

Milwaukee County Small-to-Medium Photovoltaic Power Station Site Suitability

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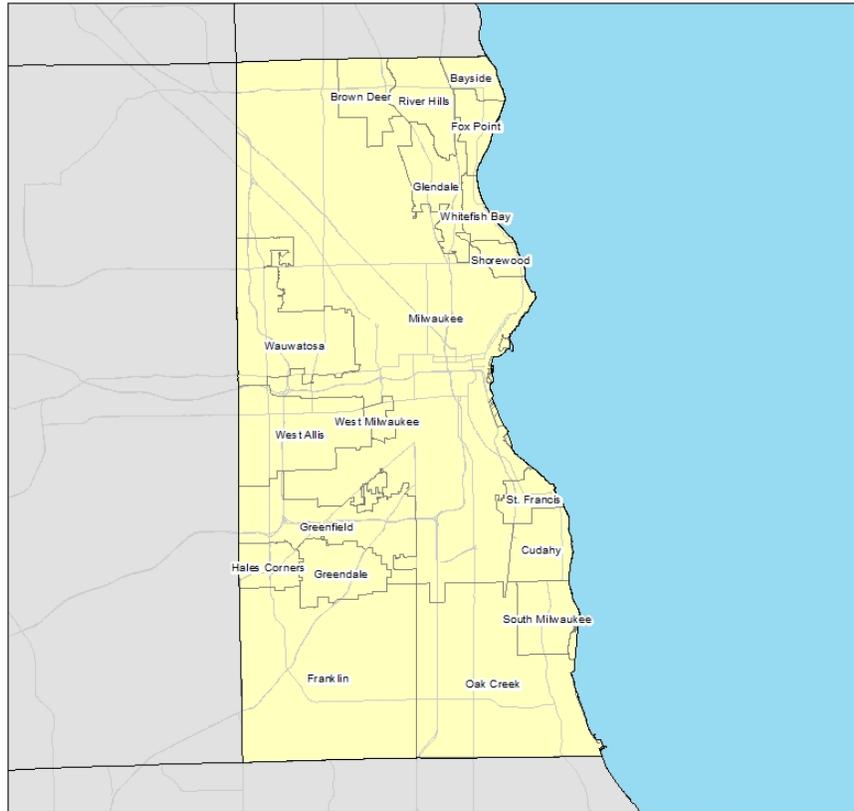
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Capstone Statement

Wisconsin currently generates roughly 50% of the state's power from coal, while under 10% of energy generated comes from renewable resources. Solar energy is a globally-recognized source for responsible energy production based on its renewability and its potential to significantly lower carbon emissions. Our project aims to identify and rank any potential suitable sites for a small to medium sized solar power collection station in Milwaukee County, WI while taking into account economic, environmental, and technical conditions.

Introduction & Background

As the solar industry continues to grow worldwide, we seek to identify places in Milwaukee County that would be most suitable for a photovoltaic solar power station. Literature suggests that site selection is crucial in the cost-effectiveness of a power station (Al Garni & Awasthi 2017). By using a weighted raster layer of conditions overlaid onto a layer of viable building areas, our goal is to generate a map of ranked potentially suitable sites.

In our review of the literature we came across many similar key concepts, but also discovered that the variables differed based on the climate and environment of the region of study. Building off of the key concepts highlighted in the literature, we seek to determine which variables would be most applicable to the Midwestern setting of Milwaukee County and operationalize those variables accordingly. The key concepts that we decided to use are environmental, economic, and infrastructure considerations.

Environmental aspects are important factors to use to find areas that are simply suitable or unsuitable for a solar farm before narrowing it down even further with the other key variables. The two important groups of areas considered unsuitable have been deemed floodplains and sensitive sites. Floodplains pose a risk to the solar panels so building on them is unwise. Environmental sensitive sites includes wetlands because building over these natural resources can be undesirable (Uyan 2013). While some of these spaces theoretically offer an area where the solar panels could be built, they are not optimal spaces due to the extra work that would be required to be allowed to build there or make them suitable to be built upon. One other environmental factor addressed in this project is aspect, or the compass direction in which a slope faces. For

Milwaukee County, a southern facing aspect would ensure a higher solar power output (Chaves 2010).

The economic key concept is based on the idea that there are conditions that may be barriers for a solar power station's cost to build or operational profitability. When considering station construction, slope should be taken into account because the cost to build on a steep terrain would render a project impractical (Al Garni & Awasthi 2017). Technology progresses day by day, but currently efficiency is at low enough levels that the biggest contributor to how much electricity that you can generate is how much horizontal space you can cover with photovoltaic panels. There are quite a few estimates on how efficient panels are in powering numbers of homes, but there seemed to be a general consensus in the literature that roughly 5 acres is necessary to provide one megawatt of power (Marsh 2018). That one megawatt of power can then go on to power roughly 1,000 homes (Brown 2002). In order to find that megawatt of power at low cost, the idea is to find land that can be acquired cheaply in order to produce solar power as efficiently as possible. That will be accomplished by looking at the land use code to find the median prices of various land-use categories to filter for land that is more easily acquirable. Additionally, sensitive sites not related to the environment, such as historic sites, are included here due to the practice of excluding sites of cultural importance (Al Garni & Awasthi 2017).

Infrastructure is an enormous factor when trying to determine a suitable site for a photovoltaic farm. Since we are looking at the most ideal sites in Milwaukee County, this leads to the splitting infrastructure down into two main variables: grid proximity and distance from roads. Distance to roads is important because construction costs

increase dramatically if you cannot access sites without developing land to get machinery in. There are also strict legal rule around not building in the right-of-way of roads, so that area must be taken into account when excluding roads from our analysis while attempting to locate areas near them (Al Garni & Awasthi 2017). The variable grid proximity, or distance to transmission lines, deals with cost of connecting a power station to existing energy transmission infrastructure. If a station is built too far from existing infrastructure, the costs of connecting the two can also make a project economically inefficient (Szabó *et al* 2017). Both power substations and transmission lines could be used to connect to the grid, but substations would only be useful if they were already connected on transmission lines route. For this reason, we chose to simplify the expression of grid proximity as only distance to transmission lines.

Throughout this paper, we will explain the methodology we decided to use and discuss our project conceptualization and implementation. We will also discuss the results of our project and an analysis of the output, as well as any potential limitations of our project. Finally, we will address the results with respect to our original project goals in the conclusion and mention any future research we would consider delving into should we seek to revisit the topic.

Methodology

Conceptualization

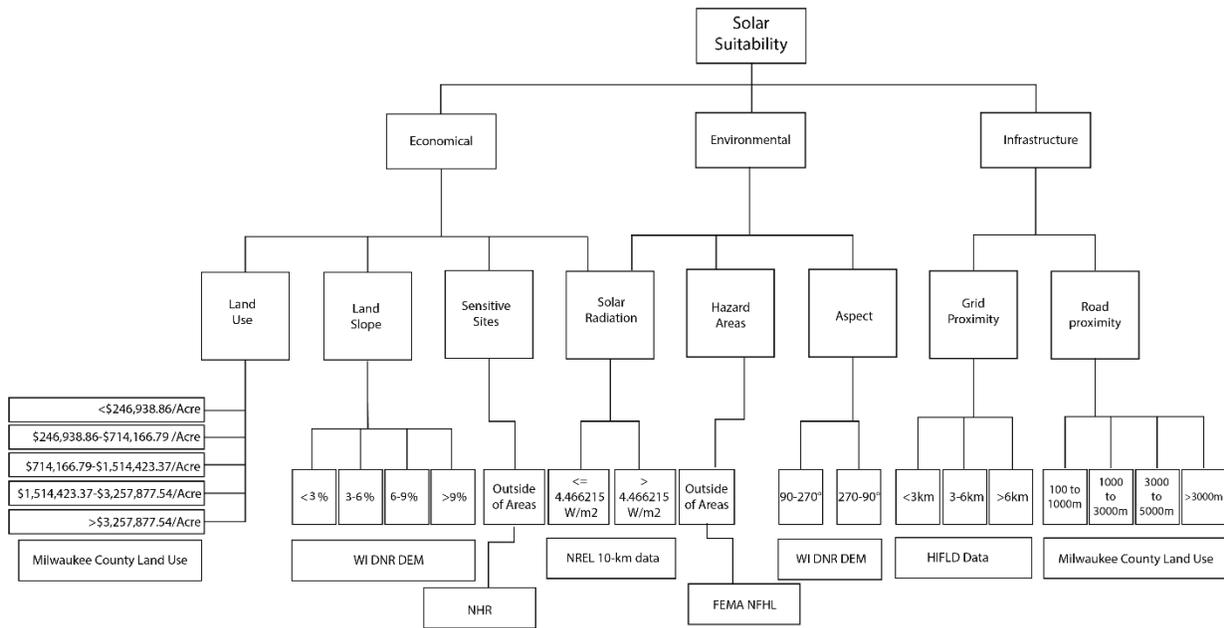


Figure 1. The Conceptualization Diagram

Key Concept: Environment

For the excluded environmental variables, suitability was determined by whether or not a space is outside of these areas. The literature reviewed never covered the actual distances to be away from environmental features, just that they should not be within them, so Boolean logic has been selected for identifying both floodplains and sensitive sites. Placing solar panels within floodplains opens them up to the danger of being damaged so an entity would be well advised to build outside of them (Uyan 2013). Environmental sensitive areas, like areas containing natural resources, can also be difficult to build on or face regulatory challenges that prohibit acquisition (Uyan 2013). There was no defined criteria in the literature for how far away a potential site should be

from any of these features so they are treated as Boolean “in” or “out.” Although aspect is not included in the exclusion layer, it is still deemed an environmental consideration. Aspect was broken into the two categories North-facing and South-facing. In the northern hemisphere, more solar output can be derived from sites with a South-facing aspect (Chaves 2010). As such, any aspect facing South (90-270°) was ranked as 1 and any aspect facing North (270-90°) was ranked 2 (Watson 2015).

Key Concept: Economic

When considering initial construction cost, slope is often addressed by many studies. While flat terrain is ideal, there is still potential for sites that have a mild slope. Although some studies used one slope percentage as cutoff, we decided to score slope using fuzzy logic to hopefully give a clearer estimate of where the project would be most economically practical. The variable of slope was then split into four classes and assigned a score, partially based on the scoring system of a site suitability study conducted by Mevlut Uyan in 2013. This study uses a very strict threshold of 3% slope as a cutoff. We found this to be quite limiting in our area of study and extended the threshold to 9%, adapted from on the scores used in another study (Carrión *et al* 2008). The ideal slope of less than 3% was given the score of 1 to reflect the lowest hillside development cost. A slope of 3-6% was scored as 2, 6-9% was scored as 3, and any slope greater than 9% was scored as 4 to reflect the rises in cost and potential issues in solar radiation reception (Carrión *et al* 2008). Land use is our original data layer, and was split up using the Jenks natural breaks. This is due to the fact that we would ideally like to use the cheapest land possible, while trying to keep similar categories closer than

other categories. Jenks natural breaks fulfills this need by assigning categories in order to minimize the squared deviation within classes (Remedial Priority System n.d.). Finally, economic sensitive sites were derived from identifying parcels containing historic sites by using data from the National Historic Register. A Boolean query was used to determine if a parcel could or could not be developed upon.

Key Concept: Infrastructure

Land availability and distance from roads has been broken up into a cost and a distance, respectively. Both were graded using categories to determine their contribution to the overall fuzzy scoring. Distance from roads is the second major category. As distance to roads increases, there is an increased cost and possibility of environmental damage (Charabi & Gastli 2011). The fuzzy logic scoring was derived from the aforementioned study for Turkey. Road distances of 100-1,000 meters was scored as 1, 1,000-3,000 meters was scored as 2, and distances greater than 3,000 meters was scored as 3 (Uyan 2013). Building very close to roads leads is not ideal and even less efficient than building at an area greater 3,000 meters from a road. Thus, any areas less than 100 meters from a road will not be considered. When addressing the other infrastructural variable, grid proximity, the site suitability conducted by Uyan was again utilized for its fuzzy scoring logic. Any distance less than 3 kilometers was scored as 1, distances between 3-6 kilometers were scored as 2, and distances greater than 6 kilometers were scored as 3 (Uyan 2013).

A logical breakdown of all key concepts, variables, and operationalized variables can be seen in Figure 1, the Conceptualization Diagram.

Original Data Layer

Our original data layer is a modified land use table, created by implementing a scoring system for the cost of acquisition of parcels in the final scoring. The Wisconsin Department of Revenue hosts a database capable of producing reports given various queries. In order to come up with a scheme appropriate for our project, we searched for reports on Milwaukee County for various categories appropriate for the land use code qualifications within the past eighteen years. Once those reports were downloaded, we determined the median for each category, as well as the median lot size. The median was chosen due to the worry that there would be excessive skewing of the mean due to extreme outliers on prices for certain properties.

Once we obtained a median price and a median lot size, we used these to determine a median price per acre. Armed with that knowledge, we plugged each number into the land use code, which keeps a shape size, in order to estimate a value for each individual parcel. There were issues in missing data from the Wisconsin Department of Revenue for acquiring costs of larger infrastructure items such as airports or truck depots and places like parking lots. In order to find as accurate an estimate as possible, the search for cost values was expanded to the state, or even the region in order to find prices. When all else failed, we used parcels that entirely coincided with the land use table to determine a cost based on the median of total assessed value from the 2017 Milwaukee parcels. A visualization of land use based on cost can be seen in Figure 2.

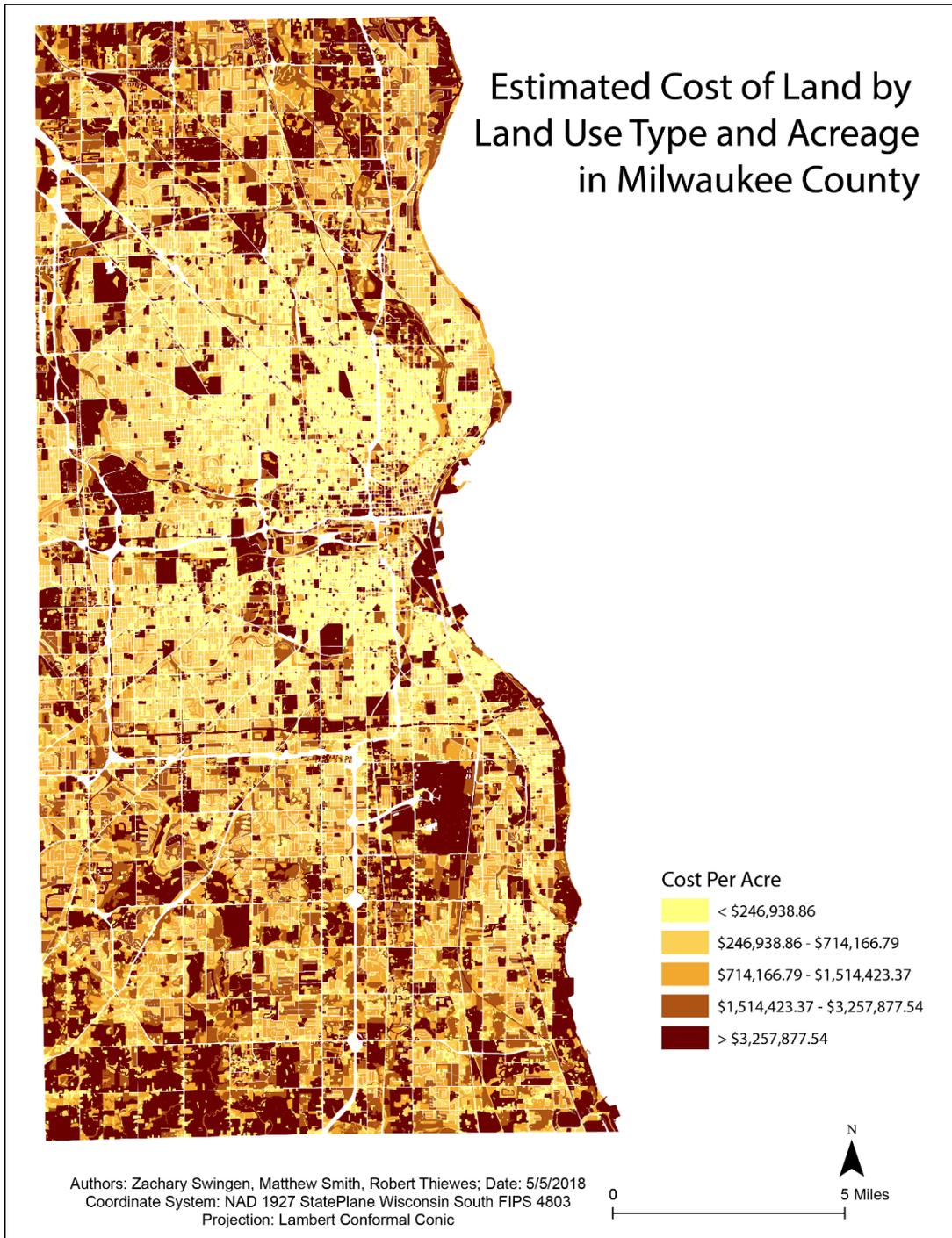


Figure 2. Land use code visualized by cost per acre in Milwaukee County.

Implementation

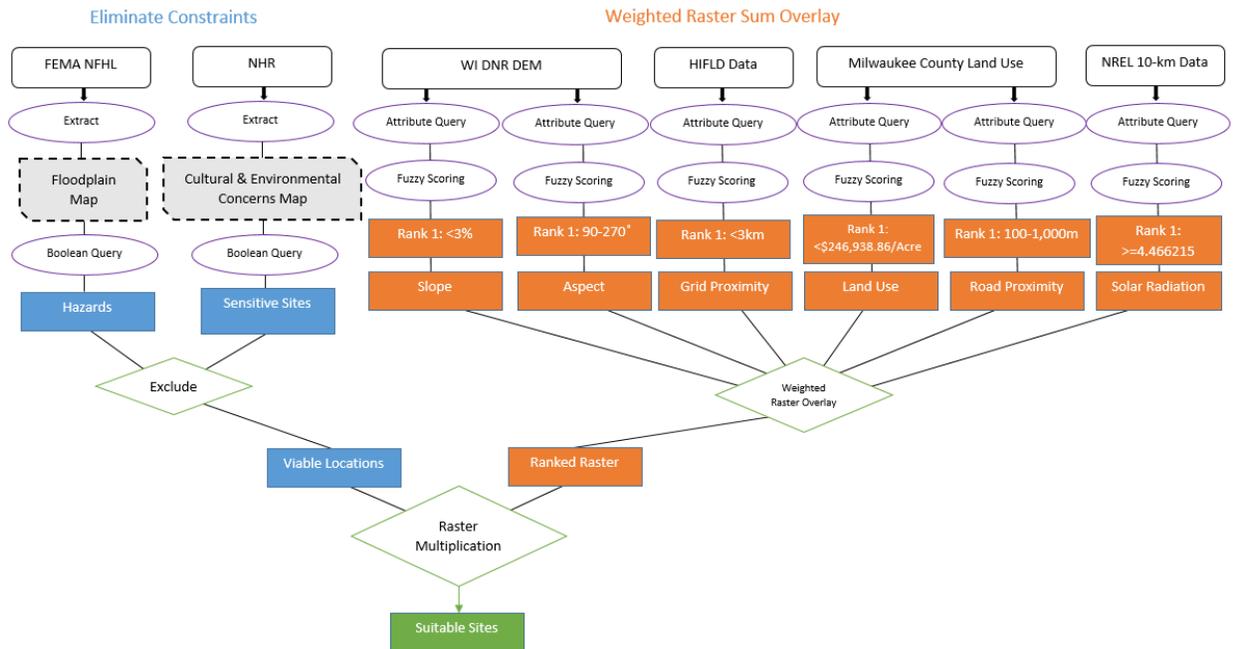


Figure 3. The Implementation Diagram showing the methods used to determine suitable sites.

The first step in our implementation was to create a layer of constraints to exclude any areas from our analysis where construction would not be able to take place. We extracted the floodplain from the Federal Emergency Management Agency's National Flood Hazard Layer, cultural sites from National Historic Register data, park locations and road locations from Milwaukee County data, and wetlands from Wisconsin Department of Natural Resources data. All polygons were then merged to create a layer representing constraints to photovoltaic station development and then converted to raster layer.

Layer Name	Fuzzy Score	Values
Aspect	1	90-270°
	2	270-90°
Slope	1	<3%
	2	3-6%
	3	6-9%
	4	>9%
Grid Proximity	1	<3km
	2	3-6km
	3	>6km
Road Proximity	1	100-1,000m
	2	1,000m-3,000m
	3	>3,000m
Solar Radiation	1	$\geq 4.466215 \text{ Watts/M}^2$
	2	$< 4.466215 \text{ Watts/M}^2$
Land Use	1	$< \$246,938.86/\text{Acre}$
	2	$\$246,938.86-\$714,166.79 / \text{Acre}$
	3	$\$714,166.79-\$1,514,423.37/\text{Acre}$
	4	$\$1,514,423.37-\$3,257,877.54/\text{Acre}$
	5	$> \$3,257,877.54/\text{Acre}$

Table 1. Fuzzy scores were developed for each variable based on scores established in reviewed literature.

In order to determine the potential development suitability across Milwaukee County, we decided to execute a weighted raster sum overlay using the fuzzy scores mentioned above and compiled in Table 1. Slope and aspect were derived from the Wisconsin Department of Natural Resources LIDAR 5-foot Digital Elevation Model, grid proximity was developed by creating buffers around data from the Homeland Infrastructure Foundation-Level Data, road proximity and land use were generated using Milwaukee County Land Use data, and solar radiation was determined from National Renewable Energy Laboratory data. Once all layers were in raster form at the 5 by 5 pixel size, attribute queries were conducted and fuzzy scores were assigned. Our raster layer weights were mostly based off of weights established in literature, with the exception of aspect and solar radiation because they were not included as variables in the cited study (Uyan 2013). We decided to maintain that land use and grid proximity

remain the most influential layers and rank aspect similar to slope and solar radiation very low because it was often not included in other studies. The full ranked layer weights can be found in Table 2.

Raster Input Layer	General Variable	Raster Layer Weight (%)
1	Land Use	41.25
2	Grid Proximity	33.705
3	Aspect	11
4	Slope	8.1
5	Road Proximity	3.195
6	Solar Radiation	2.75

Table 2. Each raster layer was weighted based on project development influence in order to conduct the weighted raster sum overlay.

One issue we ran into was that our land use table was not entirely accurate as some sections of the land use code were showing up as being free land because they were of a land use code that was missed on the table, drastically skewing our results before we even removed areas that were not to be used. Due to the heavy weight on land use in determining a low price, this needed to be fixed immediately. The land use code was then altered to be more accurate. We then used raster multiplication with our weighted sum raster layer and the constraints layer and removed areas that could not be accessed by adding an extra class through scoring unusable areas as 0 and viable areas as 1. The workflow of our project can be seen in Figure 3, the Implementation Diagram.

Results, Analysis, and Discussion

The raster multiplication produced a layer that included all areas that were viable and well suited for photovoltaic farms, but did not have a size restriction. The output can be seen in Figure 4, where the rankings were broken into seven classes using Jenks natural breaks. The original project goal was to identify areas that could house at least a one megawatt facility, so areas that were less than five acres were removed from our results. This generated 2,506 areas from our top class output. With our new five acre plus layer, it was possible to attach parcels that completely encompassed these 2,506 areas to find the most viable plots of land to be purchased. These parcels were then sorted by total cost and put into seven classes using Jenks Natural Breaks. This final output can be seen in Figure 5. This produced our final result, with 1,612 parcels in the lowest cost class containing at least five acres of land from the best possible class from our weighted sum overlay. These 1,612 parcels add up to approximately 46,830 acres, which if it all were hypothetically developed, could produce 9,366 megawatts of power which could power 9,366,000 homes. While this is simply a top classification based on natural breaks that could vary depending on how many categories used, we find these results to be very promising regarding future development. This is especially encouraging as technology improves.

The high ranking of land use makes it a very influential layer within our project. Potential errors may have arisen due to the missing data on land use. We tried to address these issues by removing areas with missing land use code and calculating estimated costs of larger infrastructure items such as airports or truck depots. However, the land use and parcel datasets for Milwaukee are so large that going through and

validating the data for each parcel and area was impractical. As GIS technology and influence continues to develop, we hope to see more accurate land use data in the future to reduce the limitations we encountered.

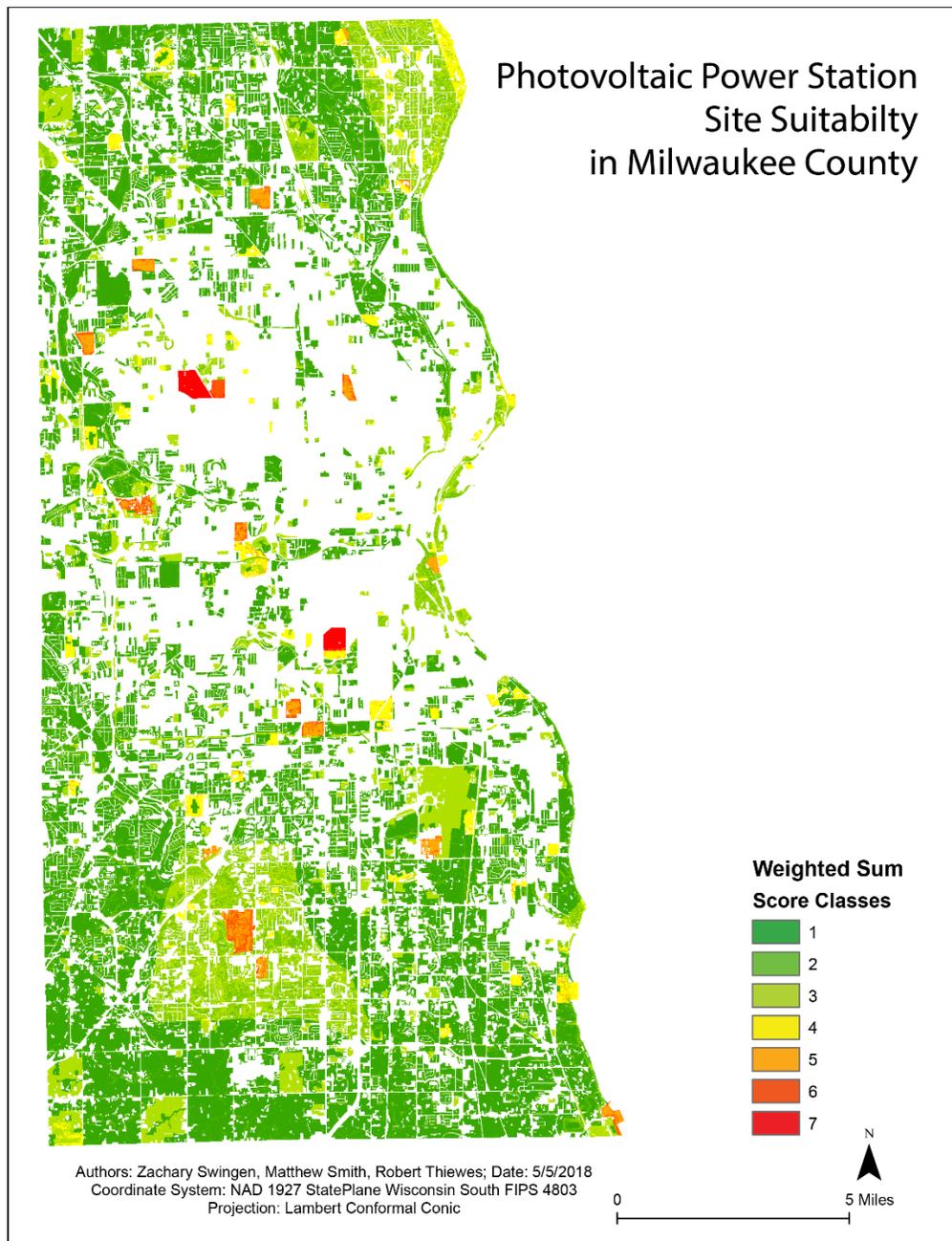
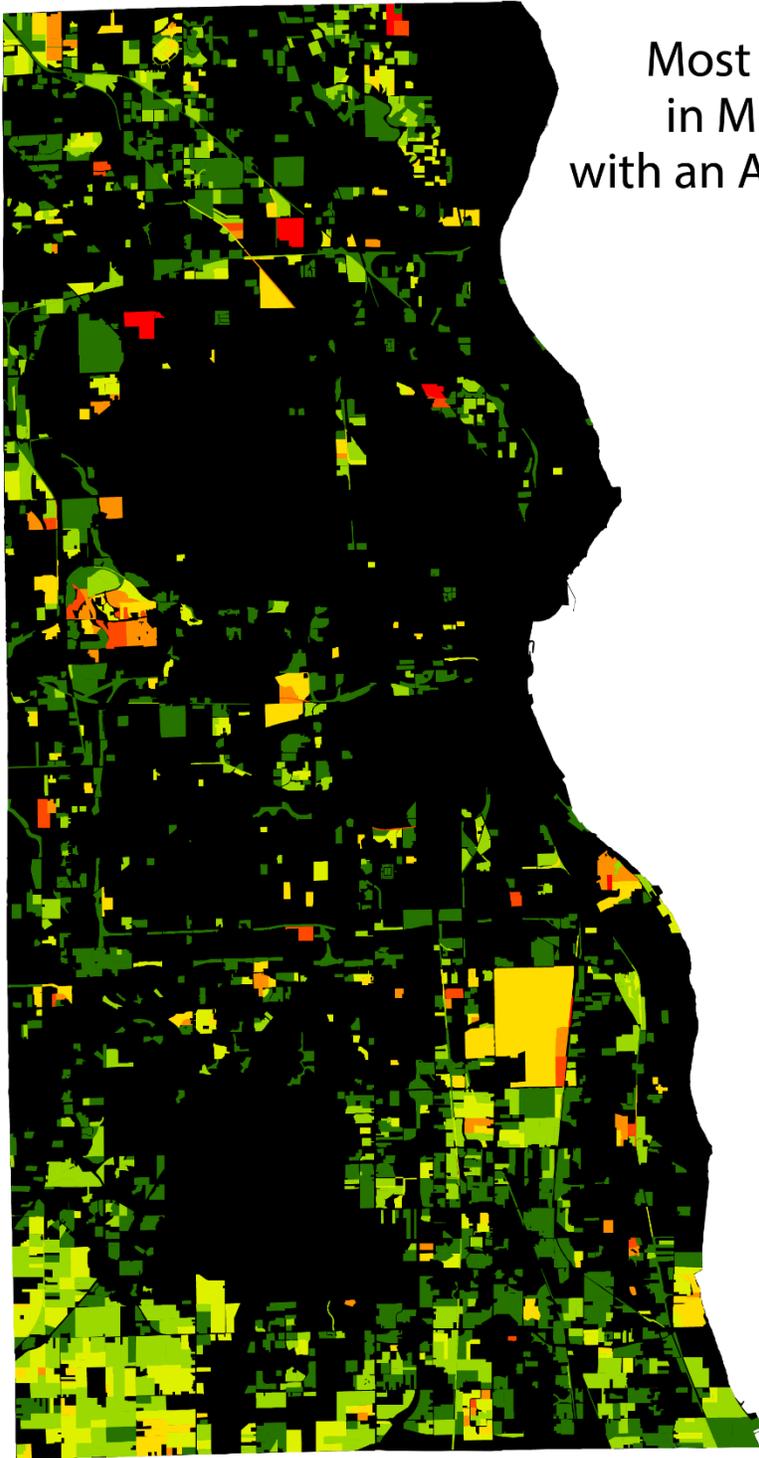


Figure 4. The output results of the weighted raster sum overlay, with no consideration to price or land size.

Most Suitable PV Sites in Milwaukee County with an Area Greater than 5 Square Acres Ranked by Cost



Total Parcel Cost

- < \$1,076,010
- \$1,076,010 - \$2,577,123
- \$2,577,123 - \$5,009,344
- \$5,009,344 - \$9,188,832
- \$9,188,832 - \$15,508,737
- \$15,508,737 - \$31,304,187
- > \$31,304,187

Authors: Zachary Swingen, Matthew Smith, Robert Thiewes; Date: 5/5/2018
Coordinate System: NAD 1927 StatePlane Wisconsin South FIPS 4803
Projection: Lambert Conformal Conic

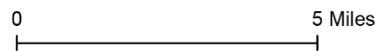


Figure 5. Parcels in the top weighted raster sum class sorted by total parcel price. All parcels shown have an area of at least 5 square acres.

Conclusions and Future Research

By utilizing a weighted raster sum overlay to determine county-wide site suitability and raster multiplication to remove any development constraints, we were able to identify 2,506 areas that rank in our highest class and are over five square acres in area, as seen in Figure 4. Of these areas, there are 1,612 parcels that cost under \$1,076, 010, which is the lowest cost class we developed. Those 1,612 parcels can be identified in Figure 5. We believe that there is relatively ample opportunity for an entity interested in building a photovoltaic power station big enough to produce at least one megawatt of electricity in Milwaukee County, WI.

In addition to acquiring more accurate land use data, we would have also liked to have taken land cover into consideration. We did not come across literature that detailed the costs associated with developing a photovoltaic power station on different land types, such as grasslands, forests, or paved parking. Clearing out a forest may present a huge challenge or cost to an entity seeking to construct a photovoltaic power station. As investment and reliance on solar power continues to grow throughout the world, we hope that research and recorded practices regarding development continue to grow in order to inform the site suitability selection process.

References

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Appendix: Additional Output

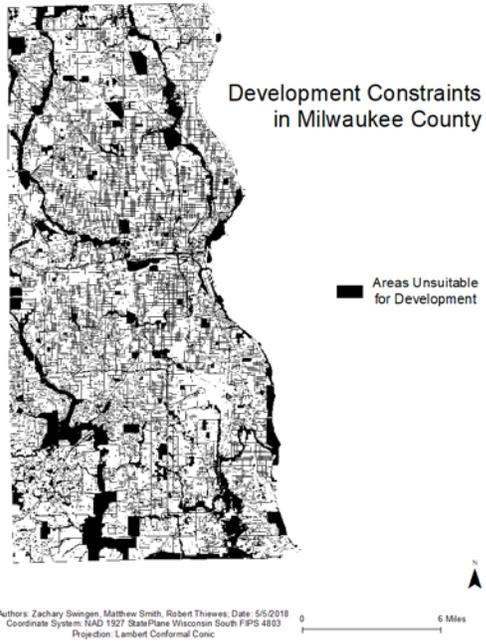


Figure 6. Constraints layer in raster form.

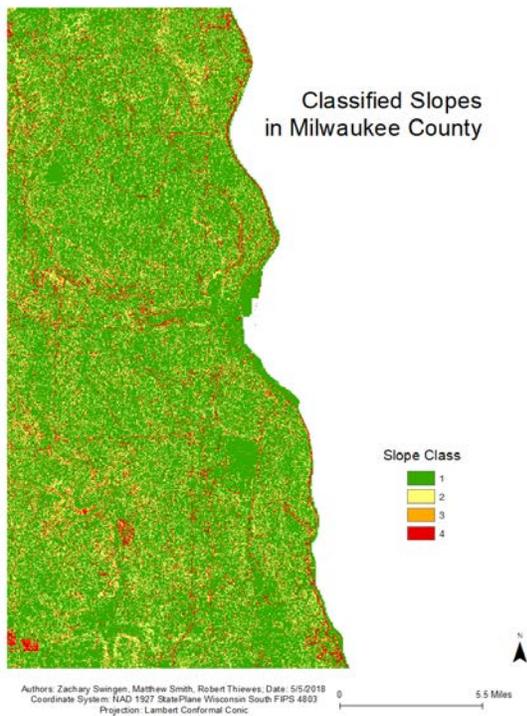


Figure 7. Slope classification based on the values in Table 1.

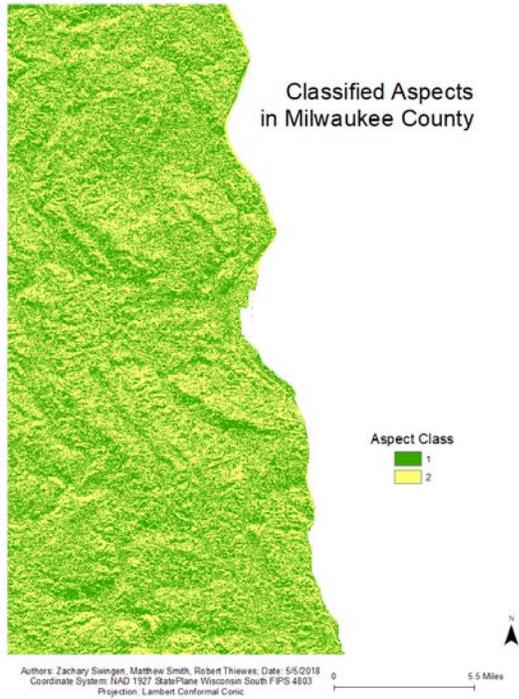


Figure 8. Aspect classification based on the values in Table 1.

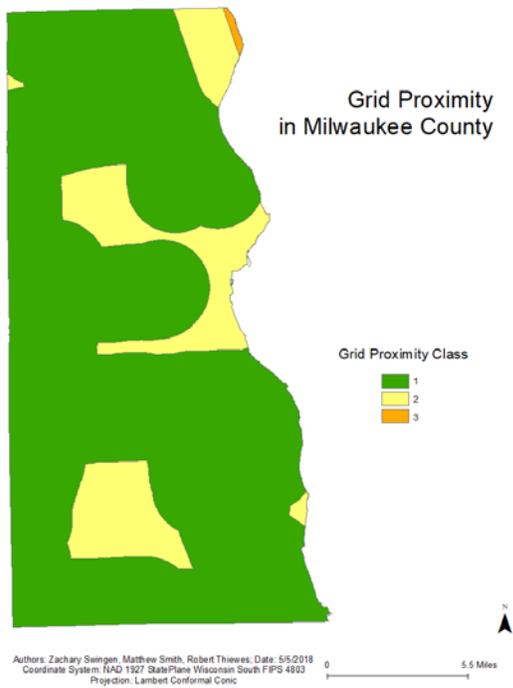


Figure 9. Grid proximity classification based on the values in Table 1.

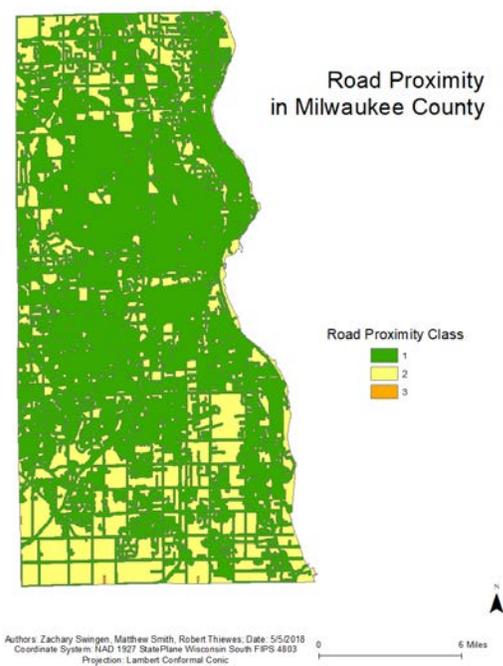


Figure 10. Road proximity classification based on the values in Table 1.

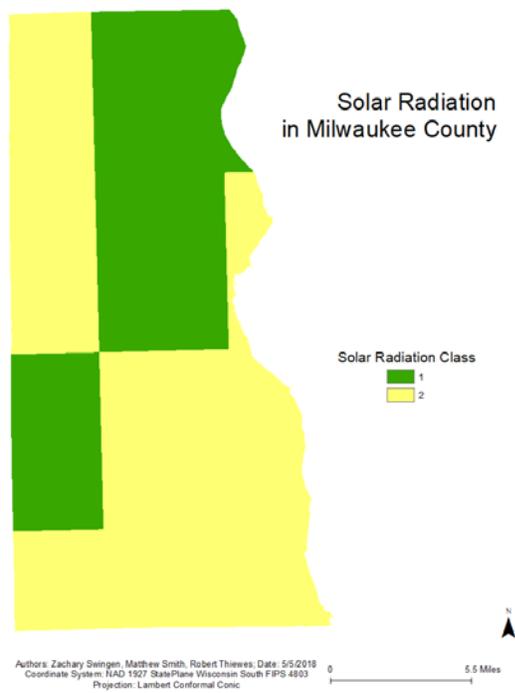


Figure 11. Solar Radiation classification based on the values in Table 1.