Spatial misallocation of utility-scale renewable energy across Minnesota

Jerrilyn Goldberg, Zifeng (Eric) Wang, Archibald Fraser

Advised by Aaron Swoboda and Arjendu Pattanayak

Abstract

Location is a critical factor in renewable energy (RE) projects harvesting solar and wind energy. In this study, we used geospatial analysis to investigate the economic efficiency of Minnesota's current utility-scale solar and wind energy sites. We built a profitability model to predict optimized distributions of MN's current solar and wind capacity, and compared the current distribution to those predicted by our model. Our model suggested that wind turbine site-selection was more driven by profitability than was solar site-selection. Socioeconomic factors including population, income, age, education level, and presence of Xcel Energy were correlated with a county's deviation from the predicted solar capacity, but not for wind. In part, we attributed the difference between the solar and wind siting patterns to the source of project investment. We found that communities hosted more solar installations, while utilities installed more wind turbines. As wind followed our profitability model, this suggests that utilities may consider profitability more when choosing a site. However, within a county, we did not find significant relationships between inefficient siting and county demographics.

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1. Introduction

Fossil fuel consumption is a major contributor to global greenhouse gas (GHG) emissions[1] (IPCC, 2014). Decarbonizing the electricity generation system, which is heavily skewed towards coal and natural-gas in the United States[2], is an important step towards mitigating anthropogenic climate change--to be accomplished primarily through the integration of renewable energy (RE) technology into the grid (Martinot, 2016). In 2007, the state of Minnesota enacted the Minnesota Next Generation Energy Act to reduce the state's emissions of GHGs, with the target for reductions set at 30% below 2005 levels by 2025, and an 80% reduction by 2050.

The law promoted RE adoption by mandating that utilities diversify electricity generation technologies by integrating renewables, requiring most state electrical utilities to increase their proportion of RE electricity sales to 25% by 2025 (Minnesota Commerce Department, 2016; EIA, 2015). Notably, the Next Generation Energy Act left it up to the utilities to follow through on this mandate, with little government oversight over the siting or grid-integration processes.

The flexibility incorporated into the Next Generation Act enables individual utilities to invest how they see fit, but this creates grid-level risks. RE projects located in close proximity are subject to the same temporal and climatic variation of the resources, so siting considerations focused on the individual project scale can present a significant risk to grid stability (Tabone et al, 2016). As the proportion of the grid's energy generation by RE technologies increases, the risk of inadequate electricity supply to meet demand grows concurrently. If climatic variation leads to grid instability, utilities will compensate by increasing reliance on traditional fossil fuel electricity plants which do not depend on daily weather (Drechsler et al., 2017). Therefore, MN's transition to RE could be threatened by site-based inefficiency in the net RE investment.

Individual investments are also highly sensitive to site location because solar and wind energy are location-dependent natural resources. For example, wind turbines are most profitable when located in places with strong and stable wind, good access to electricity transmission infrastructure, high wholesale electricity prices and no restrictions on wind farm development (Lin, 2016). For solar sites, geographic factors like solar radiation, temperature, land cover, and access to roads and transmission lines are critical criteria to be considered in project site-selection (Janke, 2010). Efficient siting is thus important to the viability of RE projects

[1] IPCC, 2014: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

[2] U.S. Energy Information Administration, *Electric Power Monthly*, February 2017; retrieved from https://www.eia.gov/energyexplained/index.cfm?page=electricity_in_the_united_states.

because RE installations are a sunk cost once constructed (Tabone et al, 2016). Geographic Information Systems (GIS) provide a powerful toolset for optimizing the siting of RE projects based on the natural and economic variables informing the viability of a site.

In this research, we constructed a profitability model using GIS to analyze the distribution of current solar photovoltaic and wind sites with capacities over 1 MW across MN. Our model generated an optimized distribution of RE sites based on predicted profitability, which we then compared to the current distribution of RE sites. We used this to investigate whether profitability was a key priority in RE siting across the state. Using R, we then considered potential socioeconomic factors correlated with the difference between our predictions and the observed distribution to see if factors other than profit influence site-selection decisions.

2. Research Context and Literature Review

Geospatial analysis enables explicit connection between the distribution of natural resources and the socioeconomic characteristics of a landscape. This is particularly pertinent for the analysis of solar and wind energy because the greatest indicator of profitability for a given installation is resource availability (Lin, 2016; Luque & Hegedus, 2011). With GIS software, research teams have designed models using both spatially-based environmental resources (e.g. solar irradiation and wind speed) and economic variables (e.g. land value and proximity to transmission infrastructures) to select suitable sites for RE projects (Janke, 2010; Brewer et al., 2015; Sacchelli et al., 2016). Other studies have incorporated spatial social preference variables to account for resistant and encouraging attitudes from local actors (Bell et al., 2005; Yenneti and Day, 2016). The modeling methods adopted by the previous scholars informed our study by highlighting some factors that may affect the suitability of sites for RE installations.

2.1 GIS modeling of renewables

Solar and wind RE siting are both heavily studied within the literature. In general, published studies follow two approaches: either an economic cost-benefit analysis of potential sites (Lee et al., 2009; Van Haaren & Fthenakis, 2011), or a grid-wide analysis examining if RE distribution is efficient or equitable (Drechsler et al., 2017; Grunewald, 2017). GIS modeling is a commonly used method for studying how spatially-dependent variables impact suitability for renewables.

Each approach begins by defining a combination of geographic (elevation, slope, wind speed, solar irradiation), environmental (land cover, presence of threatened species), and economic (land price, grid access, road access) factors to determine how suitable a site is for renewable development. These factors can then be interpreted using a suitability index, which assigns values to preferred characteristics in the model to compare sites (Janke, 2010; Latinopoulos & Kechagia, 2015; Rodman & Meentemeyer, 2006). Studies typically differ in their suitability indexes, as models assign different preferential weights to variables.

Some studies reach beyond financial variables by employing multi-criteria suitability analyses which quantify non-economic spatial attributes such as presence of endangered species or aesthetic impacts (Al Garni & Awasthi, 2017; Anwarzai & Nagasaka, 2017; Bhandari et al., 2015). For example, Stoms et al (2013) considered the negative environmental impacts of solar energy facilities and transmission line construction. These impact models prioritized siting PV solar projects on the most ecologically degraded land with low potential conservation value, offering landowners financially-viable land use alternatives and reducing the ecological burden on the land.

GIS models can therefore define a variety of metrics to compare the suitability of different sites. One of the most commonly used measures is profitability, the net financial gains which can be generated from a site; this is as a justifiable metric because RE developers aim for the highest economic return from a site to satisfy investors and make profits (Russo, 2003). Profitability models account for both fixed costs (machinery investment) and spatially variable costs (grid connection, transmission), thus offering insight into which factors most influence the total cost of an installation (Gigović et al., 2017; Lee et al., 2009; Al Garni & Awasthi, 2017). A study of wind turbine placement in New York State found grid connection costs to be as high as 10% of overall wind farm cost—while the spatially-invariant cost of the turbines was 68-84% of the total (Van Haaren & Fthenakis, 2011). This indicates that spatially dependent variables (project siting) can affect the "levelized cost of electricity" (LCOE) of a project—and its financial viability. LCOE is the unit-cost of electricity generation over the lifetime of a RE facility, allowing comparisons between different power generating schemes and their ultimate costs to consumers (Drechsler et al., 2017). Profitability models identify sites with the lowest production costs, ideally so that RE can compete with fossil fuel sources.

Beyond theoretical models, spatial models that compare predictions to existing sites can evaluate current siting strategy and industry trends, and provide insight regarding social influences in the process. One such study, Lin (2016), divided the contiguous U.S. into 10 x 10 km cells and built a GIS model predicting the profitability of wind power in each cell. Lin found that a relocation of the 1,770 utility-scale wind projects installed nationwide before 2014 to the 1,770 most profitable cells across the country could increase the total profits from these projects by 47.1%. Moreover, 80% of this profit distortion could be addressed with a redistribution of projects within state boundaries (Lin, 2016). For Minnesota, the potential profit to investors from relocating the wind projects within the state was predicted to be between 20.6% and 48.5%, depending on the measurements used to calculate wind resources and electricity price.

This profit distortion indicated that investors are influenced by more than just economic factors in their siting decisions--a result also found in other studies (Maruyama et al., 2007; Masini & Menichetti, 2013; Islar & Busch, 2016). To identify specific variables correlated with RE placement, Lin (2016) gathered county socio-economic and voting data, then performed a linear regression with each county's profit distortion. Lin found that counties with higher "green preferences" (measured by support for the Democratic and Green parties in the latest presidential election) hosted wind farms in sites with less profitable wind resources and lower overall performance. This has significant repercussions when considering the need for RE technologies to be viewed as a profitable alternative to coal and natural-gas power plants.

2.2 Siting renewables in Minnesota

Currently, MN government oversight of RE projects varies by site generation capacity. Under the MN Power Plant Siting Act (PPSA), only "large electric generating plants" (>50 MW capacity) are required to go through a state permitting process (MN Department of Commerce, 2015; "216E.03 - 2017 Minnesota Statutes"). For RE facilities generating less than 50 MW, local counties and zoning authorities grant permits, not the state. Investors must conduct an Environmental Assessment Worksheet (EAW), which is the start of an environmental impact analysis, if the project generates between 25 and 50 MW, or at the request of local government or citizen petition. Facilities under 5MW are exempt from state environmental review unless development will convert greater than 80 acres of agricultural, native prairie, forest, or naturally vegetated land (MN Department of Commerce, 2015). These permitting processes occur only after the developer has already decided upon their investment site and thus limit the ability for the government to influence wider industry development patterns. Understanding the variables that RE developers consider before investing in a project will provide important insight into RE grid integration trends of the RE industry.

While natural and economic variables define site profitability, public perception also effects project viability. A survey conducted by MIT found that respondents choosing between the local siting of a nuclear, coal, natural gas, or wind power plant were concerned about environmental safety. While they favored nuclear, natural-gas, and coal implementation for the perceived cheaper electricity cost, local siting (within 25 km) of these plants faced overwhelming opposition (Ansolabehere & Konisky, 2009). This follows the traditional "Not In My Backyard" (NIMBY) framework, which suggests that communities mobilize to prevent the siting of locally undesirable land uses (LULUs) (Schively, 2007). On the other hand, the authors found that wind had active support for local siting (Ansolabehere & Konisky, 2009). Another study considering the community around the 112.5 MW Wolf Ridge wind farm on the Texas-Oklahoma border found broad public support for wind farms and RE technologies in general, but less favorable public attitudes toward siting turbines on respondents' private property. This suggests that the public reception of RE may not follow the traditional NIMBY framework (Bell et al, 2005; Swofford & Slattery, 2010). Those against local siting dwelled on the acoustic and visual disruption of wind turbine placement, but studies have found that as awareness of the technology grows, the public increasingly views turbines as visually-appealing (Devine‐Wright, 2005; Swofford & Slattery, 2010). Traditional frameworks for understanding community response to power plants may not fit RE technologies. Depending on community perception, renewable energy installations can be seen as amenities, detriments, or both.

These positive or negative perceptions have definitive impacts on RE distribution efficiency and equity. Recently, surveys on distributive patterns were sent out to German citizens, with half preferring a spatial allocation that minimized the total number of power plants—an efficient allocation—while 35% preferred the burden of development to be more equitably spread across the states, and consequently have lower electricity generated per plant (Drechsler et al., 2017). In the United States, construction of individual RE sites is driven by private investment, leading market structures to prioritize total output and neglect to account for efficient state-wide distributive patterns (Carley, 2009; Grunewald, 2017). Models can build in preferences for efficient or equitable distributions, but there is currently no government or utility company framework within the U.S. for grid-wide siting (Carley, 2009).

2.3 Research design

The passage of the Next Generation Energy Act spurred rapid construction of utility-scale RE sites, increasing use of wind and solar resources from 6% in 2005 to 21% in 2015 (Energy Action Plan, 2016). This remarkable growth in MN's renewable capacity has not been studied in a systematic way to investigate whether the newly installed megawatts have been placed in an efficient manner. As suggested by the findings of Lin (2016), the spatial misallocation of renewable capacities within the state could significantly compromise the efficiency of the renewable transition. Thus, in our study, we sought to identify and quantify the potential spatial misallocation of Minnesota's renewable capacities. To achieve this end, we followed Lin (2016)'s methodology by comparing the actual distribution of Minnesota's RE capacities against ideal, as in equitable and efficient, distributions predicted by a profitability model.

Given the findings of Lin (2016), in our study of MN's distribution of utility-scale RE facilities we expected to find that counties with higher percentages of Democratic Party voters, a variable Lin associates with the "green preference", host more megawatt (MW) capacity than predicted by our profitability model. Following the RE siting literatures discussed previously (Ansolabehere & Konisky, 2009; Bell et al, 2005; Swofford & Slattery, 2010), we believed that wind and solar would be perceived as amenities in Minnesota. Thus, we expected wealthier and more educated counties in Minnesota to also host more than predicted RE capacities because they are better positioned to attract desirable types of land uses.

3. Data & Methods

In her research addressing the distribution of wind projects in the United States, Lin (2016) put forward an innovative method for studying the misallocation of renewables. As a first step, Lin built a GIS model to predict a "most profitable" distribution of renewable projects and compared the distribution of the actual projects against it. Lin defines *distortion* as the difference between the profits realized by the existing projects and the maximum possible profit as predicted by the model. Distortion values were then interpreted with regression analysis to investigate the possible social factors correlated with observed misallocations.

Lin's research offers both an ingenious way to quantify the spatial misallocations of RE and a feasible method to identify underlying non-economic factors affecting them. Although Lin (2016) used this method only for the study of wind projects, we added solar energy to our analysis as we believe it is equally applicable within the method. Following the research framework of Lin, we also divided our study into two parts--GIS profit-modeling and distortion analysis.

First (Section 3.1), we constructed a model predicting the potential profit of solar and wind RE development in MN. After an evaluation of the model and a review of its limitations (Section 3.2 & 3.3), we conduct a distortion analysis (Section 3.4), in which we identified the deviation of MN's current RE distribution from an ideal distribution predicted by the model. We then used linear regressions to investigate the possible socioeconomic factors causing the observed deviations (Section 3.5).

3.1 Profitability Model Construction

Profit measures the difference between earned income and expenses. This can be understood formulaically as:

$$P = R_t - C_t,$$

where P is net profit, R_t is total revenue, and C_t is total cost. These components can be further broken down with R_t, expressed as the function: $R_t = Q * p$, where Q is the quantity of units sold and p is their market price. C_t follows the equation: $C_t = C_{fixed} + C_{var}$, where C_{fixed}

includes all of the fixed costs associated with installation and production and C_{var} includes all of the spatially variable costs. For our model specifically,

$$C_t = C_{install} + C_{land} + C_{intercon},$$

where we incorporated installation, land, and interconnection costs, and in each cell the annual revenue (R_{Annual}) from wind and solar installations were

$$R_{\text{annual Solar}} = DNI\ (kWh/m^2/day) \times A \times 365\ days \times \varepsilon \times p$$

$$R_{\text{annual Wind}} = 0.3\ MW \times Cf \times 365\ days \times 24\ hrs \times 1000\ (kW/MW) \times p,$$

which considers Direct Normal Insolation (*DNI*), area installed (*A*), efficiency of the solar technology in use (ε), capacity factor of wind (*Cf*), and electricity price (*p*).

Following the profit equation, $P = R_t - C_t$, and the methods laid out by Lin (2016), our profitability model considered site-dependent variables (solar and wind resources, interconnection cost, and land values), and site-independent variables (transmission loss, installation cost, and electricity price). Additionally, we applied an exclusion layer based on terrain and land-cover types to remove sites unsuitable for RE development. We defined profitability (P) as the average annual net profit that can be generated by solar / wind installation in a 30 × 30 m cell over an installation's lifetime. Our spatial resolution differed from Lin, who used 10 × 10 km large cells, because we focused on a smaller area and thus sought to create a model capable of capturing spatial variations at a finer scale. With regard to our wind profitability model, we used the same set of variables and exclusion layer as Lin (2016). For the solar model, we used solar irradiation data to parallel the wind resources in Lin's method.

The following section discusses the data and calculation methods used in our model-construction, followed by an evaluation and critique of our model outputs. All the dollar values used in our model-construction were adjusted to the 2017 value, assuming an annual inflation rate of 2%[3]. Figures A1 and A2 in the Appendix visually summarize the processes and data sources through which we derived our solar and wind profitability models.

a. Solar resource

National Renewable Energy Lab (NREL) provided the annual average daily *direct normal irradiance* (*DNI*) for Minnesota in kWh/m^2/day at the scale of 1 km² cells[4]. We derived our solar

[3] Lin (2016) used a 3% inflation rate without much justification. We replaced this with the government produced rate of 2%. U.S. Bureau of Labor Statistics, "Databases, Tables & Calculators by Subjects; retrieved from https://www.bls.gov/data/#prices.

[4] NREL, NSRDB Data Viewer; retrieved from https://maps.nrel.gov/nsrdb-viewer/.

resource layer from this NREL DNI dataset by first converting it into a 30 × 30 m raster (A = 900 m^2), then computing the harvestable solar insolation in each raster cell following the formula :

$$Insolation\ (MW) = DNI\ (kWh/m^2/day) \times A \div [24\ hrs \times 1000\ (kW/MW)],$$

where DNI is the direct solar irradiation and A is the area of the cell (Bhandari et al., 2015). In our model, we assumed that the solar panels would be able to cover the full 900 m^2 area in each 30 × 30m cell so that the installed PV capacity would be equivalent to the total solar insolation of a cell:

$$\kappa_{solar}\ (MW) = Insolation,$$

where κ_{solar} is the capacity of a solar installation.

Only a portion of the solar energy hitting the ground is converted into electricity due to the limited efficiency of current PV solar modules. Based on a review of the technologies used for solar installations across MN[5], we assumed a solar module efficiency (ε) of 25.8%, the best efficiency achieved with fixed-tilt crystalline silicon PV cells according to an NREL review of current PV technology research (NREL, 2016). Thus, the annual solar electricity output yielded by each cell was computed as:

$$Solar\ Resource\ (KWh/year) = \kappa_{solar} \times 365\ days \times 24\ hrs \times 1000\ (kW/MW) \times \varepsilon\ .$$

b. Wind resource

The amount of electricity that a wind turbine can generate is positively correlated with the wind speed of a given site (McGowan & Connors, 2000). Thus, higher wind speed at a site is correlated with a higher *Capacity Factor*, the efficiency at which wind generators convert wind resources into usable electricity (Lin, 2016). The value of *Capacity Factor* defines the ratio of annual total electricity generation and the maximum annual electricity generated at full capacity.

To calculate *Capacity Factor*, we used a map of annual average wind speed across MN[6] and NREL's Eastern Wind Dataset which simulated capacity factors of 240 hypothetical wind turbines in Minnesota[7]. To derive the capacity factor of potential wind installations from the wind speed map, we followed Lin (2016) by running a linear regression between the capacity factor of each simulated wind plant from the NREL dataset against the wind speed value at its

[5] Minnesota Commerce Department, "Project Database"; retrieved from https://mn.gov/commerce/energyfacilities/Docket.html.

[6] Minnesota Commerce Department, "30 Meter Wind Speed Map"; retrieved from https://mn.gov/commerce/industries/energy/technical-assistance/maps.jsp.

[7] National Renewable Energy Lab (NREL), "Eastern Wind Dataset", retrieved from https://maps.nrel.gov/windprospector/#/?aL=wbDr04%255Bv%255D%3Dt%261N8iNG%255Bv%255D%3Dt%261N8iNG%255Bd%255D%3D1&bL=groad&cE=0&lR=0&mC=44.24126379833976%2C-92.61474609375&zL=7.

site. The East Wind Dataset data points were distributed in areas in MN with an annual average wind speed ranging from 5.29 to 6.80 m/s, corresponding to capacity factors from 0.335 to 0.453. However, the range of wind speed all over Minnesota given by the wind speed map was between 2.52 to 7.83 m/s--there is a mismatch between the wind speed range of the "training data" and the range of wind speeds from which we tried to predict the capacity factor. This mismatch suggested that we would have more confidence in our capacity factor predictions at locations where wind speed fell within the range of the training data than at places where wind speeds were outside the range.

The regression revealed a positive linear relationship between wind speed and wind power capacity factor ($p < 0.001$, adjusted R-squared = 0.403, N = 240; See Appendix Figure A5). Using the slope and y-intercept from the regression, the relationship between wind *Capacity Factor* (*Cf*) and wind speed was estimated by the following equation

$$Cf = (0.05 \times Wind\ Speed\ (m/s)) + 0.11$$

A 30 × 30m raster layer was then created showing the capacity factor of each cell in MN (Appendix Figure A4).

Similar to solar, wind capacity determines how much energy a cell can generate. We assumed that each 30 x 30m cell can host 0.3MW of wind power (κ_{wind} = 0.3 MW/cell), approximately the output of a 30-m diameter wind turbine rotor (McGowan & Connors, 2000). The assumption was appropriate even for much larger-scale wind farms since the capacity of wind turbines are roughly proportional to their rotor sizes, so that two 30 m-diameter wind turbines will have about the same capacity as one 60-m turbine (McGowan & Connors, 2000).

Given the 0.3MW per cell κ_{wind} and the capacity factor (*Cf*) calculated from the wind speed map, the annual wind energy output of each cell was (Lin, 2016):

$$Wind\ Resource\ (kWh/year) = 0.3\ MW \times Cf \times 365\ days \times 24\ hrs \times 1000\ (kW/MW)\ .$$

c. Interconnection Cost

As suggested by Lin (2016) and others (Van Haaren & Fthenakis, 2011; Al Garni & Awasthi, 2017), two of the most significant spatially-dependent variables are grid interconnection cost and land rental cost. We used *Interconnection Cost* ($C_{Intercon}$) to capture the cost of constructing the transmission facilities (transmission lines, converters, transformers, etc.) needed to connect the RE generators to the nearest electric substations (the larger facilities that transmission lines are connected to). This cost depended on a utility project's capacity and its distance to the nearest transmission facilities (Delucchi & Jacobson, 2011). Lin (2016) assumed that the interconnection cost per MW was proportional to the distance from the nearest power transmission line. Based on this assumption, Lin derived her interconnection cost functions by running a linear regression between the actual interconnection cost of wind projects against their distance to transmission lines and capacity.

Following Lin's methods, we extracted the interconnection cost data for all U.S. solar and wind projects constructed between 2004 and 2012 from the EIA 860 data series[8]. We excluded projects in which new electric substations were constructed because of the significant extra investment. Each project's distance to the nearest transmission line and electric substation was calculated based on the locations of those facilities, provided by the Homeland Infrastructure Foundation-Level Data (HIFLD)[9]. In our regressions we found that the interconnection costs of existing solar and wind projects were better predicted by their distances to the closest electric substations than by their distances to transmission lines (See Appendix Figures A6.1/6.2, A7.1/7.2) . Therefore, in our model we predicted the interconnection costs based on a regression of each project's interconnection costs against the product of its capacity and distance to the closest electric substation (See Appendix Figures A8 & A9). The regressions for solar and wind projects both returned significant positive correlations[10].

For solar, the dataset from which we derived the predictive trendline for interconnection costs included 165 individual projects with a range of capacity of 0.4 to 154 MW and the range of distance to substation was between 0.3 m and 33.5 km[11]. For wind, the dataset contained 128 projects whose capacity ranged from 0.6 to 300 MW and their distance to electric substations ranged from less than 10 m to 29.5 km[12]. Those data points included wind and solar projects not only in Minnesota, but all over the continental United States. Across Minnesota, the distance to electric substations ranged from 0 to 66 km, and the range of existing project capacity was 1.3 - 100 MW for solar and 1.3 - 205 MW for wind[13]. Similar to the case for wind capacity factor, we would have more confidence in the predicted interconnection costs at locations where the distance from electric substations are within the range of the "training data".

Using the slopes and y-intercepts from the regression, the interconnection costs of solar and wind in each 30 x 30m cell were:

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[8] EIA, form EIA-860; retrieved from https://www.eia.gov/electricity/data/eia860/.

[9] Homeland Infrastructure Foundation-Level Data (HIFLD), layer "Electric Substations"; retrieved from https://hifld-geoplatform.opendata.arcgis.com/datasets/electric-substations.

[10] p-value <.001; Adjusted R^2 = 0.334 and 0.291, n = 165 and 128, for solar and wind respectively.

[11] Range of *Capacity* × *Distance* was 0.3 to 36,100 m*MW.

[12] Range of *Capacity* × *Distance* was 177 to 2,650,000 m*MW.

[13] Note that wind or solar projects in Minnesota whose capacity were lower than 1 MW were excluded from our study.

$$C_{intercon\,(solar)}\ (\$/cell) = 4.99 \times d\ (m) \times\ \kappa_{solar}\ +\ \$142,000$$

$$C_{intercon\,(wind)}\ (\$/cell) = 3.61 \times d\ (m) \times \kappa_{wind}\ +\ \$399,000\ ,$$

where d is the distance of a project to the closest electric substation in meter.

Visualizations of the Interconnection cost layer we created are presented in Figures A8 & A9 in the Appendix.

d. Land value (C_{land})

To determine land price, available areas were first classified into cropland, pasture, and forest using the National Land Cover Database (NLCD) 2011 dataset[14]. These areas were then valued using the MN AcreValue dataset[15], which contains average cropland, pasture, and forest prices per acre by county (See Appendix Figure A10 & A11). Cell value was then adjusted from the per acre valuation to one based upon a 30 × 30 m cell size.

e. Exclusion layer

Cells overlapping areas deemed unsuitable for utility-scale RE projects in MN were excluded from the profitability model. Following the methodology of Lin (2016), land in the NLCD 2011 dataset designated as urban, wetlands, and perennial snow areas was excluded. Areas with a slope steeper than 20 degrees were also marked as not suitable using the 30-m resolution Digital Elevation Model for Minnesota provided by the U.S. Geological Survey[16] (see Appendix Figure A12).

f. Installation cost ($C_{Install}$)

We extracted the installation cost of wind or solar projects per MW directly from the 2015 EIA-860 generator cost dataset[17]. This was assumed to be a spatially-independent cost and it captured the expenditures for purchasing and installing the generator. For the solar projects, we assumed the use of fixed-tilt crystalline silicon, a common type of PV cell used in Minnesota

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[14] National Land Cover Database (NLCD), “National Land Cover Database 2011”; retrieved from https://www.mrlc.gov/nlcd11_data.php.

[15] Granular, “AcreValue Map”; retrieved from https://www.acrevalue.com/map/.

[16] Minnesota Geospatial Commons, “Minnesota Digital Elevation Model - 30 Meter Resolution”; retrieved from https://gisdata.mn.gov/dataset/elev-30m-digital-elevation-model.

[17] EIA, “Construction cost data for electric generators”; retrieved from https://www.eia.gov/electricity/generatorcosts/.

according to a Commerce Department project database[18]. The predicted installation costs for solar and wind in each cell would thus be:

$$C_{install\ solar} = \$2,930,000 \times \kappa_{solar}$$

$$C_{install\ wind} = \$1,734,000 \times \kappa_{wind}\ .$$

This method yielded an installation cost of $2,930,000/MW for solar and $1,734,000/MW for wind.

g. Calculating profitability

The annual profitability of RE electricity production on a given patch of land is the difference between the total revenue generated and the total cost incurred. The total cost formula for solar or wind installation in each cell was estimated as the sum of the *Installation cost*, *Land cost*, and *Interconnection cost* values. Land cost for wind projects was multiplied by a factor of 0.05 because we assume wind turbines occupy at most 5% of a wind farm's total acreage (McGowan & Connors, 2000)

$$C_{t\ solar} = C_{install} + C_{land} + C_{intercon}$$

$$C_{t\ wind} = C_{install} + (0.05)\ C_{land} + C_{intercon}\ .$$

Since we were interested in the annual net profits of the potential solar and wind projects, we amortized the total costs over the lifetime of a project to obtain an annual cost. Based on the works of Bhandari et al. (2015) and Lin (2016), project lifetime *k* was assumed to be 30 years for solar and 15 years for wind. We assumed an annual inflation rate of 2%. Following the formula given by Gabriel (1937), the amortized annual cost for RE installation in each cell was:

$$C_{annual} = C_t \times 0.02 \times 1.02^k \div (1.02^k - 1)\ .$$

The total revenue that can be generated at each location, on the other hand, was a product of the amount of electricity produced and the price at which the power was sold. For our study, we assumed the price of electricity to be $0.1021 / kWh ($p$ = $0.1021/kWh), the 2017 average retail electricity price of Minnesota given by the EIA[19]. Furthermore, we also assumed that 4.7% of the electricity produced was lost in transmission, based on the regional-level transmission loss

[18] Minnesota Commerce Department, "Project Database"; retrieved from https://mn.gov/commerce/energyfacilities/Docket.html.
[19] EIA, "Average Price for Electricity to Ultimate Customers by End-Use Sector"; retrieved from https://www.eia.gov/electricity/annual/html/epa_02_10.html.

data given by Denholm & Sioshansi (2009). Therefore, the annual revenue from RE installation in each cell was:

$$R_{\text{annual solar}} = DNI\ (kWh/m^2/day) \times A \times 365\ days \times \varepsilon \times p$$

$$R_{\text{annual wind}} = \kappa_{wind} \times Cf \times 365\ days \times 24\ hrs \times 1000\ (kW/MW) \times p$$

where we assumed $\varepsilon = 0.258$, $A = 900\ m^2$, $\kappa_{wind} = 0.3$ MW/cell, and $p = \$0.1021$/ kWh.

Finally, the *Profitability* value for each cell was calculated by subtracting the amortized annual cost from the annual revenue of wind/solar installation:

$$P_{annual} = R_{annual} - C_{annual}$$

Figure 1 and Figure 2 below offer a visualization of the profitability model we created. The value stored in each 30 × 30 m raster, *Profitability* (P_{annual}), show the annual net profit available if the area is converted from the current land use into solar / wind renewable generation. For example, since the Carleton College wind turbine is located in a cell where P = \$22,400, the 1.6 MW project is predicted to yield a net profit of about \$119,500 per year during its 15-years' lifetime (k)[20]. Ideally, the profitability map would identify the most profitable sites for solar and wind installations in MN. However, due to the assumptions we made when constructing the model, analytical results must be interpreted with great caution. The following section reviews the assumptions and limitations in our model-construction.

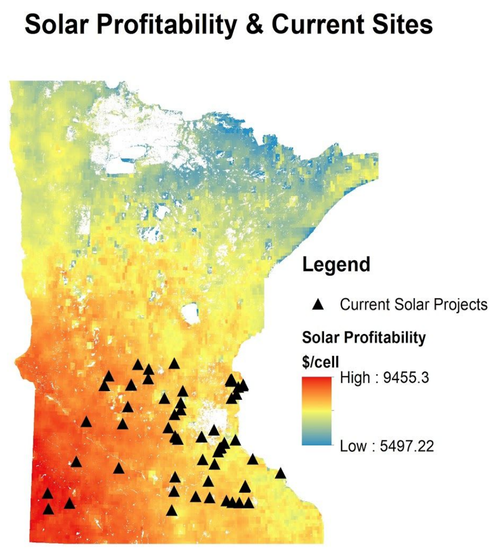

Figure 1: Map of solar profitability with current solar projects (unit: \$/cell/year); B (right). Our model predicted the annual profit generated by solar, respectively, across Minnesota. On both maps, red corresponds to the

[20] (1.6 MW / 0.3 MW) × \$22,400

highest level of profitability and blue to the lowest. Overlaid upon the profitability map are current solar and wind installations. Note that the color scale corresponds to different values than the solar profitability map above (Fig. 2).

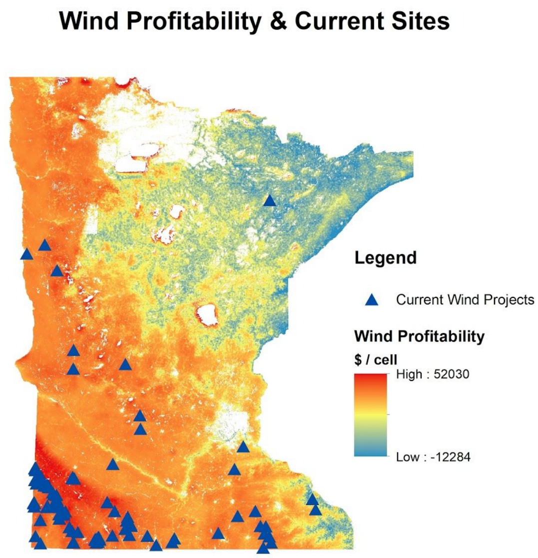

Figure 2: Map of wind profitability with current wind projects (unit: $/cell/year). Our model predicted the annual profit generated by wind, respectively, across Minnesota. On both maps, red corresponds to the highest level of profitability and blue to the lowest. Overlaid upon the profitability map are current solar and wind installations. Note that the color scale corresponds to different values than the solar profitability map above (Figure 1).

3.2 Evaluation of the Profitability Model

Overall, our model predicted that the potential annual profits available from a solar installation in MN ranged from $5,497 to $9,455 in each 30 x 30 m cell. For wind installation, the annual profitability values ranged from a net loss of $12,284 to a profit of $52,030 per cell. The maximum profitability value for wind was much higher than for solar in $/cell, potentially because solar is more land-intensive and less efficient (Chiabrando et al., 2009). The predicted installed wind capacity in each cell in our model was on average twice that of solar (0.3 MW versus 0.15 MW). For those sites with current RE installations as of October 2017, the profitability values translated into an annual mean profit of $56,342 and $116,190 per MW installed capacity[21], or a net present value (NPV) of about $1,690,000 and $1,743,000 per MW, for new solar and wind projects respectively[22] (Table 1). With regards to wind, the NPV returned

[21] Mean profit per MW was calculated following the formula:
Profit per MW = *Mean Profitability per Cell* / (mean) *Installed MW*. Mean profitability was only calculated from those sites that have existing solar/wind installations.

[22] Assuming a discounting rate that equals to the annual inflation rate (2%), the per MW net present value for the renewable installations was calculated following the formula:
Net Present Value = *Profit per MW* × *Lifetime,* where *Lifetime* = 30 years for solar, and 15 years for wind.

from our profitability model was 50% higher than the $804,000 to $1,287,000 per MW NPV estimated from Van Haaren & Fthenakis's (2011) study in New York[23]. Several assumptions we made in our model construction could lead us to overestimate the profitability of wind, which is discussed further in Section 3.3.

Interpreted in terms of levelized costs (LCOE), our profitability model suggested that on average, current sites could produce solar energy at a cost of 7.9 cents/KWh, and wind at 6.9 cents/KWh[24] (Table 1). Scholars researching the profitability of solar projects in North America report a wide range of LCOE because of the different assumptions made about technologies, project size and locations, pricing schemes and module lifetime (Branker et al., 2011). According to the 2017 *Annual Energy Outlook* report issued by the EIA, the average total-system LCOE of new solar and onshore wind plants entering into service in 2022 were estimated as 7.5 cents/KWh and 5.7 cents/KWh, respectively[25]. The values we obtained from the profitability models were within 15% of the EIA averages. Compared with findings from the empirical works of other scholars, the mean LCOE for solar generation we estimated was lower than the 10.25 and 10.58 cents/KWh found by Darling et al. (2011) for Boston and Chicago, but very close to the value of 7.77 cents/KWh found for Sacramento[26]. For wind turbines, the mean LCOE we estimated was within the range of 5.35 - 7.61 cents/KWh reported by Acker et al. (2007) in a study conducted in Arizona[27].

Although our final profitability values were within a reasonable range of those reported by other scholars, our results should be interpreted as the relative profitability between locations rather than the actual monetary values. This is because our assumptions gave us huge uncertainties over the specific numbers we got, which we discuss in more detail in Section 3.3.

[23] Converted to NPV/MW from the original NPV measures for 50 MW wind farms; dollar values were adjusted to 2017 dollars assuming a constant inflation rate of 2%.

[24] Mean levelized cost for energy production was calculated following the formula from Darling et al. (2011):
Mean levelized costs (*$/KWh*) = *Mean Total Cost ($/MW*) ÷ (*Mean Total Revenue* ($/MW) ÷ 0.1021 (*$/KWh*))
Mean annual revenue and mean total costs and mean solar/wind resources was only calculated from those sites that have existing solar/wind installations.

[25] EIA, "Levelized Cost and Levelized Avoided Cost of New Generation Resources in the Annual Energy Outlook 2017"; retrieved from: https://www.eia.gov/outlooks/aeo/electricity_generation.php. Dollar values were adjusted to 2017 dollars from original assuming an annual inflation rate of 2%.

[26] Dollar values were adjusted to 2017 dollars from original assuming a constant annual inflation rate of 2%.

[27] Dollar values were adjusted to 2017 dollars from original assuming a constant annual inflation rate of 2%.

	Mean R_t **($/ installed MW/year)**	**Mean $C_{intercon}$** **(Amortized $/ installed MW/year)**	**Mean $C_{install}$** **(Amortized $/ installed MW/year)**	**Mean C_{land}** **(Amortized $/ installed MW/year)**	**Mean C_t** **(Amortized $/ installed MW/year)**	**Mean P** **($/ installed MW/year)**	**Mean Levelized Cost** **($/ KWh)**
Wind	$356,300	$104,820 (43.66%)	$134,905 (56.18%)	$385 (0.16%)	$240,110	$116,190	$0.069
Solar	$245,073	$42,560 (22.55%)	$130,971 (70.46%)	$15,200 (8.05%)	$188,731	$56,342	$0.079
Confidence	Low in absolute values, but high in relative terms	Low	High	Low	Relatively high	Low in absolute values, but high in relative terms	

Table 1: Breakdown of results for our profitability models. To better understand the degree to which our costs and revenue calculations followed reality, we broke down the profitability model into its different components, and evaluated the level of our confidence in each of them. Note that to make our results comparable to results obtained from the literature, we converted the units we used from $/ cell/year from the profitability models into $/ installed MW /year. Mean costs and revenues presented in the table were calculated from the cost and revenue values of those cells that have current wind/solar installations[28].

3.3 Limitations of the Profitability Model

To inform a more appropriate interpretation of our profitability models and the distortion analyses conducted based on them, in this section we provide a comprehensive diagnosis of the assumptions and limitations in different parts of our model. All of our key limitations listed below arose from arbitrary assumptions made to simplify real-world variability and the would likely lead to lowered confidence in the numbers we obtained from our model. Indeed, our level of confidence in the accuracy of certain components of our profitability model was very low (Table 1). Because each model input may significantly impact the final profitability value we obtained from the model, a sensitivity analysis quantifying the impact of each variable on the final profitability output would be highly desirable to test the robustness of our model to altered assumptions (Crosseto & Tarantola, 2001). However, due to the limited time available for this research project, we did not conduct thorough sensitivity tests.

[28] As for solar, per-MW costs and profits were estimated based on the average predicted installed capacity in each cell of 0.15MW. For wind, a 0.3MW installed capacity in each cell was assumed.

Nevertheless, while we had little confidence in the accuracy of many of our costs and revenue inputs, their effects were mostly evenly-distributed over- or under-estimations across the whole study area (e.g: interconnection cost, energy price, and land price; as discussed below). In other words, those errors would not affect the relative profitability of cells for making comparisons across the state. On the other hand, the major determinants of the relative renewable site profitability in our model, the availability of solar/wind resources, was an input variable that we were more confident about as they were obtained directly from reliable sources (Table 1)[29]. Since we ultimately used our quantitative profitability model to examine statewide trends in RE capacity distribution rather than to calculate the precise profitability for specific RE siting instances, a coarse but reasonable model like ours should be capable of serving the purpose of our research.

a. Interconnection cost ($C_{intercon}$)

According to a report issued by the European Wind Energy Association (EWEA) in 2009, the actual turbine made up 75.6% of the total upfront investment for a 2 MW wind farm, while grid-connection costs constituted only 8.9% of it (EWEA, 2009). Van Haaren & Fthenakis (2011) in their study of New York State found grid connection costs to take about 10% of the overall wind farm cost (Van Haaren & Fthenakis, 2011). Compared to EWEA's and Van Haaren & Fthenakis' estimations, we overestimated our interconnection costs by a large margin (Table 1). This was likely a result of calculating interconnection cost on a per-cell basis. This assumed that the installation in each 30 x 30 m cell was connected to the grid separately, when only one set of interconnection infrastructures must connect an entire project to the grid. Out of all our model variables informing total cost, we had the least confidence in interconnection cost.

Notably, the actual range of variation in predicted interconnection costs due to location was quite small. The difference between the highest and lowest predicted interconnection cost (in amortized $/year) was only about $600 for solar energy and $5,570 for wind, merely 0.3% and 2.3% of the total annual cost for solar and wind, respectively (See Figure A8 and A9 in the Appendix). Therefore, the overestimate for interconnection cost offsets our total cost value by a constant factor, but caused only minimal distortion in the total cost between cells. If anything, this makes both energies more profitable across all of MN, but more importantly does not impact the qualitative trends we discuss later on.

b. Linear assumption about wind resource and interconnection cost

We assumed perfect linear relationships when conducting regressions for the wind resource and interconnection costs in our model. Although our linear regressions revealed a significant

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[29] The uncertainty we had about the *Total revenue* values was mostly caused by our assumption about electricity price.

correlation between wind speed and capacity factor, and between interconnection costs and distance to electric substations, significant statistical correlation does not directly imply a linear relationship. Capacity factor, for example, increases at lower wind speed, but displays a tendency to saturate at high wind speed (EWEA, 2009; Also see Appendix Figure A5). Scholars like Pallabazzer (1995) and Albadi & El-Saadany (2009) actually suggested that a quadratic model with a “cut-off” threshold is more appropriate than a linear model for predicting wind power efficiency. However, we chose to follow Lin (2016)’s use of a linear model for the sake of simplicity.

Although using a linear model lowers our confidence in the absolute wind profitability values, we are confident in our model’s ability to capture the relative distribution of Minnesota’s wind capacity because we found a significant correlation (i.e. sites with better wind resources will have higher profitability values) (Table 1). Furthermore, we calculated a capacity factor based on finer-resolution wind speed data rather than the categorical wind-power class data employed by many previous models, which adds sensitivity to our predictions (Lin, 2016; Van Haaren & Fthenakis, 2011).

Our method of deriving the distance-based interconnection cost is similarly concerning. When two variables are not exactly linearly related in the real world, estimations based on a linear assumption often causes significant deviation from realistic values. We observed this in our estimation of the interconnection cost, where the variations in observed interconnection costs were huge and did not really fit a linear pattern (See Appendix Figures A6 & A7). This further reduced our confidence in the interconnection costs. However, given our project timeline, we opted to maintain Lin’s methodology despite these limitations.

c. Solar technology efficiency and panel coverage

We also oversimplified our solar resource layer by considering the efficiency of only one panel technology. Combining individual site data from the Minnesota Commerce Department [30] with E.I.A. data[31], we identified that over half of solar installations rely on crystalline silicon (c-Si) panels, but a large portion also rely on Cadmium-Tellurium thin-film technology. Further, developers can choose from a variety of silicon panel technology; even just considering the best-research efficiencies compiled by NREL, c-Si panels range from 21% to 27.6% efficient (NREL, 2016). Further, NREL’s list features the world-record efficiency values, which are all established in standardized testing conditions and thus overestimate the productivity of PV cells in the real world. We arbitrarily chose to consider single-crystal non-concentrator silicon panels,

[30] Minnesota Commerce Department, Project Database; retrieved from https://mn.gov/commerce/energyfacilities/Docket.html?searchSubject=Power+plants&searchStatus=All&searchCoverage=&dateStart=&dateEnd=&B1=Submit

[31] EIA, form EIA-860; retrieved from https://www.eia.gov/electricity/data/eia860/.

with the goal of comparing our observations to ones built upon the efficiency of multicrystalline cells, as these two compose the majority of the global PV market (Fraunhofer 2018). While we were unable to compare results during this iteration of our study, the efficiency value alters profitability by a constant amount and does not affect the relative profitability of cells.

We also assumed that a given solar installation covered 100% of the cell. This calculation gave us an average predicted land capacity of 0.15 MW per 900 m^2 cell (6,000 m^2/ installed MW), which was 25-40% lower than the land requirement estimation from other studies (Chiabrando et al., 2009). Realistically, a minimum distance between each row of solar modules would be required to avoid mutual shading, which would reduce the surface area of solar panels that can possibly be installed in a given area (Chiabrando et al., 2009).

d. Land valuation

Our land pricing model assumed a homogeneous landscape within counties and neglects how proximity to urban areas like Minneapolis/St.Paul and Duluth affect real estate values. Additionally, variations in soil quality, slope, crop or forest type, economies of scale (purchasing 500 acres as opposed to a 30 x 30 m cell size), and other price factors remain unaccounted for with this method. In this vein, we were unable to create a measurement of opportunity cost for each cell, which could have incorporated broader market forces into our model.

We also made the assumption that the land used for the renewable installations was acquired in a one-time purchase, when in reality wind and solar farms may pay annual rent to the landowner. This may significantly increase the cost of maintaining an RE investment. However, the land cost is a very small component of our total cost for renewable generation, 8% for solar and a measly 0.16% for wind. Notably, several models in the literature choose not to include land price within their suitability model, under the assumption that rural land price is cheap enough to ignore (Van Haaren & Fthenakis, 2011). We thus justified our uncertainty because our land cost is similarly marginal compared to other factors.

e. Electricity pricing and policy incentives

Due to the large amount of energy generated by each unit per year (totaling over 360,000 KWh per cell for solar and 1,040,000 KWh per cell for wind), on average, a one-cent change in the pricing assumptions could lead to greatly different results in the *Total revenue* on the magnitude of thousands. The retail price received by electricity end users in our model, $0.1021/KWh, was likely an overestimation of the revenues generated by the power producers, who are likely to sell the power through a wholesale retailer. Van Haaren & Fthenakis (2011) used a $0.083 / KWh price that was 20% lower than ours.

Lin (2016) in her model considered both retail price based on over 4000 national price units and wholesale electricity prices given by the 24 electricity trading hubs of the country. She then assumed that the electricity price presented by the closest trading hub/price units equalled the price received by a RE project. Lin's different energy prices resulted into significantly different predictions from her model and distortion analysis. This suggested to us that the failure to account for the different possible pricing schemes faced by the utilities could be a major limitation in our revenue calculation. Because we applied one single energy price uniformly throughout the state, changing our assumption about the price value would significantly alter our absolute profitability numbers, but would not have any impact on the distribution of relative RE profitability across Minnesota.

We also did not take into consideration the effects of subsidies or tax-credits on the prices received by the energy producers, though Lin (2016) considered the presence of supportive policy to compare state-level distortions. At our research scale, we would need to observe county-level variability in these rewards to consider impact on price. Instead, we observed a variety of rewards for residential installations and state-level support programs, neither of which impact the relative profits of sites within the state.

f. Additional costs unaccounted for in the model

Several cost factors that may constitute a significant part of the total cost of RE in real world contexts were not considered in our model. For instance, many models consider distance to roads as an important determinant of site suitability for both solar and wind farms, because access roads need to be sufficiently wide to support the installation processes (Acker et al., 2007; Janke, 2010; Van Haaren & Fthenakis, 2011). This could be a substantial construction cost, Van Haaren & Fthenakis (2011) set the price at $82,000 per km to the nearest existing major road, accounting for approximately 1-5% of the total installation costs.

We also left out operation and maintenance (O&M) costs incurred each year due to the repair, administration and regular maintenance of the generators. These O&M costs have been estimated to account for 2-5% of the total investment for a wind project (EWEA, 2009). In the study of Darling et al. (2011), the authors assumed a fixed O&M cost of approximately $10,000/MW/year for solar. Furthermore, solar PV cells experience efficiency degradation at an average rate of 0.5-1% over each operational year, reducing the amount of electricity that can be generated from the module (Branker et al., 2011; Bhandari et al., 2015). Through these exclusions, we likely overestimated RE profitability in MN.

3.4 Distortion Analysis

To investigate the efficiency of RE project siting in MN, we conducted capacity and profit distortion analyses that compared the current distribution of the state's solar and wind capacities to the distribution predicted by our profitability model. This drew directly from Lin's methodology. The *Capacity Distortion* estimated the difference between the RE capacity each county currently hosts and how much would need to be installed for an ideal distribution of MWs. Ideally, each county hosts MW capacity proportional to the suitable area within its border, as defined by a threshold within the range of profitability values produced by our model. In the second distortion analysis, we followed the methods laid out by Lin (2016) to calculate a *Profit Distortion* that presents the percent difference between the profits made by the current RE projects in each county and the highest profit that could possibly be achieved from a re-distribution of the capacity within a county. Because both of our distortion variables compared the profitability of potential renewable sites in relative rather than absolute terms[32], we minimized the impact of the uncertainties in our model (as discussed in Section 3.3).

Like Lin (2016), we assumed that the ideal scenario for capacity distribution within a county occurs when all the renewable projects are relocated to the most profitable sites within the county when calculating the county-level *Profit Distortion.* Lin also calculated a state-level *Distortion* with the same assumption. However, this relocates all renewable capacity in MN to a single area with the highest profitability values. On the scale of our project, this assumption was not realistic and did not yield valuable insights. Due to the uncertainties in the absolute numbers produced in our profitability models and their high resolution (30 x 30 m as opposed to Lin's 10 x 10 km), we could not definitively identify that the most profitable cell in MN was actually better for renewable installations compared to the second, third, or 10,000th most profitable cell. As a result, focusing only on the "best" site of the whole-state could lead us to neglect many potential sites that were equally suitable for an investor's consideration.

Therefore, for an ideal re-distribution of Minnesota's renewable capacities at the state level, we broadened the criteria for what was defined "suitable" for installation as those cells generating the top 20% (and 10%) highest values predicted by our profitability models. Through this, we consider an equitable distribution of installed capacity as discussed by Grunewald (2017), and developed the *Capacity Distortion* variable to replace Lin's method for the state-level analysis. Compared to that used by Lin (2016), this method would give greater flexibility in the selection of potential sites.

[32] For *Capacity Distortion*, we concerned only whether a cell was in the top 20% value range compared to all the cells in Minnesota; for *Profit Distortion*, we used the percentage difference in profitability between a cell and the most profitable cell in the county, rather than the absolute difference values.

To characterize the current distribution of MN's renewable capacities, we calculated the total capacity of installed solar and wind in each MN county as the sum of individual project capacities in each county[33]. According to the EIA dataset, as of October 2017, Minnesota hosts 58 solar projects (totaling 413.3MW) and 123 wind projects (totaling 3492.5 MW) that have installed capacities of over 1MW (Figure 3). The county boundaries were retrieved from the 2017 TIGER data provided by the U.S. Census Bureau[34].

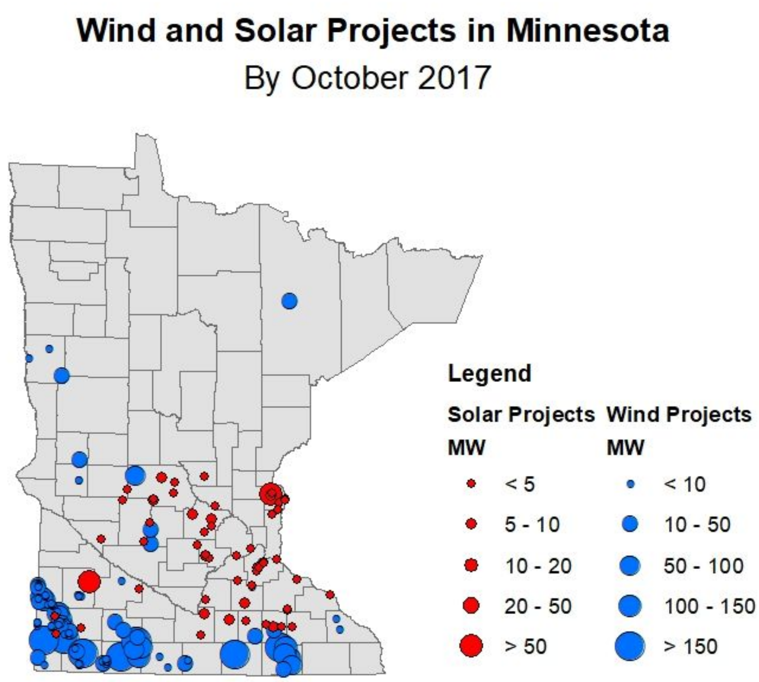

Figure 3: Current Solar and Wind Projects in Minnesota. The RE sites are denoted by red dots for solar and blue for wind projects, with their size corresponding to the capacity of the project (in MW). The gray background marks the boundary lines of the 87 counties in Minnesota as of October 2017.

a. Capacity distortion

In the first distortion analysis, we defined cells as "suitable" if their profitability value were in the top 20% of all profitability values from our model, and calculated the number of "suitable cells" in each MN county. To adjust for the effects of arbitrarily selecting the top 20% threshold as our cutoff point, we conducted another round of analysis defining "suitable cells"as those with

[33] EIA, "U.S. Energy Mapping"; retrieved on February 2018 from https://www.eia.gov/state/maps.php.

[34] U.S. Census Bureau, "2017 TIGER/Line Shapefiles: Counties (and equivalent); retrieved from https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2017&layergroup=Counties+%28and+equivalent%29.

profitability values in the top 10% of all cells in MN[35], which led to a predicted distribution in which the wind capacities are more concentrated in the areas with the highest predicted profitability values. Then, assuming the total capacities of wind/solar in MN stay constant, we expected an ideal distribution of renewable capacities would be one in which the capacities hosted in each county were proportional to the number of suitable cells within the county:

$$Predicted\ capacity = Total\ capacity\ in\ MN \times \left(\frac{Number\ of\ suitable\ cells\ in\ the\ county}{Total\ number\ of\ suitable\ cells\ in\ MN}\right)$$

In this case, the *Capacity Distortion* value for each county equaled the difference between its predicted MW and that currently installed. Therefore, a negative *Capacity Distortion* value would imply that the county had an underdeveloped renewable resource and a positive *Capacity Distortion* value would indicate an overshoot.

$$Capacity\ distortion\ (MW) \ = \ Actual\ capacity - Predicted\ capacity$$

A visualization of the *Capacity Distortion* values by county in Minnesota is presented in Figure 4 below.

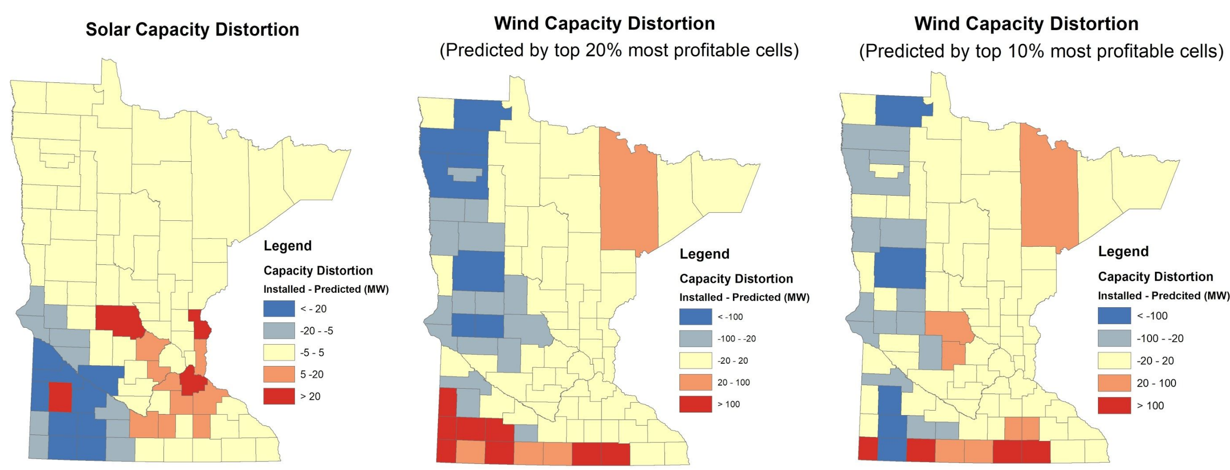

Figure 4. Maps for County-Level Capacity Distortion (MW) Variable for Solar (A, left) and Wind (B, middle and C, right) Energies. Capacity distortion of a county was defined as the extent of overshoot (red) or under-development (blue) of wind/solar capacities compared with the ideal capacity predicted by the distribution across counties of suitable sites in Minnesota. For solar, "suitable sites" were defined as cells with the top 20% profitability values within the state (A, left). For wind, we used both a top 20% (B, middle) and a top 10% threshold (C, right) for defining suitable cells.

35 Because we found that the distribution of solar capacities in Minnesota did not align with even the top 20% most profitable cells (Figure 3, left), it would be pointless for us to further narrow down the suitability threshold for solar as we did for wind.

b. Profit distortion

In the second distortion analysis, we estimated the number of cells affiliated with each current renewable project covered by dividing each project's total nameplate capacity by the power of solar insolation of the cell at the project's location given by the EIA data[36]. Because the EIA data recorded only the centerpoint of an entire wind or solar project, some project coordinates happened to lie inside the exclusion layer (on a road or an administrative building, for example). This happened for 13 out of the 58 solar projects and for 10 out of the 123 wind projects. For such cases, we used the value from the profitability layer as an approximation of its profitability. The *Realized profit* by each of the current project could then be obtained by multiplying the project's size (in number of cells covered) by the *Profitability* value of the cell in which the project was located.

$$Realized\ profit = Project\ size\ (\#\ of\ cells\ covered) \times Profitability$$

The *Realized profits* of all individual renewable installations in a county were summed to obtain an estimation of the total realized profit of the current RE capacity within the county. Similarly, we calculated the *Project size* as the sum of total number of installed cells in each county. Counties with less than 1 MW of total installed capacity (for both solar and wind) were considered to have no existing installation, and were thus excluded from our profitability distortion analyses.

Then, we calculated the maximum possible profit in each county if the same renewable capacities were relocated to the most profitable places within the county. We approximated these sites by taking the product of the number of currently installed cells in each county and the *Profitability* value of the most profitable cell in the county:

$$Predicted\ maximum\ profit = Total\ project\ size \times Maximum\ profitability\ value\ in\ the\ county$$

Finally, following the formula from Lin (2016), the *Profit Distortion* we used for our analysis was the percentage difference between the predicted maximum possible profit and the profit currently realized:

$$Profit\ distortion = \frac{(Predicted\ maximum\ profit - Total\ realized\ profit)}{Predicted\ maximum\ profit}.$$

A visualization of the *Profit Distortion* values by county in Minnesota is presented in Figure 5 below.

[36] EIA, "U.S. Energy Mapping"; retrieved on February 2018 from https://www.eia.gov/state/maps.php.

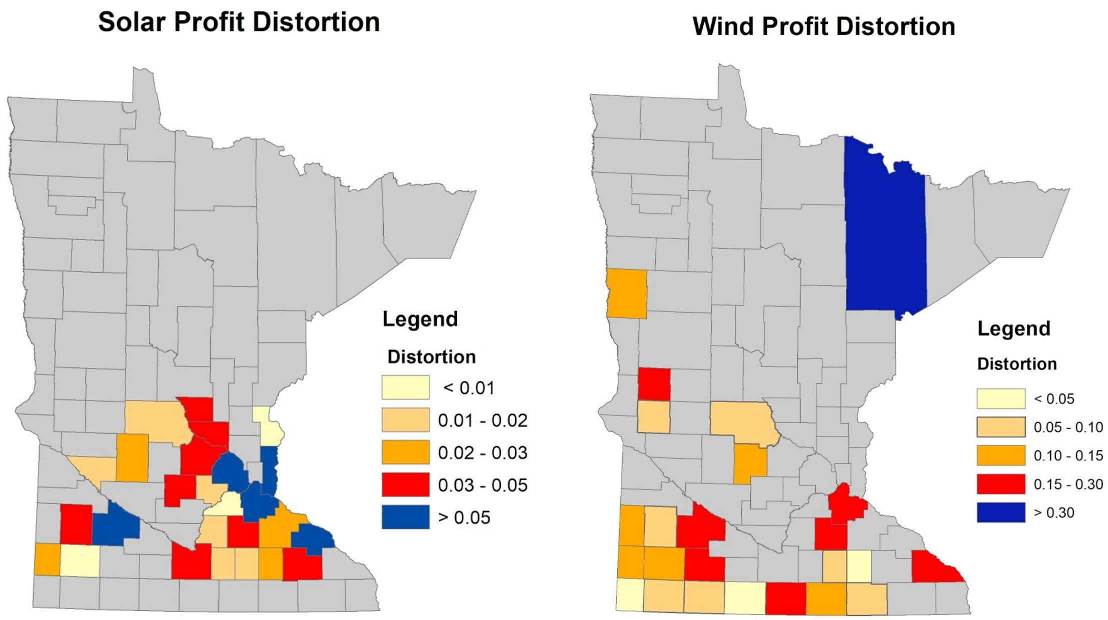

Figure 5: Maps of County-Level Profit Distortion Variable for Solar (A, left) and Wind (B, right) Energies. Counties with total installations less than 1 MW (including no installation at all) were excluded from our profit distortion analyses and are displayed in grey. Note that the values associated with each color vary between the two maps.

3.5 Correlation Analysis of Distortions

a. Methods

We adapted our methods for correlation analyses between the spatial misallocation of renewable capacities and the host counties' characteristics from Lin (2016). With the Minnesota counties as our samples, we followed Lin's methodology and ran single-variable linear correlation analyses in the software R Studio with the *Capacity Distortion* and *Profit Distortion* variables as the dependent variables and the socioeconomic data extracted from the 2011-2015 five-year estimates of American Community Survey (ACS) forms as the independent variables[37].

Following Lin (2016)'s methods, the ACS data used in our analysis included population variables, age, racial composition, and income, among others[38]. To consider any impact of the

[37] Social Explorer, American Community Survey (ACS) 2011-2015 (5-Year Estimates); retrieved from https://www.socialexplorer.com/explore/tables.

[38] Specific ACS-based variables we used in our correlation analyses included: total population, population density, percentage of population below age 25, percentage of population above age 55, % white, % black, % Native American, % population who are high school and college graduates, median household income, per capita income, % household below the statewide median income of Minnesota, GINI coefficient, number of occupied housing units, and average commuting time to work (an approximation of proximity to urban centers). See Tables 2 & 3.

residents' political attitude on siting of RE projects, we ran univariate linear regressions of our distortion variables against each county's voting support rate for Republican and Democratic Parties in the 2016 presidential election[39].

Initially, we excluded counties where predicted and observed installed capacities were both zero; and in the profit distortion analysis, counties with an installed capacity less than 1 MW were also excluded. These exclusions translated to different sample sizes for the two analyses. We also excluded Hennepin County, which encompasses the metropolitan area of the Twins Cities, in all of our statistical analysis. Hennepin County was a consistent outlier in plots of distortion against demographic characteristics (for example, population density, political affiliation, income and education level), which we attribute to its nature as an urban center.

b. Results

At the state level, our analysis revealed that if the current solar and wind projects were relocated to the most profitable sites within their current county, the total profit generated could be increased by 2.58% and 10.58%, for solar and wind, respectively (Figure 7)[40]. Our result for the potential profit increase for wind from this redistribution was within the 8.65-20.37% range of profit increase calculated for Minnesota by Lin (2016)[41]. Table 2 presents the results of both the capacity and profit distortions analyses.

[39] Rogers, "U.S. election 2016: How to download county-level results data"; retrieved from: https://simonrogers.net/2016/11/16/us-election-2016-how-to-download-county-level-results-data/.

[40] This was calculated as the percentage difference between the sum of all the existing projects' *Realized profit* and the sum of their *Maximum potential profit* from the profit distortion analysis.

[41] Those numbers were derived from Lin (2016)'s conclusion that a within-state redistribution in Minnesota can increase total wind profit by 20.65% - 48.5%, and that 42% of this can be addressed by within-county redistribution (a national average).

Table 2 Result Table for the Correlation Analyses on Two Distortion Variables

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	Capacity Distortion		Profit Distortion	
	Wind	**Solar**	**Wind**	**Solar**
Total Population (1,000 person)	-0.01	**0.38**	**0.365**	**0.351**
Pop. Density (person per mile^2)	-0.004	**0.36**	0.016	0.312
% Population Below 25	-0.076	**0.297**	-0.069	0.082
% Population Above 55	0.056	**-0.52**	0.08	-0.064
% White	0.052	-0.08	-0.065	-0.194
% Black	0.049	**0.31**	-0.023	0.159
% Native	-0.09	**-0.25**	0.382	0.182
% High-School Graduate	**-0.211**	**0.41**	0.156	0.054
% College Graduate	-0.084	**0.39**	0.187	0.142
Median Household Income ($1000/ yr)	-0.051	**0.49**	-0.177	-0.037
Per Capita Income ($1000 / yr)	0.002	**0.30**	-0.03	0.068
% Pop. Below State Median Income	0.042	**-0.53**	0.172	0.036
GINI Coefficient	0.083	**-0.39**	0.268	0.135
Average Commuting Time (min)	-0.03	**0.56**	0.117	-0.037
# of Occupied Housing Units (1000 households)	-0.009	**0.38**	**0.401**	**0.115**
% Voting Democrat	0.023	0.24	**0.52**	0.22
% Voting Republican	-0.015	**-0.27**	**-0.505**	-0.216
Sample Size	65	47	24	25

Correlation Coefficients determined from R^2 values. Color coding scheme: Negative, highly significant correlation $\alpha \leq 0.01$; negative, significant correlation $\alpha < 0.01$; insignificant; positive, significant correlation $\alpha = 0.05$-0.01; positive, highly significant correlation: $\alpha \leq 0.01$.

Our correlation analyses identified few significant relationships between the profit distortion and underlying social factors for both energy sources. We did observe a significant positive correlation between *Profit distortion* for wind installations and the percent of Democratic voters in 2016, and a small negative correlation with percent Republican voters in that election. This means that counties with more Democratic affiliation were more likely to earn less than the theoretically available profits given their current installed wind capacity. On the contrary, counties with higher Republican affiliation earned profits closer to those predicted by our model. We used Democratic affiliation as a proxy variable for environmental values and Republican affiliation for lack of interest, so our profit distortion may suggest that wind turbine developers in MN sacrificed some profitability in favor of communities within a county with strong environmental values that were thus more willing to support an installation (R.E. Dunlap et al, 2001; Lin, 2016).

Regarding *Capacity distortion*, our results suggested that counties with certain socioeconomic characteristics tend to host a larger fraction of Minnesota's current solar capacity than would be explained through profitability. Over-installation of solar capacity tended to occur in counties with higher incomes, better educated residents, and those farther away from urban centers (suggested by a longer average commuting time). On the other hand, counties with a relatively high percentage of people over 55 or low-income households tended to host fewer MW of solar than predicted by the model. The correlations between solar *Capacity distortion* and these variables were strong and statistically significant ($p < 0.05$). We also identified marginal correlations between solar *Capacity distortion* and total population, population density, and the percentage of black and native American population ($p < 0.1$), but a closer look at the data revealed that these marginally significant results were likely caused by outliers. We identified co-linearity between several factors using variance influence factor (VIF) analysis[42] . This indicates that our regression results should be interpreted with caution, since we could not identify which among the collinear significant community factors was actually contributing to the overall observed trends.

Some of our insignificant relationships were surprising. For example, we hypothesized that Democratic Party affiliation would be positively correlated to *Capacity distortion*, but found that neither wind nor solar capacity distortion were significantly related to Democratic Party affiliation in the 2016 election. We did find a marginally negative correlation with GOP voter base ($p < 0.1$).

[42] Variables within the solar model with VIF < 10: percent above 55, percent Native, percent high school attendance, GINI coefficient, commute time, and percent registered Republican. VIF values greater than 10 indicate the presence of multicollinearity.

In contrast to solar energy, none of the socioeconomic or political affiliation variables correlated with the capacity distortion for wind, except a marginally negative correlation between wind capacity distortion and percent high school graduates ($p < 0.1$). We also considered a 10% most-profitable region threshold to test whether changing our assumption of a suitable site would affect the results. Our results were consistent across the two thresholds (Table 3).

Table 3 Capacity Distortion Results Based on the Assumption of Top 10% vs 20% Most Profitable Area as Suitability Threshold for Wind

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	Top 20% Threshold	**Top 10% Threshold**
Total Pop. (1,000 person)	-0.01	0.048
Pop. Density (person per mile^2)	-0.004	0.05
% Population Below 25	-0.076	-0.02
% Population Above 55	0.056	-0.017
% White	0.052	0.06
% Black	0.049	0.102
% Native	-0.09	-0.049
% High-School Graduate	**-0.211**	-0.062
% College Graduate	-0.084	-0.054
Median Household Income ($1000 / year)	-0.051	-0.007
Per Capita Income ($1000 / year)	0.002	0.019
% Pop. Below State Median Income	0.042	-0.004
GINI Coefficient	0.083	0.047
Average Commuting Time (min)	-0.03	-0.005
# of Occupied Housing Units (1000 households)	-0.009	0.049
% Voting Democrat	0.023	0.163
% Voting Republican	-0.015	-0.153
Sample Size	65	64

Correlation Coefficients determined from R^2 values. Color coding scheme: Negative, highly significant correlation α≤0.001; negative, significant correlation α= 0.05-0.01; insignificant; positive, significant correlation α= 0.05-0.01; positive, highly significant correlation: α≤0.001.

Generally, compared to the predicted distribution, wind energy tended to be over-installed along the southern boundary of the state and underdeveloped on the western border; and the current distribution of current wind capacities in Minnesota aligned more closely with that predicted by the 10% profitability threshold (Figure 5B). With regard to solar PV, the current distribution of the capacities did not align with the predicted distribution pattern. The counties on the southwest corner of the state, where solar resource is most abundant, were consistently under-installed, and solar was consistently over-installed in the east of the state around in areas around the Twins Cities (Figure 5A).

In our *Capacity distortion* analysis, we found that the wind projects were better aligned with our hypothesis that investors prioritize profitability compared to solar projects. As of October 2017, 107 of the 123 (87.0%) existing wind projects were within the top 20% most-profitable area for wind in MN, and 95 (77.2%) were within the top 10% most-profitable area. For solar, only 10 out of the 58 (17.2%) of solar projects were located inside the top 20% most-profitable area (Figure 5). The results of a regression between predicted and installed capacity suggested that the profitability model predicted the capacity of installed wind in each county better than the capacity of installed solar ($p=0.241$ for solar; for wind, $p < 0.001$, adjusted $R^2 = 0.343$). This finding suggested that profitability and social-political factors impact wind and solar siting to different extents.

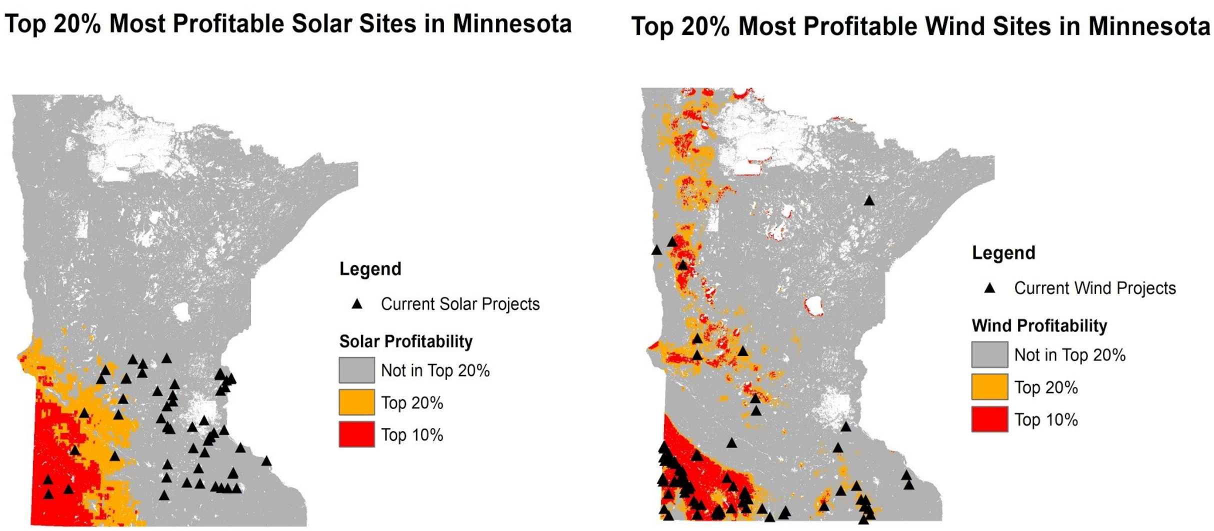

Figure 5: Profitability Thresholds and Current Solar Projects (A, left) and Wind Project (B, right) in Minnesota. Top 10% and 20% most profitable sites portrayed in red and orange, respectively. Current solar sites do not cluster in these regions, causing a large capacity distortion for solar sites; however, current sites cluster in these regions, and thus wind has a lower capacity distortion.

4. Discussion

Our distortion analysis results revealed significant divergence in the the distribution pattern of solar and wind farm capacities across the state. We identified no significant systematic siting inefficiencies at the county level for solar installations, as shown in our profit distortion analysis. For wind, we identified significant correlation between the percent of Democratic or Republican Party voters and the profit distortion, which corresponds with the finding of Lin (2016) on the effects of "green preference on RE siting". In her book "Flight Maps", Jennifer Price discusses the virtuousness many modern environmentalists experience through visible signs of 'being environmental' (2000). In this context, our wind profit distortion correlations may suggest that certain communities work to attract RE installations for social or psychological gain, to the detriment of the installation's profitability.

In our *Capacity distortion* analysis, we found that MN's wind installations aligned well with predicted profitability, supporting our hypothesis that the site-selection of MN wind farms is driven primarily by profitability. We observed no significant correlation between *Capacity distortion* and county demographics for wind. In contrast, the distribution of MN's installed solar capacities did not follow the predicted distribution, suggesting the influence of factors other than profitability in solar investors' decisions. Moreover, solar profitability had less spatial variation compared to wind within our study area (a range of $4,000/cell/year for solar compared to $64,000 /cell/year for wind), which may partially explain why site profitability was less prominent a concern for solar siting relative to wind.

Further, we found significant relationships between county demographics and MW *Capacity distortion* for solar. This suggested that communities with certain characteristics may be systematically over- or under-installing solar compared to the predicted distribution of solar MW capacity across the state. Given MN's goals of transitioning to RE and our definition of profitability, this discord represents an inefficient harvesting of solar energy compared to wind at the state level (Doig et al., 2016). The economic success of current investments in RE can beget future investments in MN and in similar regions with a different political climate, and thus the social factors impacting solar siting deserve further exploration (Russo, 2002; Massini & Menichetti, 2012).

The observed difference in solar and wind energies could possibly be explained by the different characteristics of project investors. In MN, only one wind installation officially claims to be communally owned, while the majority[43] of PV projects are community solar gardens

[43] 35 out of 58 MN (62.1%) solar projects are explicitly classified as CSG by the EIA860 dataset and the Minnesota Commerce Department.

(CSGs). Unlike utility-scale installations which diversify fuel resources for the entire consumer base, CSGs rely on active-interest and opting-in from the host community. CSG members can reap positive benefits in addition to fiscal savings through their active participation in this sustainable behavior (Verdugo, 2012; Landry and Chakraborty, 2009; Maruyama and Nishikido, 2007). Local-scale environmental benefits of RE technologies are often overshadowed by discussions of global climate change, but the development of wind or PV solar farms provides an income-generating land-use for the community. In drought-prone agricultural areas, the change can lead to important regional water savings and the potential for vegetative regrowth after intensive farming (Swofford & Slattery, 2010).

Cooperider & Fry (2012) discussed the psychological benefits to individuals by pursuing sustainability within a larger social infrastrastructure (such as the community network required to develop a CSG), noting that "as people come together to accomplish 'doing good'...they activate their...mechanisms for flourishing". With specific focus on community RE development, Warren & Fayden (2010) saw economic and community revival alongside individual psychological benefits in a community that invested in a community-owned turbine compared to the neighboring community which hosted many utility-owned installations. Our correlation analysis suggested that certain communities reap these benefits more than other communities.

While community owned, MN's CSGs are connected to the local grid and thus must comply with local utilities. Considering each utility's service area, we found the majority, 43 out of 58 (74.1%), of CSGs are located within Xcel Energy's territory as of October 2017 (Fig.6). Statewide, all the existing solar projects are located in counties with some Xcel service area[44]. A linear regression between each county's coverage of Xcel service area against solar *Capacity distortion* showed that solar tended to be over-installed compared to predicted capacities in counties served by Xcel ($p < 0.01$, adjusted $R^2 = 0.260$ and 0.232 for number of Xcel cells and % Xcel coverage, respectively; See Table A1 in the Appendix). Current regulation permits Xcel customers to subscribe to solar gardens developed and managed by private companies, whereas in other utilities, residents can only subscribe to solar gardens hosted by the utility itself (Clean Energy Resources, 2018).

Further, Xcel earns credits towards its Next Gen. Act requirement of 30% RE-based electricity sales by 2025 even when CSGs are installed and managed through private developers (Minn. Stat. § 216B.1691, subd. 2f.; Eleff, 2017). This nuance may have implications in the justice of MN's RE distribution because private-interests specializing in CSG development and management know how to efficiently navigate both the community and institutional sides of RE installation and thus can address all of regulatory work required in the process. Because different

[44] Source of the utility service area layer: Minnesota Geospatial Commons, "Electric Utility Service Areas, Minnesota, December 2015"; retrieved from https://gisdata.mn.gov/dataset/util-eusa.

counties and utilities have unique criteria for RE installations, the tools provided to Xcel customers by these private entities may not be transferable to others (MN Dept. of Commerce, 2015). Groups interested in CSGs outside of the Xcel-region need to navigate the process specific to their county and utility, and thus may face a systematic barrier to switching to RE promoted by the current regulation.

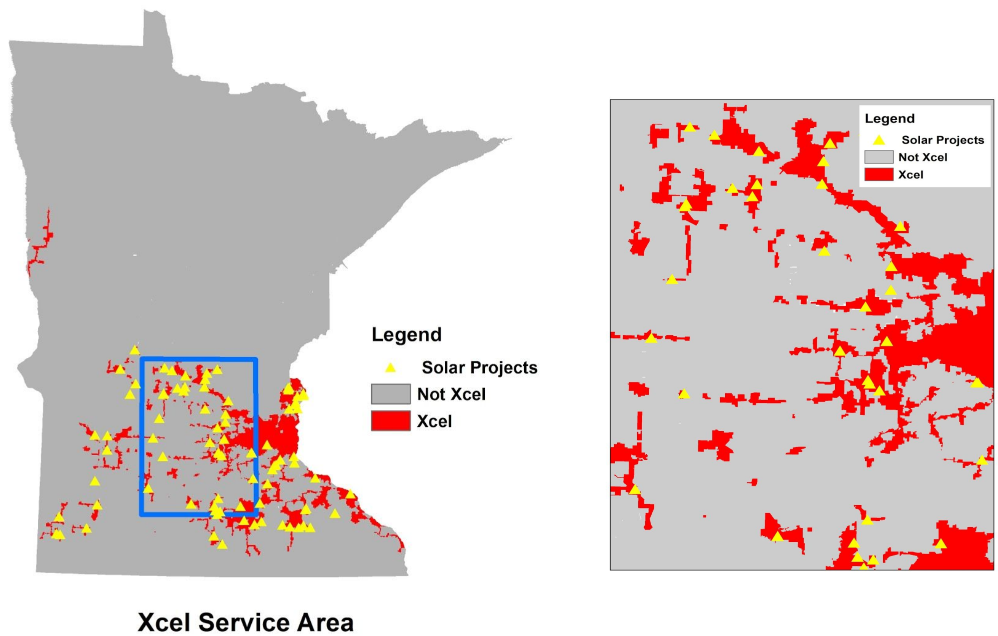

Figure 6: Current Solar Projects and Xcel Service Area. Xcel Energy's service area reaches those regions of the state with higher population density, and we identified a positive correlation between the presence of Xcel and the over-installation of solar. The inlay, right, demonstrates the high observation rate of solar projects (>1MW) within Xcel service area.

The role of private investors in some CSG siting may have amplified the capacity distortion beyond that already in place through the current CSG legislation benefiting Xcel territory. Eckerd (2017) designed a simulation to examine the distribution of amenities like CSGs or undesirable land-uses like landfills. He found that amenities were concentrated in neighborhoods dominated by groups (majority or minority) defined as privileged, while undesirable land uses followed the opposite siting pattern. Our analysis provides some support for Eckerd's findings on amenities: we identified positive relationships between distortion and some demographics--wealth and education--that define traditional forms of social privilege, suggesting that some communities more effectively advocate to host solar gardens (Lenski, 1966).

Overall, the significance of the relationships between social characteristics and solar capacity distortion highlighted a discord between the economic and sociopolitical forces acting to guide MN solar siting not observed for wind. Following the results of our analysis, wind projects followed an efficient distribution in MN but solar sites do not. Considering the grid-scale risks of clustered RE installations (Tabone et al., 2016), our results indicate that a gridwide policy may better guide solar installation to meet the Next Generation Act mandates. In addition, solar siting primarily within Xcel territory may lead to an inequitable statewide distribution of RE benefits (Grunewald 2017).

5. Limitations in the Correlation Analysis

In general, our correlation analysis was limited by three key issues derived from our profitability model: 1) economic correlations derived from arbitrary political boundaries; 2) mismatch between the scale of analysis and the actual scale of decision making; 3) failure to account for the external of RE projects beyond the county level, and 4) using one method to analyze both utility-owned and community-owned RE installations.

Our capacity distortion considered how MN's current MW capacity could be most profitably distributed across the state. We found significant correlations between counties that hosted more than their predicted share of installed MWs and specific demographic characteristics. However, a lot of solar siting considerations cannot occur at the state level because of MN's utility structure. This suggests a potential mismatch between our methods and our hypothesized justice-framework because we looked at political borders rather than economic borders when considering the economic implications for the RE industry.

By studying and analyzing RE capacity and distortion variables at the county level, our research was subject to the modifiable areal unit problem (MAUP) and scaling issues that commonly constrain GIS analysis. County boundaries are artificially defined and vary in size, which limits the ability to reflect real socioeconomic variable distribution or attitudes towards renewable energies (Rengert & Lockwood, 2009). Data collection limited our study to county scale. Future studies may use an areal apportionment method to better account for the actual community affected by RE installations. Furthermore, the county scale may not be the level at which the decisions about renewable installations are made, and projects located in one county may actually serve the demand of people outside the county. RE projects located near the boundaries of counties are also likely to have impacts on both counties but our correlation analysis method only captured the relationship between a site and the single county that contains the project's coordinates.

Because we conducted our correlation analyses at the county level, we did not consider the external benefits of RE projects that are not limited to the county boundaries. For example, the positive impacts on air quality affiliated with RE use are distributed across a broad region.

This is particularly relevant to MN, where particulates from coal-fired power plants contribute to respiratory complications, among other health concerns (Prehoda & Pierce, 2017). Other positive externalities also extend beyond county boundaries: RE projects can reap positive psychological effects for those who support environmentalism by demonstrating the state's support for RE (Haslam et al, 2009). Individual RE projects can also have state-level economic impacts on the RE industry, which could have a multiplier-effect on general economic activity, such as through job creation (Wei et al., 2009).

The abundance of CSGs rather than utility-run installations in MN required us to acknowledge a major assumption we made: that we can apply Lin's research model to installations other than those managed by utilities. CSGs abide by different zoning and permitting processes than utility-owned power plants, and our correlation analysis suggests that social factors impact the installations in different ways. This assumption points to a limitation in our study of MN's solar capacity: our 1 MW cutoff prohibited our ability to study smaller CSGs and thus to know if some communities simply own smaller solar installations. Electricity demand is not interchangeable with population, but can provide an approximation at a local scale. A list of CSGs[45] in MN and a quick review suggests our list does overlook some installations. Accordingly, our conclusions may point to false relationships between capacity distortion and social factors if other communities actually host PV. This conflict challenges our assumption that we could use the same methodology for utility scale installations as for CSGs: if a factor in CSG design is tailoring capacity to the size of the community, then our approach is inadequate for gaining insight into this side of the solar industry. Future iterations of the model applied to CSG installations should test the sensitivity of our over and under installation predictions by comparing our results to those generated by considering all CSGs in the state.

Generally, our model overestimates the need to redistribute both solar and wind capacities because it does not aptly account for large installations in acceptable regions. Instead, the model evenly distributes the total installed capacity over the region deemed available, as determined by the profitability threshold we selected for analysis. Accordingly, we do not use these results as critique of the current distribution and instead use them to consider the sensitivity of the model. This methodology would be strengthened by considering profitability of RE installations compared to long-standing power plants reliant upon traditional fuels to better understand grid parity.

[45] List of MN's CSGs via the Clean Energy Resources Team

6. Suggestions for Future Research

Many of the assumptions we made in following Lin's methods offer opportunities for future research rooted in improving our methods. For instance, we assumed linear relationships when modelling interconnection cost based off of distance and capacity to simplify our model, but our data does not appear to follow a linear relationship. Identifying a better model for this relationship, perhaps through logarithmic or other transformations would improve the overall accuracy of this type of modelling (See section 3.3.a. and b. for further discussion). We also recommend considering the differences between our methods and those of others relating wind capacity factor and interconnection cost to strengthen the wind profitability model. Similarly, we assumed many constants within our model that oversimplify reality beyond an acceptable limit. For example, we simplified our solar profitability model to consider only one technology when in reality multiple are in use across the state, and did not account for dirt or snow impacting panel efficiency (Section 3.3.c).

We also did not account for variation in grid infrastructure age or efficiency across the state, both of which may significantly increase the cost of an installation in certain areas of MN. In a similar vein, we reduced land-cost variation within counties thus overlooking the higher costs of available land near cities such as Duluth, the Twin Cities, or Rochester. We also assumed a constant electricity price received by utilities across the state, and recommend exploring pricing schemes used across the state to make the model more robust when compared to the reality in Minnesota.

We examined the efficiency of RE siting through an economic perspective, but MN's RE industry has a significant foundation in state legislation. Among other areas, laws regarding public utilities, CSGs, grid variability, RPS, permitting, and tax credits impact when and where utilities and private entities invest in RE technologies. These policies determine investment stakeholders, as well. Our method over-simplifies the decision-making process involved in switching to RE by ignoring policies in our analysis, and future analysis that considers the efficiency of RE siting in the legal and policy contexts would complement our research.

Even over the course of this project, MN's installed renewable capacity increased significantly with an estimated 700+ MW solar contributing as of January 1st, 2018, and as of March of 2018 the state surpassed the initial RE sales goals outlined in the 2007 Next Generation Act (Div. Energy Resources, 2017; Hughlett 2017). Upcoming installations, projected to increase MN's solar capacity by an additional 300 MW, may provide more insight into the distribution of utility-owned solar sites that we were incapable of identifying given the current installations (Div. Energy Resources, 2017). Notably, we found that county hosting the North Star project, a

100 MW utility-owned PV installation, has the second lowest solar *Profit distortion* in the whole state. This suggests the possibility that both wind and solar utility-owned projects are sited more efficiently than community owned projects. Future spatial analysis may complement ours by testing this hypothesis with the incorporation of more utility-owned solar installations in MN.

Also, many existing solar projects including North Star are located in areas where solar is relatively more profitable than wind (See Appendix Figure A13). We found that some counties have higher predicted earnings from one technology over the other, but our data did not lend itself to conclusive insights about substitutability between solar and wind energy in MN. While this question may be addressable with additional research, we do not assume these technologies are interchangeable based on the different siting patterns we observed between the two energies. Further, we do not assume that one energy is preferable: diversifying energy sources using both wind and solar is a key component for further integrating renewables without compromising grid stability (Grunewald 2017; Tabone et al 2016). Additionally, solar and wind are not the only RE technologies available to utilities with respect to MN's Renewable Portfolio Standard, and the current total installed capacity of RE in MN is still low relative to the expected profits available across the state. This suggests significant unrealized RE potential in many counties. Future research should develop a better grasp of the functional substitutionality of different RE technologies, with a focus on how to most effectively diversify MN's portfolio.

7. Conclusion

An important step towards reducing greenhouse gas emissions in MN is the transition from fossil fuels to renewable energies like solar and wind. The viability of solar or wind generation at a site depends largely on spatially-dependent characteristics, with inefficient site-selection reducing profitability. This inefficiency may compromise the pace of MN's renewable transition. Using geospatial analysis, our research examined the difference between the predicted most-profitable and observed distribution of RE capacities, across the state (capacity distortion) and within counties (profit distortion). We found that the distribution of wind capacity aligned with the predicted most-profitable sites. In comparison, the distribution of solar was less associated with profitability, but was significantly correlated with features of the host counties like income, age, education, and political affiliation.

A potential explanation for this discrepancy is that many of MN's solar installations are community solar gardens (CSGs), while most wind sites are managed by utilities. The siting of community-owned projects may be more strongly influenced by the preferences of certain community members in comparison to utility-managed installations, with implications on the sites' efficiency and on the equity in the distribution of RE benefits (Verdugo, 2012; Landry and

Chakraborty, 2009; Maruyama and Nishikido, 2007). Given the relationships between solar siting and community characteristics, as well as with Xcel territory, we found that profitability alone does not explain the current RE distribution across Minnesota, particularly for community-owned projects. Therefore, we recommend further studies to examine the different impacts of community and utility investments on state-level RE project siting.

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8. Appendix

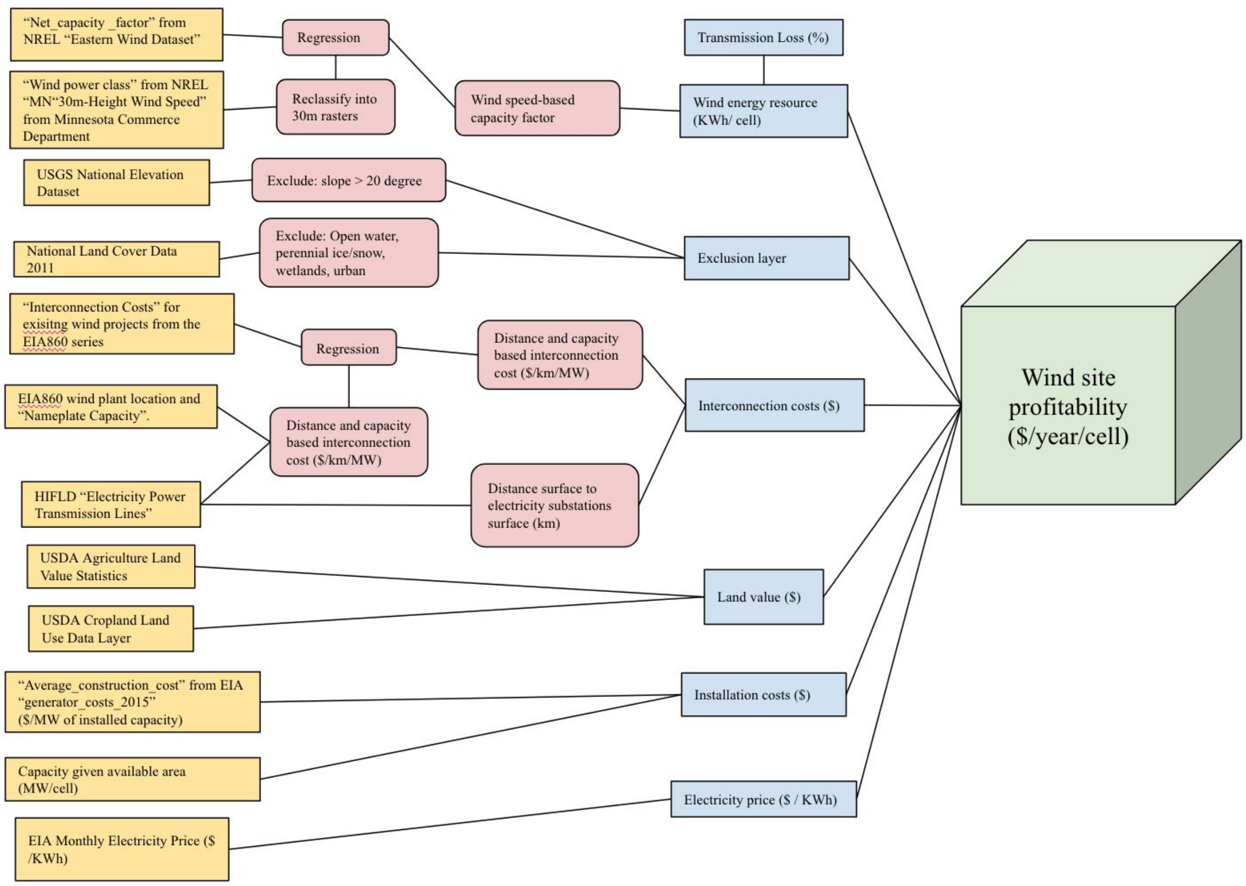

Figure A1: Data and processes for constructing the wind site profitability model. Yellow boxes signify data sources and specific variables. Red boxes represent the functions done to transform the data. Blue boxes are the final variables that will be used in the final calculations for solar profitability following the methodologies laid out by Lin (2016) and Bhandari et al. (2015)

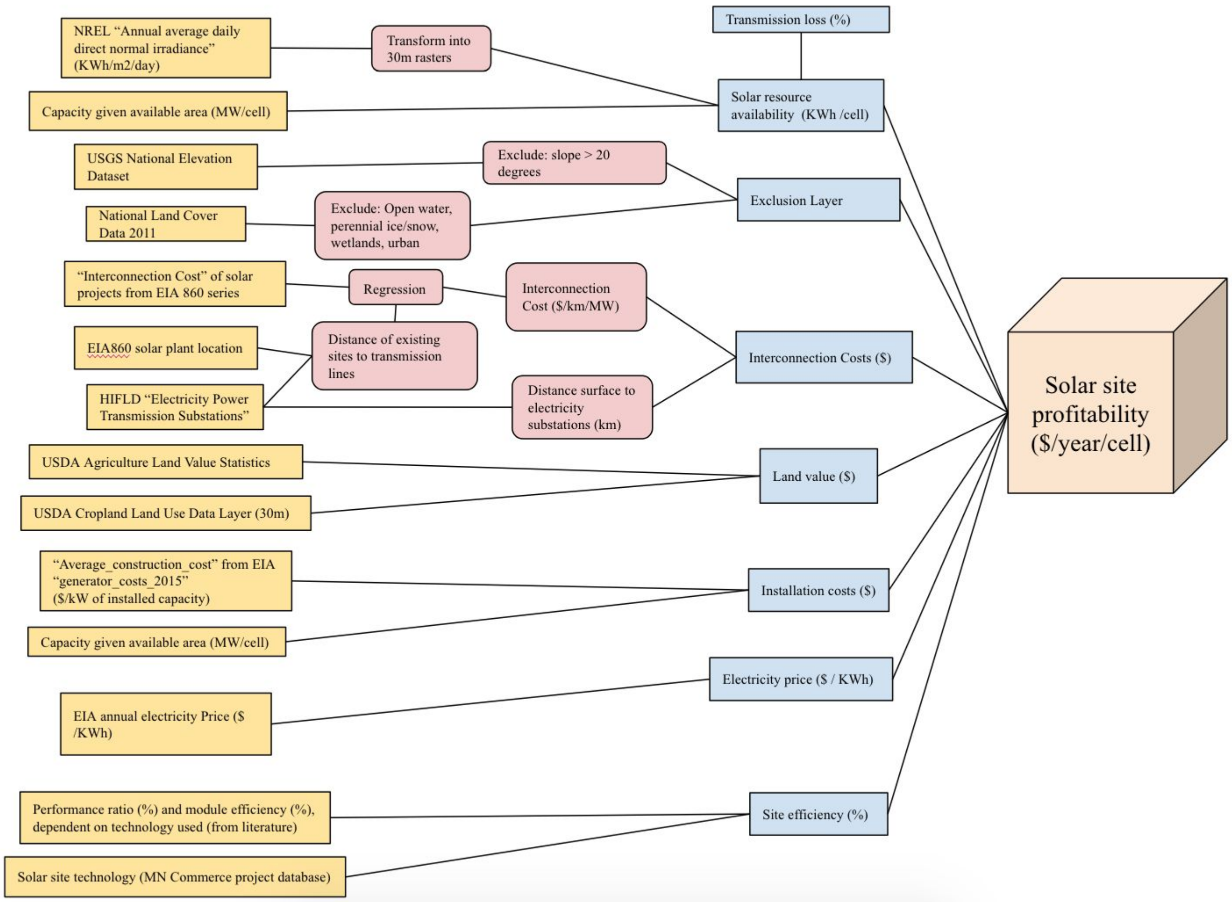

Figure A2: Data and processes for constructing the solar site profitability model. Yellow boxes signify data sources and specific variables. Red boxes represent the functions done to transform the data. Blue boxes are the final variables that will be used in the final calculations for solar profitability following the methodologies laid out by Lin (2016) and Bhandari et al. (2015)

Estimating Revenue from Wind

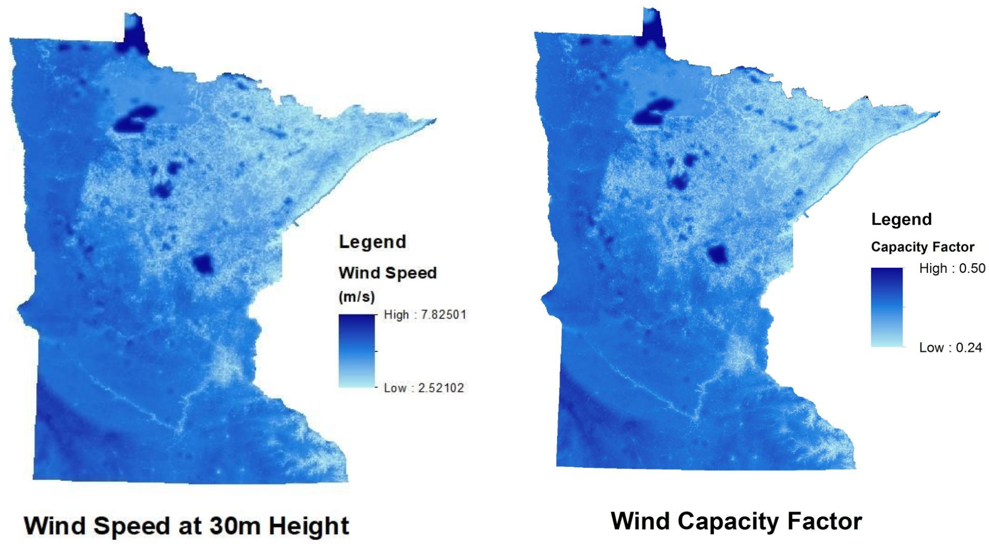

Figure A3 & A4: Annual average wind speed at 30-meter height (unit: m/s) (left) and the predicted wind generator capacity factor layer derived from it (right). Darker color corresponds to higher wind speed and higher wind generation capacity factor (right).

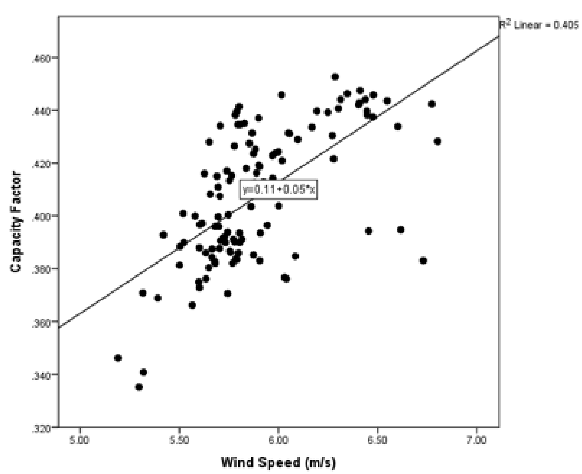

Figure A5: Scatter plot showing the relationship between the capacity factor of simulated wind projects given by NREL's Eastern Wind Dataset and the annual average wind speed at the site. Regression analysis showed a very strong positive correlation between wind speed and wind generator capacity factor ($p < 0.001$, Adjusted $R^2 = 0.403$, $N = 240$).

Selecting a Model for Interconnection Cost

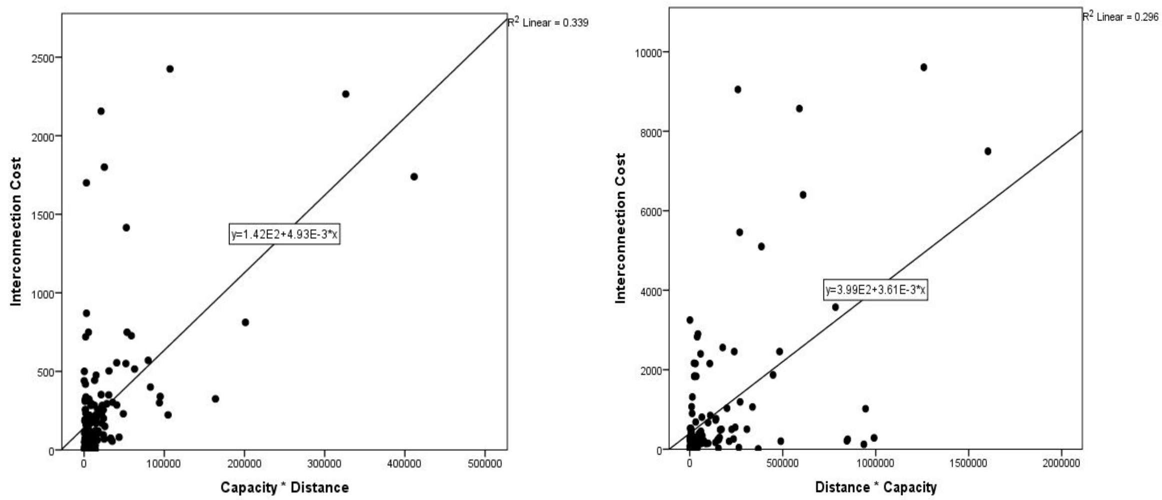

Figure A6 &A7: Scatter plots showing the relationship between solar (left) and wind (right) project interconnection costs (unit: \$1,000) and the products of the project's capacity (unit: MW) and its distance to the closest electric substation (unit: m) (Distance × Capacity). Simple linear regression showed strong positive correlations between the two variables for both solar and wind ($p < 0.001$ for both; adjusted $R^2 = 0.334$ and 0.291, n = 165 and 128, for solar and wind, respectively). Sample points represent solar (left) and wind (right) projects across the United States whose interconnection costs data are documented in the EIA-860 data series. All projects whose construction included the construction of new electric substations were excluded from the regression analysis.

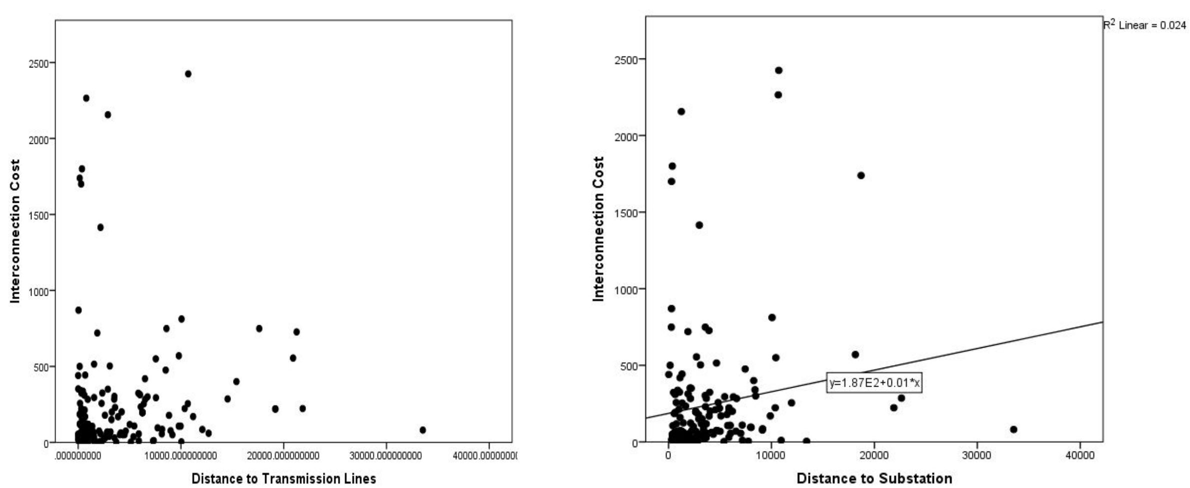

Figure A6.1 & A6.2: Scatter plots comparing the distance to transmission lines (left) and distance to electric substations (right) as predictors of the interconnection cost for solar projects (unit: \$1,000). Distance to transmission line (unit: m) alone did not predict the interconnection cost of solar projects ($p = 0.263$), while distance to electric substations was positively correlated with interconnection cost, although the explanatory power was weak ($p = 0.046$, Adjusted $R^2 = 0.018$).

Sample points in both graphs represent solar projects across the United States whose interconnection costs data are documented in the EIA-860 data series (n =165). All projects whose construction included the construction of new electric substations were excluded from the regression analysis.

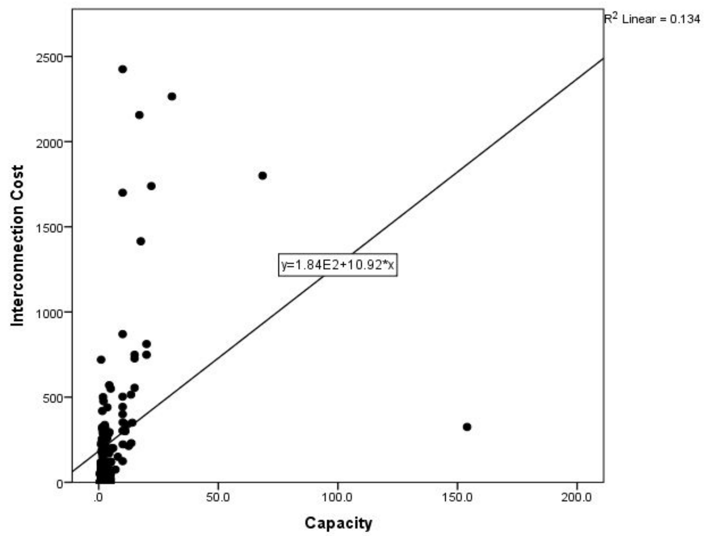

Figure A6.3: Scatter plot showing the relationship between solar project capacity (unit: MW) and interconnection cost (unit: $1,000). The regression results showed a significant positive correlation between solar project size and interconnection cost ($p < 0.001$, Adjusted $R^2 = 0.129$, $n = 165$).

Taking the product of project size and distance to substations significantly improved the predictive power of the model (See above Figure A6). Therefore, we used the product to estimate the interconnection cost in our solar profitability model.

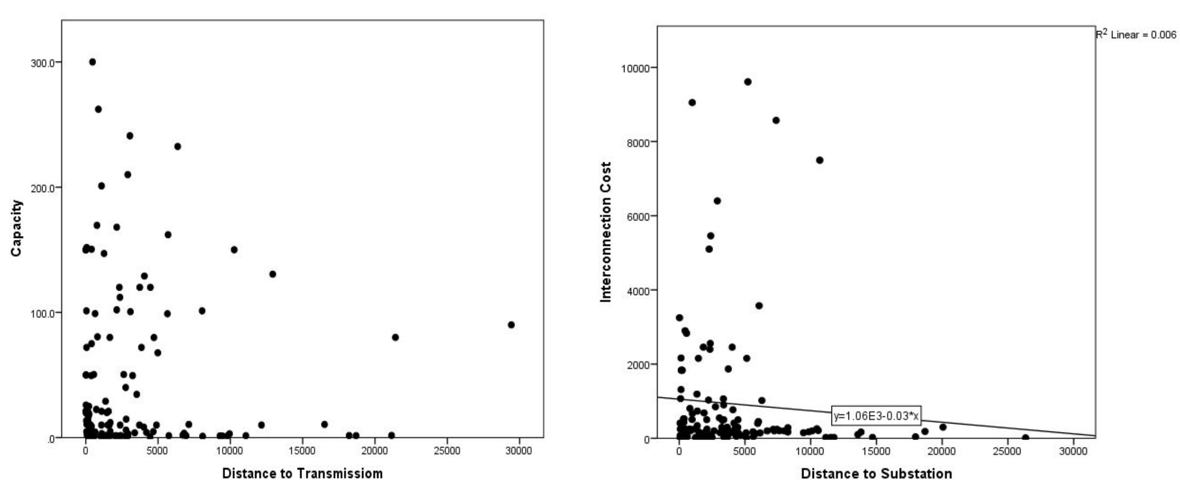

Figure A7.1 & A7.2: Scatter plots comparing the distance to transmission lines (left) and distance to electric substations (right) as predictors of the interconnection cost for wind projects (unit: $1,000). Distance to transmission line (unit: m) alone did not predict the interconnection cost of solar projects (p = 0.186), neither did the distance to electric substations (p = 0.381).

Sample points in both graphs represent right projects across the United States whose interconnection costs data are documented in the EIA-860 data series (n = 128). All projects whose construction included the construction of new electric substations were excluded from the regression analysis.

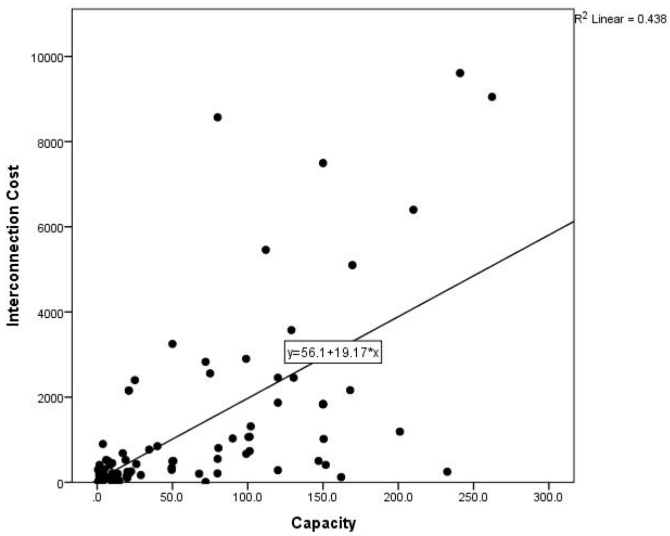

Figure A7.3: Scatter plot showing the relationship between wind project capacity (unit: MW) and interconnection cost (unit: \$1,000). The regression results showed a significant positive correlation between solar project size and interconnection cost ($p < 0.001$, Adjusted $R^2 = 0.433$, n = 128).

Taking the product of project size and distance to substations actually compromised the predictive power of the model (See above Figure A7) compared to using capacity alone. The adjusted R^2 value was lowered, but the linear correlation was still significant (Adjusted $R^2 = 0.291$ as opposed to 0.433). To keep the interconnection cost estimation consistent between wind and solar, we still used the product rather than capacity alone to estimate the interconnection cost in our wind profitability model.

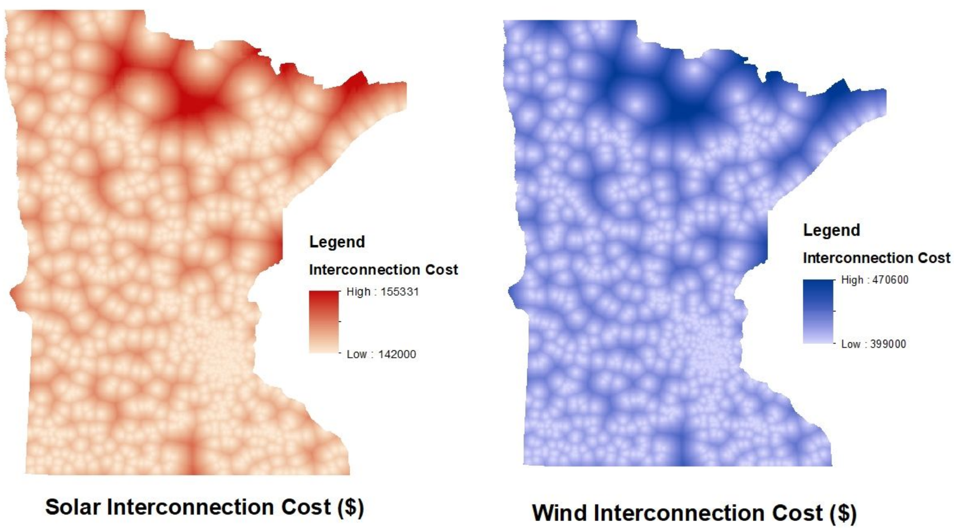

Figure A8 & A9: Predicted distribution of interconnection cost for solar (left) and wind (right) (units: $/cell). Darker color indicates higher interconnection costs. Note that interconnection costs for the two energies have different ranges.

Evaluating Land Value

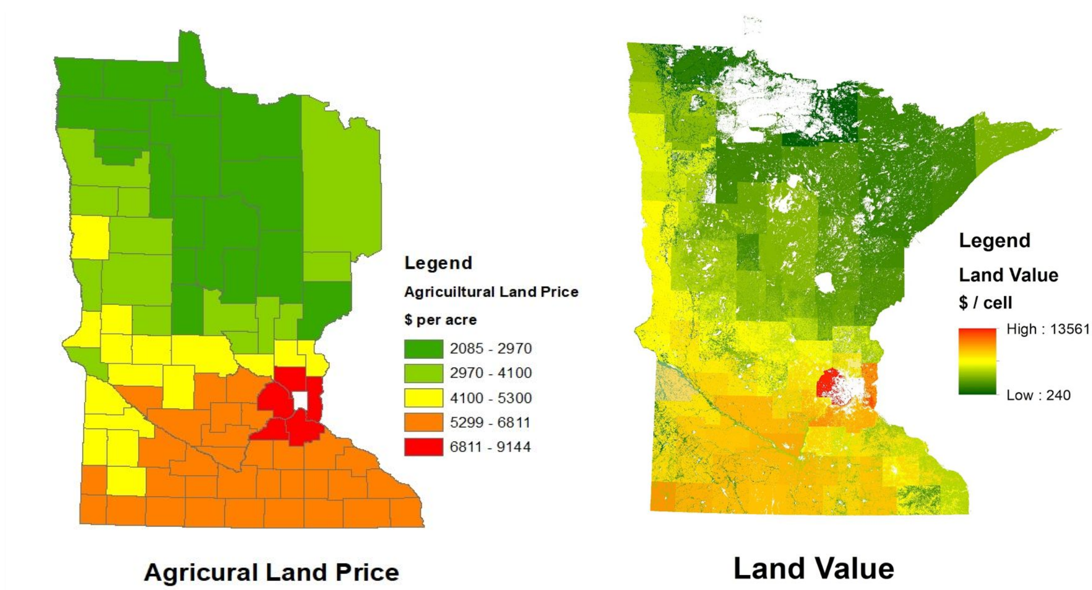

Figure A10 & A11: Map of agricultural land price by county (unit: $ /acre) (left) and predicted land cost across Minnesota (unit: $/cell) (right). In both maps, green represents relatively cheaper land areas and red represents more expensive lands. Note that both the scale and the units for the land price values were different between the two maps.

Based on the NLCD land use type data, land uses in Minnesota were first classified into cropland, pasture, and forests. Other land use types were considered as unsuitable for the development of renewable projects (See below Figure A12). For croplands, we used the Granular Acrevalue dataset at the county level (left) to estimate their prices (left). All cropland within the same county were assumed to have the same price at the county average value. Then each Land prices were also determined separately for pasture and timber lands combined with the cropland value to derive the final land value layer we used in our profitability model (right).

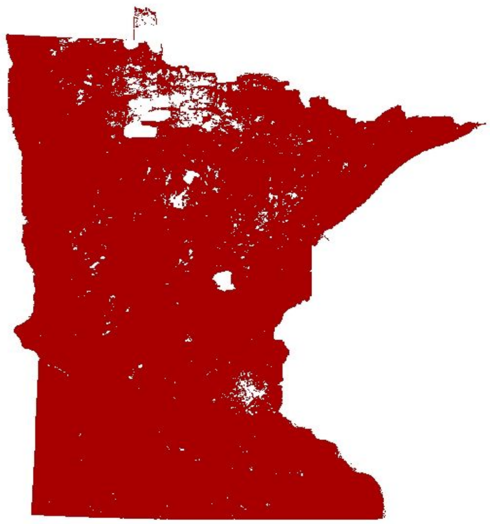

Figure A12: Map of area for RE installation in Minnesota. Cells whose land use types were classified as urban, wetlands and perennial snow by the NLCD 2011 data were defined as unsuitable for renewable installation, as were cells with a slope greater than 20 degrees.

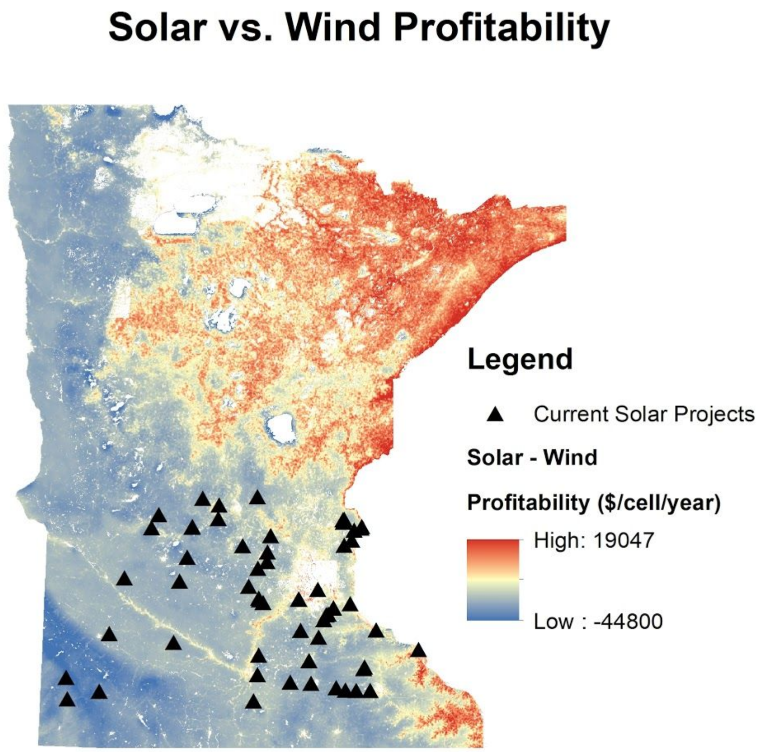

Figure A13 : Solar vs. Wind profitability and current solar project sites ($/cell/year). Map values were calculated by directly subtracting the profitability of solar from the profitability of wind at each location on the map.

Table A1 Solar & Xcel

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	Capacity Distortion	Profit Distortion
# of Xcel Cells (1,000,000 cells)		
% of Xcel Service Area		
Sample Size	47	26

Color coding scheme: insignificant; positive, highly significant correlation: α≤0.01.

Table A1. Solar Distortions and Xcel. We found significant relationships between the capacity distortion and presence of Xcel.