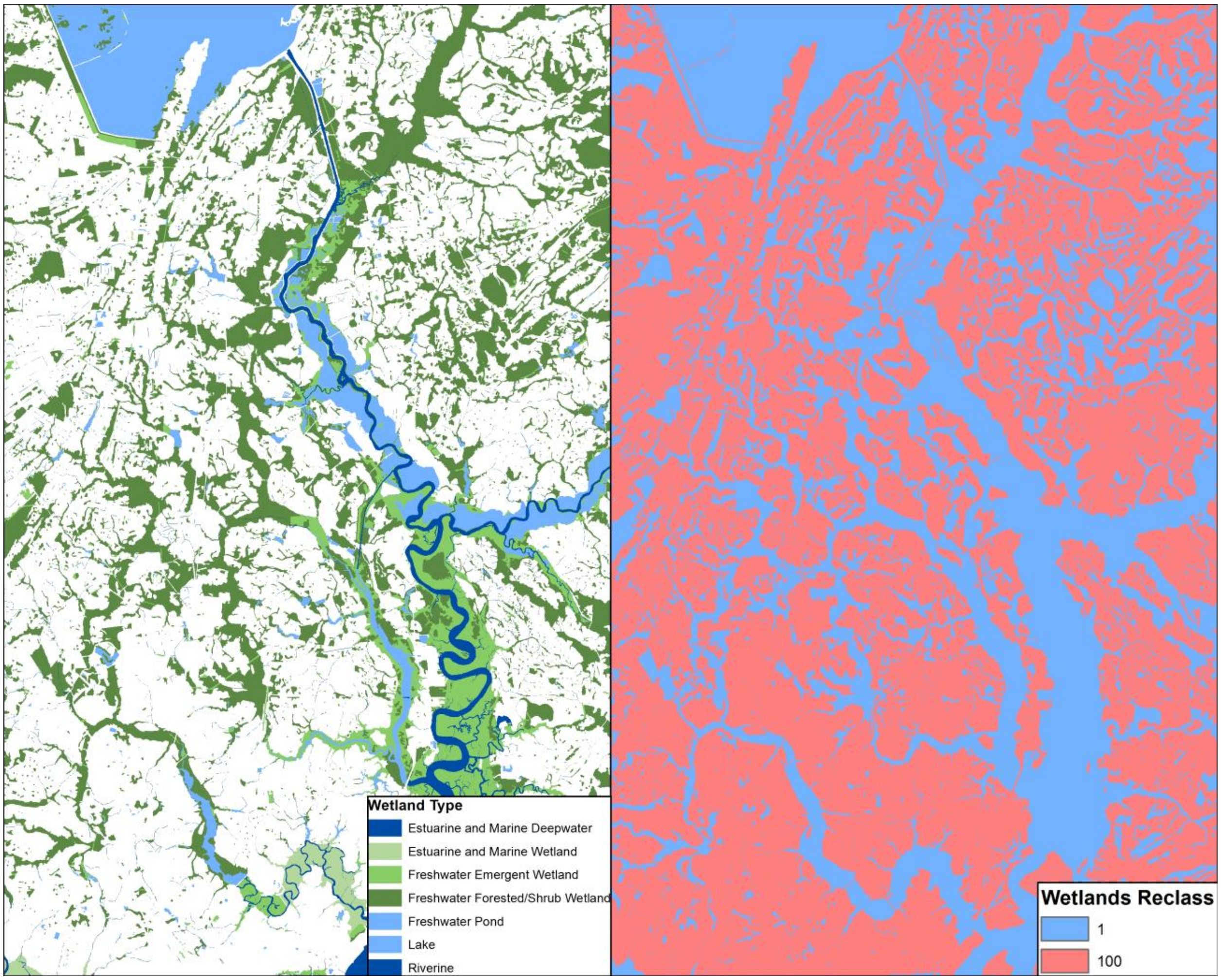

Figure 8 - NWI in its original vector format on the left, and the same dataset shown after the reclassification on the right

Soils

The USDA Natural Resources Conservation Service gSSURGO (Gridded Soils Survey Geographic) dataset is the federal government's soils inventory for the United States. This is the premier resource for understanding soil types throughout the country. Soils are classified into hydrologic soils group based on water runoff potential. 'A' soil types absorb and retain water best, while 'D' soils produce the highest amounts of runoff. Sites with higher runoff must account for this drainage while designing the project. The publicly available gSSURGO dataset can be downloaded at www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/. Poor soils will not eliminate a site from consideration; thus, this dataset receives a low weight of 3%.

Slope & Aspect

A unique component of this study was the use of high-resolution LiDAR-Derived topography for all study areas. North Carolina and South Carolina both have statewide LiDAR data coverage. Dates of LiDAR flights vary and are generally flown county-by-county or groups of counties. Dates range from 2007 to 2017.

NC OneMap maintains the State of North Carolina's impressive inventory of geospatial data. The State provides 20-foot pixel resolution bare-earth Digital Elevation Models available for download. These Digital Elevation Models give a representation of the topography of the State. Using the Spatial Analyst 'Slope' tool in ArcGIS, a slope dataset was created for each countywide DEM. ArcGIS' 'Mosaic to New Raster' tool was used to combine each countywide slope dataset into a Statewide slope dataset with a 20-foot pixel resolution. Using the 'Reclassify' tool any slope with a value of less than 10% was assigned a value of 100 and slope greater than 10% were assigned a value of 1.

In South Carolina, Digital Elevation Models with a 10-foot pixel resolution were acquired from SC DNR. This 10-foot pixel resolution slope dataset was resampled to a 20-foot pixel resolution dataset to maintain consistent with the North Carolina datasets. The same process was used to create the South Carolina slope datasets.

The slope of land is an important consideration for siting solar farms. Generally flat or slightly sloped surfaces are ideal for solar PV development. Through working with solar developers, sites with 10% or less are suitable for solar farm development. This layer received a weight of 15%.

Just as the slope datasets were created from high-resolution DEMs, so were aspect datasets. Aspect depicts the direction of the slope of the topography. In the northern hemisphere, southern facing slopes are ideal for solar PV development due to the sun most often being in the southern sky. Northern facing slopes do not receive direct sunlight and are not suitable for solar farms. Farthing et al. (2016) modeled aspect values with a horizontally shifted cosine curve to place aspects of 180 degrees at the highest point on the curve, then normalized and scaled to range from 0 to 100. Farthing et al.'s (2016) values were applied to the aspect reclassification used in this analysis, shown in Table 1. The aspect layer was assigned a weight of 11%.

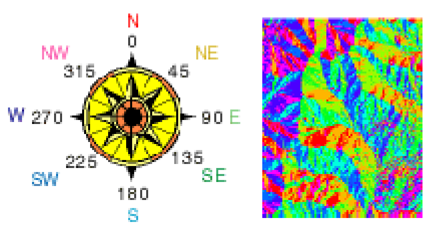

Figure 9 - Image depicting the numerical aspect values related to their compass orientation (ESRI, 2019)

Performing the slope and aspect analyses on high-resolution Digital Elevation Models and resampling the datasets to a lower-resolution, larger cell size maintains a more accurate dataset than running the same analyses on a low-resolution DEM (Hodgson, 1995).

Flood Hazard Zones

With the National Flood Hazard Layer, FEMA provides boundaries for flood hazard zones. These areas have the potential to flood and are generally avoided for solar PV development. Land in flood zones was eliminated for consideration in the analysis while land outside the flood zone, or Zone X, received a score of 100. This layer was weighted at 11%.

Transmission Lines & Substations

An essential consideration for utility-scale solar PV is the proximity to existing transmission lines. The further piece of land is from existing electrical infrastructure, the higher the development costs and the less suitable a property will be for utility-scale solar farms. Lines with voltage less than 115kv were removed from consideration. Lines with unknown voltage were kept in the analysis. If a line with unknown voltage in the data ends up being less than 115kv, this will lead to a suitability score that is higher in the analysis than it should be. Buffers of $1/10^{th}$ of a mile, $1/4^{th}$ of a mile, and ½ of a mile were created along transmission lines. This buffered layer was weighted at 15% of the weighted overlay analysis.

Depending on line capacity and the planned size of a solar farm, being near an existing substation may be beneficial. The importance of being close to substations is dependent on a developer's objectives and plans for a specific project. Due to this uncertainty, distance to substations received a lower weight of 7%.

Transmission lines and substation location data were acquired from Platts Map Data Pro.

Land Removed from Analysis

Protected Areas

The World Database on Protected Areas provides a geographic boundary for all areas that are not available for development. The dataset covers a variety of maritime and forested lands designated for conservation. Any land within these conservation boundaries was determined to be unsuitable for development.

Flood Hazard Zones

Areas of significant flood risk are not suitable for solar PV development for this analysis. Using FEMA's National Flood Hazard Layer, any geographic boundaries in an 'A' or 'V' flood zone were determined to be unsuitable for development.

Open Water/Hydrologic Features

The USGS National Hydrography Dataset is a comprehensive geospatial database of all significant water features in the United States. Any river, lake, pond, or hydrologic feature in the database was considered unsuitable for development.

Developed Areas

Using the National Land Cover Dataset, any area that has previously been developed has been removed from consideration. Many commercial and industrial rooftops, or even abandoned or vacant developed properties can be used to generate solar electricity. Removing these areas does not indicate that it is not feasible to install solar PV in developed areas. Due to a significant amount of false positive results in urban areas, these developed areas were eliminated. This is an area for future improvement with the data model.

Airport Boundaries

All airport boundaries are considered unsuitable for development.

Parks Boundaries

All Federal, State, and Local parks are considered unsuitable for development.

Parcels Less Than 2 Acres with 80 ft buffer

Properties under 2 acres are likely not worth the cost of pursuing for solar development. By eliminating these small parcels, this also removes many residential lots that are not suited for solar development.

Results

The multi-criteria decision-making technique utilizing the analytical hierarchy process was successfully implemented during the study. Over 626,000 acres were determined to be suitable for solar PV development in North and South Carolina. The resulting suitability dataset is shown in Figure 7.

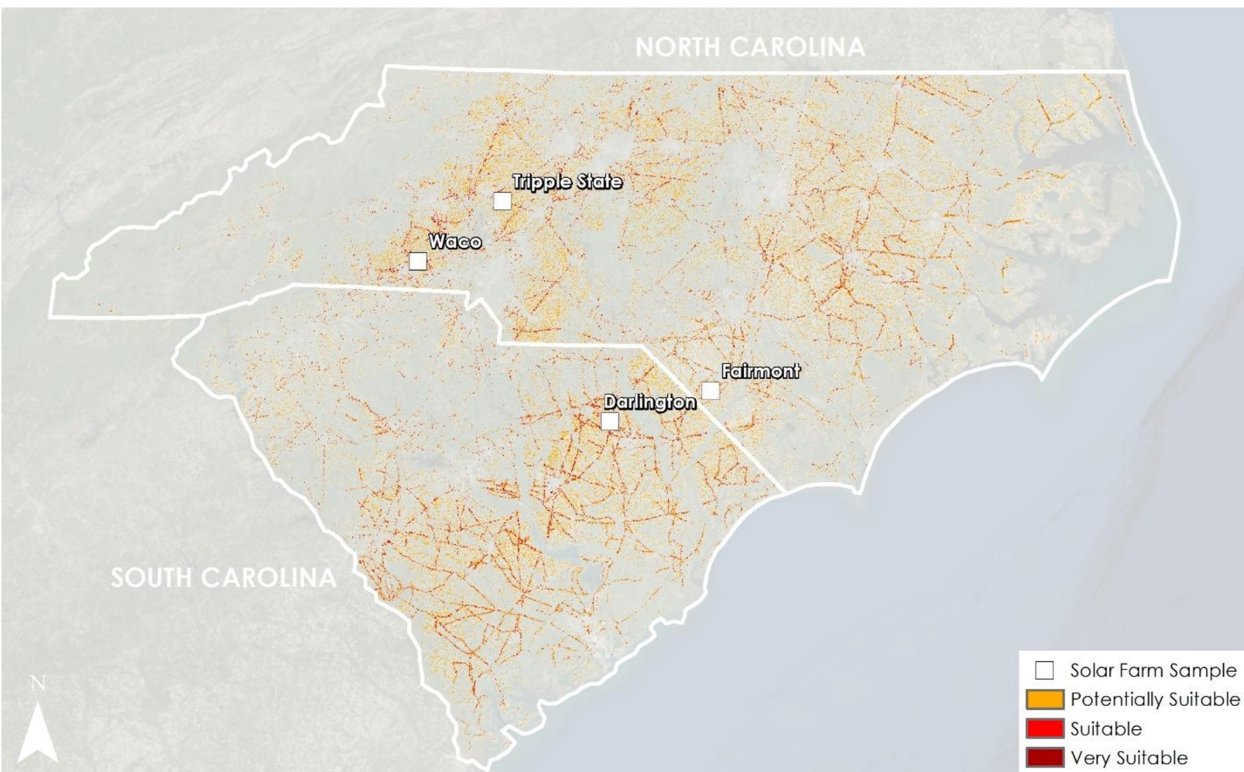

Figure 10 – This exhibit details the extent of the study area, North & South Carolina. Feasible land for solar PV development is symbolized by the level of suitability. The solar farms shown on the map are shown in mor detail in Figure 12.

Suitability by County

The results of the geoprocessing model indicate South Carolina has over 1.6 million acres of land that is potentially suitable for solar PV development, 295,579 acres that are suitable for solar PV development, and 49,792 acres that are very suitable for development. This is 8.21%, 1.74%, and 0.25% of the total area of the State respectively. While rankings for the County with the highest suitability vary on the field that is being queried, counties with large acreages and percentages of land that may be suitable for solar development are Darlington, Florence Aiken, Orangeburg, and Horry. The full tabular dataset is displayed in Table 4.

County	Potentially Suitable (AC)	Suitable (AC)	Very Suitable (AC)	County (AC)	Score Greater Than 65 (AC)	Score Greater Than 75 (AC)	Score Greater Than 85 (AC)	Score Greater Than 65 (%)	Score Greater Than 75 (%)	Score Greater Than 85 (%)
Abbeville	12,195	2,152	340	327,019	14,687	2,492	340	4.49%	0.76%	0.10%
Aiken	62,672	18,165	3,701	691,265	84,538	21,866	3,701	12.23%	3.16%	0.54%
Allendale	28,354	5,942	921	263,818	35,217	6,863	921	13.35%	2.60%	0.35%
Anderson	21,360	3,960	986	484,656	26,306	4,946	986	5.43%	1.02%	0.20%
Bamberg	27,239	5,559	805	252,937	33,603	6,364	805	13.29%	2.52%	0.32%
Barnwell	38,218	7,794	968	356,672	46,980	8,762	968	13.17%	2.46%	0.27%
Beaufort	6,725	1,556	206	393,564	8,487	1,762	206	2.16%	0.45%	0.05%
Berkeley	34,418	8,913	759	785,835	44,090	9,672	759	5.61%	1.23%	0.10%
Calhoun	31,493	9,614	1,535	251,480	42,642	11,149	1,535	16.96%	4.43%	0.61%
Charleston	12,364	2,910	262	631,151	15,536	3,172	262	2.46%	0.50%	0.04%
Cherokee	7,552	1,452	407	254,239	9,411	1,859	407	3.70%	0.73%	0.16%
Chester	11,327	2,563	424	375,265	14,314	2,987	424	3.81%	0.80%	0.11%
Chesterfield	27,106	5,490	967	515,772	33,563	6,457	967	6.51%	1.25%	0.19%
Clarendon	53,329	11,159	1,802	445,092	66,290	12,961	1,802	14.89%	2.91%	0.40%
Colleton	42,797	10,262	1,161	687,958	54,220	11,423	1,161	7.88%	1.66%	0.17%
Darlington	59,512	20,559	3,548	362,632	83,619	24,107	3,548	23.06%	6.65%	0.98%
Dillon	33,786	4,559	696	259,985	39,041	5,255	696	15.02%	2.02%	0.27%
Dorchester	26,519	7,735	900	368,549	35,154	8,635	900	9.54%	2.34%	0.24%
Edgefield	13,017	2,385	447	324,057	15,849	2,832	447	4.89%	0.87%	0.14%
Fairfield	6,571	1,197	258	454,305	8,026	1,455	258	1.77%	0.32%	0.06%
Florence	58,577	14,622	2,879	513,920	76,078	17,501	2,879	14.80%	3.41%	0.56%
Georgetown	22,527	5,073	520	542,488	28,120	5,593	520	5.18%	1.03%	0.10%
Greenville	10,461	2,683	761	508,735	13,905	3,444	761	2.73%	0.68%	0.15%
Greenwood	10,847	2,435	581	295,855	13,863	3,016	581	4.69%	1.02%	0.20%
Hampton	34,529	5,766	730	360,025	41,025	6,496	730	11.40%	1.80%	0.20%
Horry	63,666	13,495	2,459	732,456	79,620	15,954	2,459	10.87%	2.18%	0.34%
Jasper	16,701	4,369	563	427,471	21,633	4,932	563	5.06%	1.15%	0.13%
Kershaw	28,165	6,624	1,343	473,721	36,132	7,967	1,343	7.63%	1.68%	0.28%
Lancaster	10,830	2,292	487	355,317	13,609	2,779	487	3.83%	0.78%	0.14%
Laurens	14,583	3,022	629	462,981	18,234	3,651	629	3.94%	0.79%	0.14%
Lee	45,130	7,344	1,294	263,240	53,768	8,638	1,294	20.43%	3.28%	0.49%
Lexington	31,367	6,638	1,221	484,383	39,226	7,859	1,221	8.10%	1.62%	0.25%
McCormick	4,307	839	134	252,011	5,280	973	134	2.10%	0.39%	0.05%
Marion	24,611	5,932	984	316,217	31,527	6,916	984	9.97%	2.19%	0.31%
Marlboro	37,246	4,232	754	310,651	42,232	4,986	754	13.59%	1.61%	0.24%
Newberry	17,991	6,425	1,255	414,348	25,671	7,680	1,255	6.20%	1.85%	0.30%
Oconee	4,897	488	136	431,185	5,521	624	136	1.28%	0.14%	0.03%
Orangeburg	93,541	20,344	3,364	721,800	117,249	23,708	3,364	16.24%	3.28%	0.47%
Pickens	5,238	953	241	327,617	6,432	1,194	241	1.96%	0.36%	0.07%
Richland	25,068	9,514	1,752	493,528	36,334	11,266	1,752	7.36%	2.28%	0.35%
Saluda	21,395	4,412	786	295,599	26,593	5,198	786	9.00%	1.76%	0.27%
Spartanburg	16,015	3,702	998	524,400	20,715	4,700	998	3.95%	0.90%	0.19%
Sumter	49,599	13,138	2,458	436,077	65,195	15,596	2,458	14.95%	3.58%	0.56%
Union	6,104	1,337	260	330,368	7,701	1,597	260	2.33%	0.48%	0.08%
Williamsburg	54,954	12,116	1,259	599,660	68,329	13,375	1,259	11.39%	2.23%	0.21%
York	15,974	3,858	851	445,207	20,683	4,709	851	4.65%	1.06%	0.19%

South Carolina	1,280,877	295,579	49,792	19,805,511	1,626,248	345,371	49,792	8.21%	1.74%	0.25%

Table 4 - Breakdown of the acreages of solar suitability by County in South Carolina. Potentially Suitable values range from 66-75, Suitable from 76-85, Very Suitable from 86-100.

The results of the geoprocessing model indicate North Carolina has over 2.2 million acres of land that is potentially suitable for solar PV development, 331,935 acres that are suitable for solar PV development, and 37,263 acres that are very suitable for development. This is 8.18%, 1.17%, and 0.12% of the total area of the State respectively. These percentages are very similar to South Carolina's. While rankings for the County with the highest suitability vary on the field that is being queried, counties with large acreages and percentages of suitable land are Cleveland, Catawba, Wayne, Duplin, and Davidson. The full tabular dataset is displayed in Table 5.

County	**Potentially Suitable (AC)**	**Suitable (AC)**	**Very Suitable (AC)**	**County (AC)**	**Score Greater Than 65 (AC)**	**Score Greater Than 75 (AC)**	**Score Greater Than 85 (AC)**	**Score Greater Than 65 (%)**	**Score Greater Than 75 (%)**	**Score Greater Than 85 (%)**
Alamance	35,440	5,505	478	278,401	41,423	5,983	478	14.88%	2.15%	0.17%
Alexander	18,448	1,205	169	168,328	19,822	1,374	169	11.78%	0.82%	0.10%
Alleghany	5,436	226	34	150,732	5,696	260	34	3.78%	0.17%	0.02%
Anson	24,951	2,777	342	343,798	28,070	3,119	342	8.16%	0.91%	0.10%
Ashe	3,947	273	50	273,357	4,270	323	50	1.56%	0.12%	0.02%
Avery	0	0	0	158,247	0	0	0	0.00%	0.00%	0.00%
Beaufort	30,846	3,499	266	546,666	34,611	3,765	266	6.33%	0.69%	0.05%
Bertie	22,608	1,590	157	453,075	24,355	1,747	157	5.38%	0.39%	0.03%
Bladen	35,024	6,679	590	567,703	42,293	7,269	590	7.45%	1.28%	0.10%
Brunswick	14,414	2,260	254	553,159	16,928	2,514	254	3.06%	0.45%	0.05%
Buncombe	8,338	1,254	122	422,328	9,714	1,376	122	2.30%	0.33%	0.03%
Burke	6,524	2,058	224	328,849	8,806	2,282	224	2.68%	0.69%	0.07%
Cabarrus	23,947	2,965	380	233,456	27,292	3,345	380	11.69%	1.43%	0.16%
Caldwell	7,776	1,088	143	304,173	9,007	1,231	143	2.96%	0.40%	0.05%
Camden	7,784	219	4	154,649	8,007	223	4	5.18%	0.14%	0.00%
Carteret	4,950	492	46	323,528	5,488	538	46	1.70%	0.17%	0.01%
Caswell	20,128	2,007	178	274,244	22,313	2,185	178	8.14%	0.80%	0.06%
Catawba	33,326	8,661	1,369	264,790	43,356	10,030	1,369	16.37%	3.79%	0.52%
Chatham	35,817	3,265	294	453,631	39,376	3,559	294	8.68%	0.78%	0.06%
Cherokee	414	101	8	298,552	523	109	8	0.18%	0.04%	0.00%
Chowan	9,961	306	19	111,368	10,286	325	19	9.24%	0.29%	0.02%
Clay	1,131	150	42	141,093	1,323	192	42	0.94%	0.14%	0.03%
Cleveland	45,753	12,057	1,644	299,832	59,454	13,701	1,644	19.83%	4.57%	0.55%
Columbus	41,255	5,270	420	610,337	46,945	5,690	420	7.69%	0.93%	0.07%
Craven	17,941	2,121	166	465,313	20,228	2,287	166	4.35%	0.49%	0.04%
Cumberland	25,189	5,685	445	421,371	31,319	6,130	445	7.43%	1.45%	0.11%
Currituck	11,714	2,531	252	165,350	14,497	2,783	252	8.77%	1.68%	0.15%
Dare	120	39	7	241,929	166	46	7	0.07%	0.02%	0.00%
Davidson	35,412	9,896	1,420	362,786	46,728	11,316	1,420	12.88%	3.12%	0.39%
Davie	26,291	2,959	374	170,660	29,624	3,333	374	17.36%	1.95%	0.22%
Duplin	63,946	9,293	1,041	523,923	74,280	10,334	1,041	14.18%	1.97%	0.20%
Durham	5,635	631	56	190,668	6,322	687	56	3.32%	0.36%	0.03%
Edgecombe	33,529	1,742	195	324,023	35,466	1,937	195	10.95%	0.60%	0.06%

Forsyth	14,288	3,093	431	264,296	17,812	3,524	431	6.74%	1.33%	0.16%
Franklin	37,210	5,272	433	316,479	42,915	5,705	433	13.56%	1.80%	0.14%
Gaston	18,505	4,872	859	232,650	24,236	5,731	859	10.42%	2.46%	0.37%
Gates	10,888	850	62	220,214	11,800	912	62	5.36%	0.41%	0.03%
Graham	0	0	0	192,978	0	0	0	0.00%	0.00%	0.00%
Granville	28,512	3,236	269	343,505	32,017	3,505	269	9.32%	1.02%	0.08%
Greene	26,582	4,336	444	169,951	31,362	4,780	444	18.45%	2.81%	0.26%
Guilford	42,391	7,093	878	420,928	50,362	7,971	878	11.96%	1.89%	0.21%
Halifax	41,553	3,870	311	468,375	45,734	4,181	311	9.76%	0.89%	0.07%
Harnett	37,342	7,390	826	384,787	45,558	8,216	826	11.84%	2.14%	0.21%
Haywood	3,636	490	66	354,886	4,192	556	66	1.18%	0.16%	0.02%
Henderson	8,566	1,053	145	239,845	9,764	1,198	145	4.07%	0.50%	0.06%
Hertford	16,113	2,110	187	228,673	18,410	2,297	187	8.05%	1.00%	0.08%
Hoke	21,333	5,357	360	251,032	27,050	5,717	360	10.78%	2.28%	0.14%
Hyde	3,241	2	0	442,796	0	0	0	0.00%	0.00%	0.00%
Iredell	57,685	10,267	1,318	382,066	69,270	11,585	1,318	18.13%	3.03%	0.34%
Jackson	384	121	14	316,388	519	135	14	0.16%	0.04%	0.00%
Johnston	69,032	9,208	1,014	509,072	79,254	10,222	1,014	15.57%	2.01%	0.20%
Jones	13,285	1,313	94	302,739	14,692	1,407	94	4.85%	0.46%	0.03%
Lee	11,430	1,558	109	165,918	13,097	1,667	109	7.89%	1.00%	0.07%
Lenoir	31,671	5,462	601	257,732	37,734	6,063	601	14.64%	2.35%	0.23%
Lincoln	29,312	5,974	824	196,275	36,110	6,798	824	18.40%	3.46%	0.42%
Macon	0	0	0	332,545	0	0	0	0.00%	0.00%	0.00%
Madison	2,470	269	43	288,943	2,782	312	43	0.96%	0.11%	0.01%
Martin	25,170	3,363	395	295,145	28,928	3,758	395	9.80%	1.27%	0.13%
McDowell	3,707	605	91	285,919	4,403	696	91	1.54%	0.24%	0.03%
Mecklenburg	8,447	2,053	358	349,453	10,858	2,411	358	3.11%	0.69%	0.10%
Mitchell	0	0	0	142,174	0	0	0	0.00%	0.00%	0.00%
Montgomery	7,839	1,146	102	320,803	9,087	1,248	102	2.83%	0.39%	0.03%
Moore	23,212	1,633	205	451,424	25,050	1,838	205	5.55%	0.41%	0.05%
Nash	44,359	4,927	562	347,073	49,848	5,489	562	14.36%	1.58%	0.16%
New Hanover	2,662	641	187	132,226	3,490	828	187	2.64%	0.63%	0.14%
Northampton	33,733	5,371	476	352,208	39,580	5,847	476	11.24%	1.66%	0.14%
Onslow	23,809	4,945	514	488,055	29,268	5,459	514	6.00%	1.12%	0.11%
Orange	25,632	3,314	306	256,677	29,252	3,620	306	11.40%	1.41%	0.12%
Pamlico	5,083	356	22	222,057	5,461	378	22	2.46%	0.17%	0.01%
Pasquotank	12,838	395	21	146,604	13,254	416	21	9.04%	0.28%	0.01%
Pender	18,713	2,495	215	557,051	21,423	2,710	215	3.85%	0.49%	0.04%
Perquimans	15,892	1,458	113	159,834	17,463	1,571	113	10.93%	0.98%	0.07%
Person	26,634	6,089	568	258,639	33,291	6,657	568	12.87%	2.57%	0.22%
Pitt	42,913	5,274	381	418,919	48,568	5,655	381	11.59%	1.35%	0.09%
Polk	6,622	364	42	152,715	7,028	406	42	4.60%	0.27%	0.03%
Randolph	50,392	8,619	875	505,667	59,886	9,494	875	11.84%	1.88%	0.17%
Richmond	14,521	2,635	306	306,857	17,462	2,941	306	5.69%	0.96%	0.10%
Robeson	66,370	11,764	1,066	608,558	79,200	12,830	1,066	13.01%	2.11%	0.18%
Rockingham	35,366	6,536	758	366,370	42,660	7,294	758	11.64%	1.99%	0.21%
Rowan	48,072	7,727	795	335,274	56,594	8,522	795	16.88%	2.54%	0.24%
Rutherford	20,231	3,388	575	361,993	24,194	3,963	575	6.68%	1.09%	0.16%
Sampson	69,315	7,644	872	606,191	77,831	8,516	872	12.84%	1.40%	0.14%
Scotland	16,824	3,705	284	205,177	20,813	3,989	284	10.14%	1.94%	0.14%
Stanly	36,691	4,051	596	258,728	41,338	4,647	596	15.98%	1.80%	0.23%

Stokes	16,798	1,657	297	291,787	18,752	1,954	297	6.43%	0.67%	0.10%
Surry	29,126	2,936	515	344,247	32,577	3,451	515	9.46%	1.00%	0.15%
Swain	260	35	5	345,868	300	40	5	0.09%	0.01%	0.00%
Transylvania	1,313	440	103	243,516	1,856	543	103	0.76%	0.22%	0.04%
Tyrrell	4,135	136	0	255,285	0	0	0	0.00%	0.00%	0.00%
Union	71,473	9,166	1,025	409,127	81,664	10,191	1,025	19.96%	2.49%	0.25%
Vance	13,209	1,251	132	172,707	14,592	1,383	132	8.45%	0.80%	0.08%
Wake	30,996	7,159	744	548,474	38,899	7,903	744	7.09%	1.44%	0.14%
Warren	18,752	1,879	215	284,077	20,846	2,094	215	7.34%	0.74%	0.08%
Washington	19,188	1,461	99	241,519	20,748	1,560	99	8.59%	0.65%	0.04%
Watauga	1,871	262	40	199,973	2,173	302	40	1.09%	0.15%	0.02%
Wayne	52,733	13,154	1,627	356,130	67,514	14,781	1,627	18.96%	4.15%	0.46%
Wilkes	24,841	1,397	184	486,187	26,422	1,581	184	5.43%	0.33%	0.04%
Wilson	32,685	4,534	586	240,031	37,805	5,120	586	15.75%	2.13%	0.24%
Yadkin	35,764	3,970	529	215,999	40,263	4,499	529	18.64%	2.08%	0.24%
Yancey	1	0	0	200,366	0	0	0	0.00%	0.00%	0.00%
North Carolina	2,221,616	331,935	37,263	31,590,476	2,583,299	369,060	37,263	8.18%	1.17%	0.12%

Table 5 - Breakdown of the acreages of solar suitability by County in North Carolina. Potentially Suitable values range from 66-75, Suitable from 76-85, Very Suitable from 86-100.

Suitability by Landowner

Table 6 shows the twenty largest landowners in South Carolina with "Suitable" land for Solar PV development. Red Mountain Timber owns significantly more land suitable for solar PV development than any other landowner in South Carolina. Weyerhaeuser, also a timber company, owns the second most suitable land by a wide margin over McArthur Implement Company. It is interesting to note a large amount of solar suitable land owned by South Carolina Electric & Gas, the large utility that taken anti-solar policy positions in the State (Fretwell, 2018). SCE&G's high value is likely increased significantly by the heavy weighting of land close to transmission lines and substations in this model run.

Owner Name	Potentially Suitable (AC)	Suitable (AC)	Very Suitable (AC)
RED MOUNTAIN TIMBER	12,584	2,741	135
WEYERHAEUSER	7,553	1,705	137
MCARTHUR IMPLEMENT CO LLC	1,146	782	120
STATE OF SC	508	756	158
TIMBERLANDS III	3,441	740	46
USA	3,583	694	72
BAILEY MILL LLC	1,229	612	129
SC ELECTRIC & GAS	1,243	611	177
PANOLA ENTERPRISES	1,445	576	127
HEATH HILL HAROLD & HAROLD HEATH HILL	710	541	93
CLARENDON FARMS	1,541	506	65
CATCHMARK HBU	971	485	69
FLO FUND DOMESTIC LLC	1,068	438	136
CHILTON TIMBER & LAND	1,313	395	37
RAYONIER	1,856	383	8

GLOVER REAL ESTATE	675	377	53
FPI CAROLINAS LLC	656	362	125
SUSTAINABLE GROWTH LLC	1,543	354	19
HARVIN FAMILY LIMITED PARTNERS	463	352	64
C EDWARD FLOYD & KAY B FLOYD	864	346	72

Table 6 - The 20 landowners with the highest amount of "Suitable" land for solar PV development in South Carolina. Properties for all landowners were dissolved and solar suitability values for each property were combined into a total value.

Table 7 shows the twenty largest landowners in North Carolina with "Suitable" land for Solar PV development. Even after removing water bodies, parks, and protected areas, the State of North Carolina still owns the most solar PV suitable land in the State. Similar to South Carolina, the utilities Duke and Carolina Power & Light are shown as having large amounts of solar suitable land. A significant portion of land is owned by individuals. These may be excellent targets for solar developers to attempt to negotiate with.

Owner Name	Potentially Suitable (AC)	Suitable (AC)	Very Suitable (AC)
STATE OF NC	3,378	917	201
PCS PHOSPHATE CO	3,515	718	74
DUKE ENERGY	2,324	604	182
MARLOWE FARM	1,794	434	47
MARTIN MARIETTA MATERIALS	1,174	331	58
Z V PATE	1,753	314	34
CITY OF RALEIGH	380	282	31
WAGSTAFF FARMS	290	279	21
TULL HILL FARMS INC	544	278	42
TIMOTHY WILSON HERNDON	330	273	24
USA	1,456	221	37
CAROLINA POWER & LIGHT	652	216	125
WEYERHAEUSER	2,976	207	29
BURCH FARMS	984	204	12
LEE CARTRETTE MYRTLE	317	203	12
FRANKLIN W HOWEY	1,103	201	12
PELMON JART HUDSON	485	195	22
FRANK W HOWEY	376	193	24
LINDSAY WAGSTAFF & JOHN WAGSTAFF	147	190	35
COUNTY OF WAKE	809	188	36

Table 7 - The 20 landowners with the highest amount of "Suitable" land for solar PV development in North Carolina. Properties for all landowners were dissolved and solar suitability values for each property were combined into a total value.

Figure 12 shows a selection of four existing solar farms within the study area of North and South Carolina. The reclassified solar suitability layer shows values between 66-75 as "Potentially Suitable" in orange, 76-85 as "Suitable" in red, and 86-100 as "Very Suitable" in dark red. A quantitative analysis assessing the accuracy of the modeled suitability dataset was not performed, but a visual inspection of the dataset compared to existing solar farms indicated favorable results.

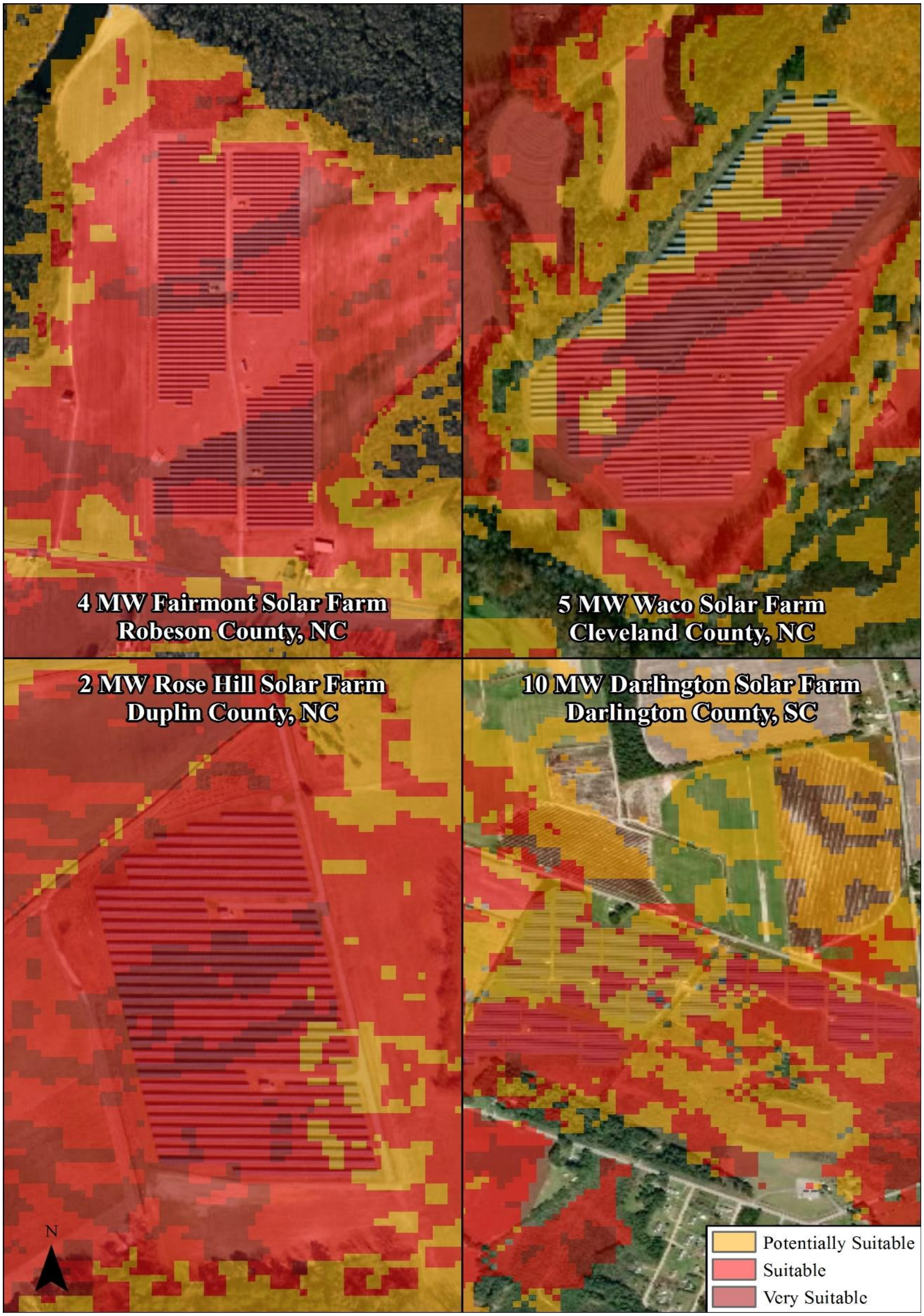

Figure 11 - Examples of existing solar farms in North Carolina and South Carolina with the suitability model results overlaid. The model results align well with the locations of completed solar projects.

Discussion

Viewing the results of this analysis as spreadsheets does not provide the same benefit as interacting with the data in a map-based format. The suitability dataset can be added to any GIS mapping application. By symbolizing the layer to make more suitable areas stand out, it will be immediately apparent to the user which parts of North and South Carolina are most suitable for PV development. The user will likely notice these areas are strongly tied to the location of transmission lines. The user can zoom in to the map to begin inspecting suitable land at the regional and parcel levels.

The solar suitability data has also been merged with property parcel data. This allows a user to view who owns land suitable for solar PV development and also how that land is broken up. Users can search to see how much land any entity owns, but also how much solar suitable land that entity owns. For example, if a user learns that the 'Carolina Lumber Company' is looking to sell their land holdings, that user can immediately search for land owned by 'Carolina Land Company.' The user will see every property owned by the entity highlighted on the map and also in a tabular format. Each property will show a breakdown of how much land is 'Potentially Suitable', 'Suitable', and 'Very Suitable'.

A user could also limit the query to a specific geographic area, either by selecting the name of a County or State or by drawing a geographic area on the map. This query would return every property with solar suitability, regardless of the suitability value. The user can also combine a geographically limited query with a specific suitability level. An example would be to only see properties in Berkeley County, SC with 40 acres or greater of "very suitable" solar PV land. The querying potential of the dataset is robust and can allow a user to be very specific to find the type of property that will best suit their needs.

Use Cases

The end goal for this dataset lies outside of this report. The solar suitability dataset will have real-world applications for a variety of users in the public and private sectors. This section will examine how users in four different fields may use this solar suitability data.

Commercial Real Estate Broker

Real estate brokers do the difficult due diligence work of buying and selling properties for property owners. Brokers will be able to use this solar farm suitability dataset in multiple scenarios.

When representing a seller, a broker will be able to pull-up their web-GIS platform, zoom to the property owned by the seller, and turn on the solar farm suitability layer. If the property is shown to have high suitability the broker will have potential avenues to pursue. He or she can reach out to parties that are interested in acquiring land to lease to solar farm developers. Or the broker can ask the seller if they would be interested in holding on to the property and leasing the land to a solar developer. Many solar developers prefer to lease properties instead of purchasing land due to the potential risk of projects falling apart before completion. If the landowner is interested in leasing their land, the broker can reach out to solar developers. The solar developers will begin their due diligence and begin putting together lease options to bring to the landowner.

When representing a buyer or solar developer, the broker will use the solar suitability dataset to find properties to pursue. Brokers are often able to secure better deals for their clients on properties before they go on the market. Just by turning on the suitability layer and viewing on a map, the broker will make quick work of his or her due diligence process. The broker could also run a quick query to search for properties with high solar suitability. The query will return a list of properties with the owner name, owner address, and sales and tax history. The broker will be able to reach out to the owner directly to see if they can potentially begin putting a deal together. The broker could also export a table of all landowners with high solar feasibility and create quick letters with mail merge to explore for potential leads on interested property owners.

This is a process that would take minutes by utilizing this solar suitability dataset in a GIS. Without this dataset, brokers have to review properties individually, often using several data sources. Each of the datasets used to build the suitability layer must be reviewed individually. If the broker does not want to review thousands of properties individually, which is not practical anyway, he may be dependent on his relationships with local landowners to come through. By not being able to proactively reach out to landowners he knows own suitable land for solar PV, he will have to hope an owner discovers this on their own and reaches out to the broker for assistance in tracking down a developer.

Land Manager

Land Managers are tasked with maintaining and running properties of various sizes often over large areas. Landowners vary from small family businesses owning properties that have been passed down for generations to publicly-traded corporations. The land manager must understand what is on each property, the history of the property, and determining the best future use for the property. Managing hundreds of properties covering thousands of acres requires large amounts of geospatial data and the ability to interpret that information. These large properties are often large and in rural areas, which often work out well for solar PV development. Using the solar farm suitability dataset, the land manager will be able to quickly determine how much land they oversee that may work well for solar farm development. He or she will be able to reach out to developers to explore new sources of revenue and secure long-term land leases.

Municipal Leader

Elected-officials and high-ranking municipal staff are responsible for the prosperity of their communities. These municipal leaders can create ordinances, regulations, and policies that can incentivize new forms of economic growth. A policy-maker could use the solar suitability dataset to analyze how much land within their jurisdiction may work well for solar PV development. If there is little land suitable, they will quickly know this is not a path worth pursuing. However, if there is a large amount of land available, they can begin reaching out to businesses to try to bring new development to their municipality. New development brings new jobs to the municipality, more money in the local economy, and increases the tax base of the municipality. More clean energy on the grid comes with environmental and health benefits. If the municipal leader is having a difficult time bringing solar to the area, he or she can work with other elected officials to create a policy to incentivize and speed up solar projects within their jurisdiction.

Solar Developer

This solar suitability dataset will likely be very beneficial to solar developers. All use cases above are tied into solar developers in one form or another. The solar developers themselves can directly reach out to landowners to acquire their property or arrange low-cost leases that provide a steady income to the owner while eliminating the cost of a broker. They will be able to use the suitability dataset to view which landowners own the most land suitable for solar PV development and contact the land manager to put together large, long term packages. The developer can directly reach out to municipal leaders who may not be aware of how much economic potential lies within their jurisdiction. They can educate elected officials and their constituents how the potential for new jobs and economic growth to encourage the creation of solar-friendly policies.

Changes in the solar market often happen quickly. With the passage of new policy through a state legislature or new long-term planning at a large utility, a market that was previously financially unfeasible can become appealing in a very short timeframe. When this happens solar developers from around the country rapidly enter the market to search for ideal land for solar farms. By having the complete solar suitability dataset accessible, a developer will have the upper hand on their competition by being able to make faster, more informed decisions without the lengthy due diligence process. This could mean the locking down long-term leases with landowners and getting to the top of the list with utilities to have their projects approved while the competition misses out.

Future Improvements

Transmission line congestion and capacity is important information for understanding where the greatest current need is for new electricity generating stations. This is maintained by the utilities and is not publicly available. This data could be easily incorporated into the cost-weighted overlay analysis were it to become available. Further research and refinement for the weighting of layers will also improve the model output over time.

The geographic scope of this analysis is limited to North Carolina & South Carolina. Expanding the dataset to cover the United States will make it much more useful to a much wider variety of potential users. Changes in policy can quickly make new markets appealing. Being able to quickly see the best properties to develop will likely be an attractive feature to solar developers.

To provide a clearer understanding of the accuracy of the data model output, existing solar farm boundaries could be digitized and intersected with the model output in a vector format. This would allow a comparison to be made between what the model shows as "very suitable" to reality (this would be assuming that all solar farms that have been built are "very suitable" for development and were not installed in an illogical location).

Conclusion

The Multi-Criteria Decision Making procedure paired with an Analytical Hierarchy Process and Geographic Information Systems was a successful methodology for identifying properties suitable based on specific criteria. The layers and weighting used created an output suitability dataset that shows existing solar PV farms as suitable for PV development. By joining the suitability dataset to property parcel GIS data, a database of property owners with the most land suitable for solar PV farm development was created. The suitability dataset was also aggregated by County boundaries, which may help elected officials have a better understanding of how suitable land is for solar within their jurisdictions.

The next step for this solar suitability data will be to see what kind of appetite there is for access to the data within the solar development community. The data will be added to geothinQ, an intuitive web-based GIS providing easy access to dozens of GIS datasets, accessible via a monthly subscription. If an individual solar company would like to run the analysis with adjustments to the layers used in the analysis, or the weighting of layers, that will be a relatively easy process since the geoprocessing model has already been created. This solar PV farm suitability data has the potential to make development teams more efficient. Costs will improve by preventing wasted time during due diligence on sites that are not suitable for development. Ideally, more efficient solar development teams will be able to complete more projects, leading to more clean energy on the grid and a faster reduction of our greenhouse gas emissions.

References

1. Bolinger, M., & Seel, J. (2018). Utility-Scale Solar: Empirical Trends in Project Technology, Cost, Performance, and PPA Pricing in the United States – 2018 Edition (No. 1477381; p. 1477381). https://doi.org/10.2172/1477381

2. Dahl, T. E., Dick, J., Swords, J., & Wilen, B. O. (2015). Data Collection Requirements and Procedures for Mapping Wetland Deepwater and Related Habitats of the United States (p. 93). Madison, WI: Division of Habitat and Resource Conservation.

3. Farthing, A., Carbajales-Dale, M., Mason, S., Carbajales-Dale, P., & Matta, P. (2016). Utility-Scale Solar PV in South Carolina: Analysis of Suitable Lands and Geographical Potential. BioPhysical Economics and Resource Quality, 1(2), 8. https://doi.org/10.1007/s41247-016-0009-5

4. Forrest, A. (2019, February 25). Trump administration to create panel to deny climate change facts almost all scientists agree on. Retrieved April 23, 2019, from The Independent website: https://www.independent.co.uk/news/world/americas/us-politics/trump-climate-change-global-warming-panel-william-happer-white-house-a8795466.html

5. Hodgson, M. E. (1995). What Cell Size Does the Computed Slope/Aspect Angle Represent? Photogrammetric Engineering & Remote Sensing, 61(5), 513–517.

6. Huang, C., Yang, L., Wylie, B., Homer, C., & Itss, R. (2011). A Strategy for Estimating Tree Canopy Density Using Landsat 7 ETM+ and High Resolution Images Over Large Areas.

7. McNerney, J., Kavlak, G., & Trancik, J. E. (2018). Evaluating the causes of cost reduction in photovoltaic modules. Energy Policy, 123, 700–710. https://doi.org/10.1016/j.enpol.2018.08.015

8. National Wetlands Inventory. (2019). Retrieved April 19, 2019, from https://www.fws.gov/wetlands/

9. Noorollahi, E., Fadai, D., Akbarpour Shirazi, M., & Hassan Ghodsipour, S. (2016). Land Suitability Analysis for Solar Farms Exploitation Using GIS and Fuzzy Analytic Hierarchy Process (FAHP)—A Case Study of Iran. Energies, 2016, 9, 643. https://doi.org/10.3390/en9080643

10. Peter McCoy. (2019, February 22). South Carolina State Representative Peter McCoy on the state of renewable energy and climate policy in South Carolina. Conducted by Brian Durham.

11. Pohekar, S. D., & Ramachandran, M. (2004). Application of multi-criteria decision making to sustainable energy planning—A review. Renewable and Sustainable Energy Reviews, 8(4), 365–381. https://doi.org/10.1016/j.rser.2003.12.007

12. Rogelj, J., McCollum, D. L., Reisinger, A., Meinshausen, M., & Riahi, K. (2013). Probabilistic cost estimates for climate change mitigation. Nature, 493(7430), 79–83. https://doi.org/10.1038/nature11787

13. Sánchez-Lozano, J. M., Teruel-Solano, J., Soto-Elvira, P. L., & Socorro García-Cascales, M. (2013). Geographical Information Systems (GIS) and Multi-Criteria Decision Making (MCDM) methods for the evaluation of solar farms locations: Case study in south-eastern Spain. Renewable and Sustainable Energy Reviews, 24, 544–556. https://doi.org/10.1016/j.rser.2013.03.019

14. Syria formally joins Paris climate agreement: U.N. (2017, November 14). Reuters. Retrieved from https://www.reuters.com/article/us-climatechange-accord-syria/syria-formally-joins-paris-climate-agreement-u-n-idUSKBN1DE2KU

15. USA | Climate Action Tracker. (n.d.). Retrieved April 23, 2019, from https://climateactiontracker.org/countries/usa/

16. Vladimir Koritarov, Chad Augustine, & Stanton Hadley. (2013). Energy Zones Study: A comprehensive Web-Based Mapping Tool to Identify and Analyze Clean Energy Zones in the Eastern Interconnection. Retrieved from Argonne National Laboratory website: https://publications.anl.gov/anlpubs/2013/11/77645.pdf

17. Watson, J. J. W., & Hudson, M. D. (2015). Regional Scale wind farm and solar farm suitability assessment using GIS-assisted multi-criteria evaluation. Landscape and Urban Planning, 138, 20–31. https://doi.org/10.1016/j.landurbplan.2015.02.001

18. Fretwell, S. (2018, April 28). Solar resistance: SC officials again back SCE&G in fight with solar industry. The State. Retrieved from https://www.thestate.com/news/business/article209964079.html

19. Crees, A. (2018). The failed V.C. Summer nuclear project: A timeline. Retrieved May 2, 2019, from Choose Energy website: https://www.chooseenergy.com/news/article/failed-v-c-summer-nuclear-project-timeline/