PREFERENCE FOR AND IMPACTS OF DIFFERENT UTILITY-SCALE ENERGY SITING DECISIONS FOR ELECTRICITY GENERATORS IN COASTAL REGIONS

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ABSTRACT

Both site selection and fuel choice decisions for utility-scale generators have important ramifications for the surrounding community. This is especially true in coastal regions, where land is often scarce due to high population densities. This study explores different aspects of site selection and fuel choice for large utility-scale energy generators in three different papers. Chapter 1 explores the public's preference for utility-scale solar energy siting in Rhode Island based on four current land types: agricultural, brownfield, commercial, and forest land. This chapter uses a discrete choice experiment survey to help evaluate how program attributes affect respondent preferences for large utility-scale solar energy siting in Rhode Island. Public's willingness to pay for a large set of solar siting decision attributes such as the size of a solar installation, visibility of solar panels, setback or a minimum distance of the solar panels from property lines, and the probability of residential development was estimated. Chapter 2 uses the hedonic pricing method and spatial difference-in-differences estimators to examine how multiple energy sources (that is, clean or dirty fuel types) impact property values in four East Coastal US states (GA, NC, RI, and SC) using Zillow ZTRAX housing transaction data and Energy Information Administration powerplant data. Geographic Information Systems (GIS) is used to

measure the distance from each property to the closest energy generators within the region. The final chapter of this study uses data from Energy Information Administration (EIA) and spatially explicit data on flood risk with a variety of measures from First Street Foundation's Flood Lab to assess the resilience of coastal community energy infrastructure and the flood risk faced by renewable energy infrastructure.

Preference for and Impacts of Different Utility-Scale Energy Siting Decisions for Electricity Generators in Coastal Regions

A Dissertation

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DEDICATION

This work is dedicated to my husband, Rev. Moses Fynn Coleman, who has been a source of strength, support, patience, and motivation for me throughout this entire experience. Also, I dedicate this work to my daughter, El-Roi Nhyiraba Coleman, for the companionship she provided and the patience she taught me throughout this Ph.D. study. Further, I dedicate this to my parents, Rev Stephen (RIP) and Mary Quainoo, who has always taught me to keep God first and to strive for excellence. To my brother, Samuel Quainoo, and sister Victory Quainoo for the guidance and love they showed me all through my studies.

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INTRODUCTION

Both site selection and fuel choice decisions for utility-scale generators have important ramifications for the surrounding community. This is especially true in areas where land is often scarce due to high population densities such as coastal communities. As populations increase, demand for energy and the associated energy infrastructure also increases; this is true in the US where total energy production and consumption continue to rise (Ritchie, Roser, and Rosado, 2022; AEO, 2022). The US Energy Information Administration (EIA) in 2022 disclosed that the net total energy generation increased to 4,243 billion kilowatt hours (kWh), up from 4,120 kWh generated in 2010. Though fossil fuel continues to constitute the majority of total energy generation sources, the introduction of renewable energy policies and regulations such as the Renewable Energy Portfolio Standard (REPS), renewable energy tax credits, federal solar investment tax credit, and the Public Utility Regulatory Policies Act of 1978 (PURPA) is enabling the rapid growth of the renewable energy sector as well (Yergin, 2006).

Energy infrastructure siting decisions face a variety of challenges. Locating near populous areas is advantageous in terms of reducing transmission costs, but this infrastructure is often viewed as a dis-amenity for local populations which can lead to residents' opposition. The availability of suitable space is also a concern, and this is especially true for renewable energy sources which typically require more land than their fossil-fuel counterparts. While this is an issue everywhere, this is perhaps an even more pronounced issue in coastal regions, where high population density often makes land scarce and expensive. Also, extreme weather events serve as a threat to the resilience of renewable energy infrastructure located close to coastlines, leading to high concern for US coastline resilience (Shepard et al., 2012).

This study explores different aspects of site selection and fuel choice for large-scale energy infrastructure in three different papers:

Chapter 1 explores the public's preference for utility-scale solar energy siting in Rhode Island based on four current land types: agricultural, brownfield, commercial, and forest land. This chapter uses a discrete choice experiment survey to evaluate how development program attributes affect respondent preferences for large utility-scale solar energy siting in Rhode Island. The chapter also estimates public willingness to pay for a set of solar siting decision attributes such as the size of a solar installation; visibility of solar panels; setback or minimum distance of the solar panels from property lines; and the probability of residential development.

Chapter 2 uses the hedonic pricing method to estimate how multiple energy sources (that is, clean or dirty fuel types) impact property values in East Coastal US states. Geographic Information Systems (GIS) was used to measure the distance from each property to the closest renewable energy installations within the region, allowing for a spatial difference-in-differences estimation procedure.

Finally, Chapter 3 uses data from Energy Information Administration (EIA) and spatially explicit data on flood risk with a variety of measures from First Street Foundation’s Flood Lab to assess the resilience of coastal community energy infrastructure and the flood risk faced by renewable energy infrastructure in North Carolina.

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CHAPTER 1: MODELING THE PUBLIC'S PREFERENCES FOR SOLAR ENERGY SITING IN RHODE ISLAND

With *Vasundhara Gaur, Corey Lang, and Gregory Howard; in Land Economics*

Abstract

This chapter explores the public's preference for utility-scale solar energy siting in Rhode Island based on four current land types: brownfield, commercial, farm, and forest land. A discrete choice experiment survey was designed to help evaluate how solar program attributes affect respondent preferences for large utility-scale solar energy siting in Rhode Island. Public willingness to pay for a large set of solar siting decision attributes such as the size of a solar installation; visibility of solar panels; setback or a minimum distance of the solar panels from property lines; and the probability of residential development were estimated. Results showed that current land use is the major constraint for public approval of large utility-scale solar siting. Respondents are willing to pay an additional monthly electric fee of \$13 - \$18 for solar installation on brownfield and commercial land. However, respondents require compensation of \$27 - \$43 to allow for solar installation on farm and forest land.

Introduction

Photovoltaic (PV) solar energy production continues to rise due to favorable state and federal renewable energy regulations and a relatively constant supply of the key resource (sun) unlike limited resources like water in hydropower generation (Blakers, 2015). In the year 2019 the US Energy Information Administration (EIA) projected that solar energy generation will increase by about 10 percent each year through 2035. This trend is illustrated in Figure 1.1 (EIA, 2019). Davis et al. (2021) stipulate the yearly average solar generation growth rate in the US is about 42% since 2010. This increase in solar generation is also attributed to a rapid decrease in construction costs. Unlike most renewable energy sources, solar energy construction costs have seen a steady and substantial decrease in recent years compared to other competing fuel types (EIA 2019). This trend is highlighted in Table 1.1.

In the first quarter of 2019, 2.7 gigawatts of solar capacity were installed in the US, increasing the overall solar generating capacity to 67 gigawatts. This capacity of solar installation increased to 89 gigawatts (GW) by the end of 2020 (Davis et al., 2021). The Solar Energy Industries Association projects even more rapid growth of solar energy generation in the coming years (SEIA, 2019). The Pew Charitable Trust (2014) also identified that the upward trend in solar energy production was related to the reduction in the price of photovoltaic (PV) panels worldwide, the abundant supply of sun resources in most US states, and favorable federal policies including tax incentives. Also, a range of state policies encourage renewable energy and contribute significantly to the growth of the sector. For instance, North Carolina in 2007 passed a Renewable Energy Portfolio Standard (REPS) which demands that 12.5% of the state's electricity be from renewable energy by the year 2021. The cost of a solar installation was reduced by more than half due to the 35% state renewable energy tax credit and an additional federal solar investment tax credit of 30%, thereby attracting more solar investments into the state. Entities that build solar energy generators in the state can be designated as Qualifying Facilities (QF) under the federal Public Utility Regulatory Policies Act of 1978 (PURPA) (The North Carolina Utilities Commission, Annual Report, 2019). This designation allows for more favorable terms for the solar facility as they sell electricity to the local utility (Strata Solar, 2015).

The site of our research is Rhode Island (RI), which in 2020 set a goal to have 100% of its total energy generation from renewable energy sources by the end of the year 2030. As of 2021, RI has achieved 555.4 MW of solar installation which covers 9% of RI residents' energy needs (The Brattle Group, 2021). To achieve its ambitious solar installation targets, the state enacted programs to help attract developers to boost solar energy generation in the state. Notable among them are Net Metering, the Renewable Energy Fund (REF), the Renewable Energy Growth (REG) Program, the RI Efficient Building Fund, and Community Choice Aggregation (CEA), which led to an increase in solar energy generation investment in the state. These upward trends in solar installations in Rhode Island are illustrated in Figure 1.2 (Rhode Island Office of Energy Resources, 2020).

Despite growth in the production of solar energy in the US (Carlisle et al., 2015; Greenberg, 2009; Jacobe, 2013), one critical factor that has the potential of curtailing this rapid progress in any US state, particularly RI, is the availability of suitable land with enough public support for the installment of large utility-scale s-*lar panels (1 MW and above solar installations). Also, Hernandez, Hoffacker, and Field (2015) identified that the future development of global solar energy is threatened by constraints such as the availability of land and environmental constraints. Solar panels are often installed directly on a field or ground and may also be installed on poles or roofs; however, large-scale solar PV electricity production requires a large amount of land relative to other fuel types (Timmons, Harris, and Roach, 2014). Typically, 1MW of solar installation requires five acres of land for installation (Ong et al., 2013). For large solar investments, weather conditions, closeness to high transmission capacity lines, and current land use (e.g., agricultural land) are critical in site selection (Uyan, 2013). Denholm and Margolis (2008) asserted that about 2% of agricultural land has installed ground-mounted solar panels in the US, and Curtis et al. (2020) asserts that most of NC solar installations are on former farmlands and 21.7% of current farmlands will be needed to increase solar generation from 4% to 12.5%. Shum (2017) projected that 78,872 to 169,198 acres of land will be converted for solar energy production between the years 2015 to 2050 in the US. Trainor et al., (2016) also stipulate that the major factor for change in land use is solar installation.

Finding suitable land that has adequate public support for the siting of utility-scale ground-mounted solar panels is a major challenge to the expansion of the solar energy sector. This is because many residents prefer the siting of ground-mounted solar panels on lands that generate fewer ecosystem services such as covered landfills and brownfields, rooftops, parking lots, etc. These siting choices are often expensive to solar developers. Carlisle et al. (2016) stipulated that though public support for the development of utility-scale solar energy production is high in opinion polls, when these projects are proposed to be sited on specific land locations they are heavily opposed by residents in that area (evidence of NIMBY (not in my back yard) attitudes). Waite (2017) outlined that renewable energy generation can be installed on lands of lower quality such as degraded and contaminated land sites. These sites tend to provide few or no ecosystem services, which makes them more attractive candidates for conversion to renewable energy generators and thus encounter the least opposition or conflicts in their selection for conversion to utility-scale solar generation (Stoms, Dashiell, and Davis 2013).

However, with favorable federal and state renewable energy policies and rising investment, more land is expected to be converted to utility-scale solar energy production. Some of these conversions may be met with public disapproval depending on various factors like current land use. For instance, RI is a small state with scarce land resources and high population density, where 63% of the state land currently exists as farm and forest land and a large number of residents support land preservation and conservation. Therefore, this study seeks to provide an in-depth analysis of the public's preferences for where large-scale, ground-mounted solar installations should be sited in a coastal state (RI). This paper will also estimate the public's willingness to pay for a large set of solar siting decision attributes using a choice experiment survey. Most notably, the survey examines how residents view trade-offs between four prior land-use types: agricultural, brownfield, commercial, and forest lands.

Objectives

This research seeks to answer the following questions:

- What are the attributes that impact residents' preference for solar energy siting?
- How much are residents willing to pay for changes in the size, visibility, and setback of a solar installation?
- How do resident preferences for solar development change as the probability of future residential development change for the proposed solar siting land?
- How does current land use impact residents' preferences for solar siting?

- How does residents' WTP for solar programs differ from one current land use type to another?

Literature Review

Solar Energy Installation Siting and Public Opinion

Federal and state policies like investment tax credits, renewable portfolio standards (RPS), clean power plans, etc. have had a significant impact on increasing solar energy generation across different states. The production of photovoltaic solar energy is projected to continue increasing in the next decade (Bhattacharya et al. 2017; Wiser et al. 2011; Yin and Powers 2010). Carlisle et al., (2014) and Carlisle et al., (2015) assert there is high support for increased solar energy generation and that individuals are even willing to pay a premium for energy from clean sources. Communities that were classified as stigmatized were more likely to accept such projects while communities with more desired landscapes were more likely to reject the siting of these proposed projects in their vicinity (der Horst, 2007).

Cohen, Elbakidze, and Jackson (2020) stipulate that most of the solar energy literature focuses on residential solar energy installation, that is, smaller rooftop installations rather than large installations on commercial properties or other large tracts of land. Their study thus focused on finding state renewable energy policies that influence firms to install solar panels on their properties. They found that state policies such as renewable portfolio standards, financing programs, and tax breaks motivate firms to install solar panels. Also, some commercial firms install solar systems to improve their image as part of a public relations strategy since they may be seen as environmentally friendly to their clients or the public. They also found that firms are most likely to adopt the installation of solar panels if they are in areas or states where solar energy can be generated most and where electricity prices are high and so avoided electricity expenditures are greatest. Carlisle et al. (2016) examined how the visibility of utility-scale solar energy production, the proximity of respondents' homes to a solar generation facility, and current land use affect public support for proposed solar projects in six southern California counties. They employed factor analysis and found that both proximities of the solar production site to respondents' residences as well as the type of land use for its installation had an impact on whether residents supported the establishment of large utility-scale solar plants in their locality. The study found that about 80% of respondents supported the development of large utility-scale solar energy generation under the condition that the solar facility can be sited near their home only with assurance by developers that the facility will not be made visible from residents' homes.

Choice Experiment Studies on Land Conversion for Renewable Energy

Bergmann, Colombo, and Hanley (2008) used a Choice Experiment (CE) to evaluate the economic and environmental trade-offs of renewable energy. They did this by describing the environmental and economic attributes of several alternative energy production sources. The attributes included landscape impact, wildlife impact, air pollution, jobs, and prices. The study found that urban and rural residents' value these attributes differently; while urban residents are more concerned about the impact of large-scale renewable energy production on landscapes, rural residents valued permanent jobs created and reduction in air pollution. Bergtold, Fewel, and Williams (2014) evaluated the willingness of farmers to choose to produce biofuel feedstocks based on different contractual conditions. The choice experiment was conducted with farmers in

Kansas to assess their willingness to produce biofuels based on different contracts. The study showed that the location of land and the type of feedstock affects farmers' willingness to accept a contract.

Convery et al (2012) examined the factors that influence farmers in Cumbria, a county in Northern England, to convert their land used for growing food crops to the growing of plant biomass for energy production. This conversion applied to marginal farmlands. The study found that monetary incentives had little influence on farmers' decision to convert agricultural farmlands for biomass energy production. However, cultural factors and farmers' desire for the price stability of food crops did affect their decision. Conversely, Wolfe, Downing, and Hoagland (2012) found that economic factors, as well as regulations and policies, affect farmers' decision to convert their agricultural lands used for growing food crops to the production of biomass for energy generation.

Renewable (Wind) Energy Siting

Rodrigues**,** Montañés**,** and Fueyo (2010) stipulated that large utility-scale production of renewable energy such as wind and solar energy requires larger land space than conventional energy sources such as nuclear and fossil fuel energy production. In their study, they developed indices for assessing the visual impact of such large-scale renewable energy production in Spain. They found that if wind energy production constitutes 16% of the total energy generated in Spain in 2007 then about 2% of the country's land area will be occupied by wind energy generation facilities. Bishop and Miller (2007) used an online survey to estimate the impact of light conditions or visibility of turbines on respondents' preference for siting of large utility-scale offshore as well as onshore wind energy production. They found that respondents' disapproval of visibility due to wind turbine siting was based on the noise the turbines generate, the killing of birds who came close to the turbines, and aesthetic factors. Torres et al. (2009) assert that though wind energy generation is considered environmentally friendly by the public, siting of large-scale production is opposed by many due to its impact on landscape aesthetics, and its visibility is measured using aesthetic impact. Urban communities often oppose the siting of utility-scale wind farms in their vicinity due to factors such as visibility. Thus, policymakers and stakeholders should consider critically the visual impact of renewable energy generation before selecting a site where they propose to install them **(**Rodrigues**,** Montañés, and Fueyo**,** 2010; Ek, 2005). Firestone and Kempton (2007) sought to gauge public opinion on utility-scale offshore wind energy generation using a survey from a sample drawn from Cape Cod Massachusetts using factor analysis. They found a huge majority of respondents thought that wind energy generation would produce more negative impacts such as impairment of oceanic lives, negative impact on the environment, aesthetics as well as colliding with fishing and boating activities. They found that younger, well-educated, and medium to higher-income respondents were more likely to support offshore wind energy generation.

Ladenburg (2008) sought to model Danish attitudes toward on-land and offshore wind energy generation. He employed a probit model and found that the public preferred offshore wind generation to on-land wind generation. However, smaller wind turbines that have fewer turbines may make on-land wind turbines more attractive for public support. Their research showed that younger people are more likely to accept wind energy generation compared to older people. The study showed that respondents whose homes were in proximity to on-land and offshore wind turbines did not show any extra negative reaction to wind energy generation than their counterparts who lived far from wind energy generation. Using samples from the same

Danish population. Ladenburg (2009) used a binary logit model to examine respondents' experience of the visibility of wind turbines. The sample was comprised of two groups; one group was respondents who lived near an offshore wind turbine and the other group lived far from an offshore wind turbine. The study showed that respondents who lived far from offshore wind turbines accept the visual dis-amenity of offshore wind turbines more than their counterparts who lived closer to these turbines. He also found that acceptance of future offshore wind turbines by the public is not influenced by the location of these turbines.

Our study seeks to contribute to the literature by quantifying perceived amenities and dis-amenities from large utility-scale solar installation based on different solar siting attributes, including current land use (brownfield, commercial, farm, and forest).

Experimental Design and Data

A discrete choice experiment (DCE) was designed and administered as part of a broader survey of Rhode Island residents. The goal of the DCE is to estimate the public's preference for solar energy siting in Rhode Island. The following attributes were included for each alternative:

1. Acres of solar installation: the size of the solar installation in acres. 1 acre of land under solar panels can produce enough power to meet the demand of nearly 22 homes in Rhode Island.
2. Visibility of solar panels: how visible are the solar panels from residents' homes or frequently traveled roads.
3. Setback or a minimum distance of the solar panels from the property lines of the proposed site.

4. Probability of residential development: the likelihood that farm or forest land will be converted for residential purposes in the next 10 years (since most farm and forest land has been zoned for residential development; this was included only for choices involving farm and forest parcels).
5. Change in the price of electricity: decrease or increase in residents' monthly electric bill if the solar program is implemented.

Also, each choice in the DCE focused on a different group of parcels, and each group of parcels had a current land use of brownfield, commercial, farmland, or forest land. This variation allowed us to estimate how preferences differ by current land use. The attributes the study sought to test are defined in Table 1.2.

Attributes levels in the CE also differ based on land use type, for instance, the probability of future residential development was assigned a non-zero probability for farm and forest lands since those are often zoned for future residential purposes. Also, change in electric bill had eight different levels for farm and forest land use types CE's (-$30, -$20, -$10, -$5, $5, $10, $20, and $30), however, for brownfield and commercial land use types change in electric bill excluded the -$10, -$20, and -$30 levels since the cost of utility-scale solar installation on commercial and brownfields are higher hence unrealistic to have such solar programs proposed to be installed on these sites reduce monthly electric bills drastically.

A D-efficient design based on the Stata dcreate command was created, the design included 60 different farm and 60 forest, 30 brownfield, and 30 commercial choice experiments (Hole, 2017). Each respondent receives 2 randomly assigned farm CEs and 2 farm CEs as well as 1 brownfield CE and 1 commercial CE. This uneven distribution of land use type CEs to respondents is influenced by the fact that farm and forest lands are the most common sites for utility-scale solar energy siting in RI which also faces the most resistance from residents.

The survey was comprised of four sections. The first section gave an introduction and background of our study. The second section asked respondents general questions about their energy use and opinions regarding different energy sources. The third section presented the choice experiment to respondents. An example is shown in Figure 1.3. The final section asked demographic questions about respondents including their age, income, highest educational level, etc.

The survey was administered online using Qualtrics and through the mail from August to December 2020. Mailings, which include the paper survey as well as information on how to fill out the survey online through Qualtrics, were sent to 3,000 individuals. 148 respondents returned a finished paper survey while 508 responded to the online Qualtrics version representing a total final sample of 656 respondents implying a response rate of 21.9%.

Each respondent was given 6 different solar development choices based on current land use. Two of the choices involved land that had a farm as the current land use; another two of the choices had forest as the current land use. Brownfield and commercial land each had one choice in the survey. CE was disproportionately assigned to current land-use types in favor of farm and forest because they serve as more common siting locations in RI and receive more disapproval from the public for their conversions to renewable energy siting compared to commercial and brownfields. In each choice, respondents had 3 alternatives to select from: Solar Program A (Choice A), Solar Program B (Choice B), or Status quo (Choice C). Which makes a total of 18 choices for each respondent to select from. Thus, the total choices made by all respondents in our sample is given as the Number of respondents x the number of choices (656*18=11,808= choices).

Methodological Framework

Discrete Choice Model

Discrete choice models are used in estimating preferences for a variety of attributes or characteristics of a choice. In our survey, respondents are presented with a series of choices. In each choice, two alternative solar energy development plans, as well as a status-quo (no change in the current situation/none of the development plans), are offered. The respondent is asked to select their preferred option. The resulting discrete choice experiment (DCE) data will be used to estimate preferences for each attribute of the solar siting decision.

Random Utility Theory

McFadden (1973) stipulates that random utility theory is mostly used for modeling respondents' discrete choices. Random utility theory is based on the assumption that respondent *i*'s utility *(U)* for a specific development option *(j)* is a function of two components which are: deterministic (V_{ij}) and random components (ε_{ij}) (Haab and McConnell, 2002). Respondents are assumed to choose utility-scale solar energy siting options that provide them with the highest utility subject to their budget constraints. The components that make up respondent utility are presented mathematically as follows in Equation 1:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{1}$$

Where U_{ij} = latent utility; V_{ij} = the observable element of utility for individual *i* from choice alternative *j*; and ε_{ij}= a random element of the utility of respondent i from the chosen alternative.

The observable or deterministic component of utility can be further disaggregated into two groups which are: attributes of the solar siting option (*X*) and respondents' characteristics, or attributes of the decision-maker or of the entire choice (*Y*). Hence the indirect utility of a respondent is represented as $V_{ij} = X_{ij} + Y_i$. Substituting this indirect utility into equation (1) yields

$$U_{ij} = X_{ij} + Y_i + \varepsilon_{ij} \qquad (2)$$

Assuming each respondent is faced with two competing solar siting options *j* and *k*, $\forall J$ and a status quo of no solar siting preference. If option *j* offers an expected utility greater than option *k* for an individual that is, $EU_{ij} > EU_{ik}$ then the individual will choose option *j* over *k*.

This can therefore be expressed mathematically as,

$EU_{ij} > EU_{ik}$, where

$$U_{ij} = X_{ij} + Y_i + \varepsilon_{ij}$$

$$U_{ik} = X_{ik} + Y_i + \varepsilon_{ik}$$

$$X_{ij} + Y_i + \varepsilon_{ij} > X_{ik} + Y_i + \varepsilon_{ik} \qquad (3)$$

The difference in probability of observed utility for the chosen alternative (j) and other alternatives is greater than zero and is presented in equation 4 below:

$$Pr_{ij}[Y = j|X_{ij}, X_{ik}, Y_i]$$

$$=Pr[U_{ij} > U_{ik}]$$

$$=Pr[(X_{ij} + Y_i + \varepsilon_{ij})-(X_{ik} + Y_i + \varepsilon_{ik}) > 0|\, X_{ij}, X_{ik}, Y_i] \qquad (4)$$

$$=Pr[(X_{ij} - X_{ik} + \varepsilon_{ij} - \varepsilon_{ik}) > 0 | X_{ij}, X_{ik}, Y_i]$$

Introducing coefficients for attribute variables and decision-maker-specific characteristics into equation (3) as,

$$V_{ij} = \beta X_{ij} + \gamma Y_i \tag{5}$$

β and γ represent a vector of parameters of the observable attributes X and decision-maker specific characteristics, Y. The random element of utility has mean zero and follows a Type 1 extreme value distribution as

$$F(\varepsilon_{ij}) = \exp(-exp(-\varepsilon_{ij})) \tag{6}$$

Under these conditions, specification is made that probability that a respondent selects alternative j as his best option from a set of J alternatives as a function of the observable component (V) as

$$\Pr(Y_i = j) = \frac{\exp(\boldsymbol{\beta} X_{ij} + \boldsymbol{\gamma} Y_{ij})}{\sum_{j=1}^{J} \exp(\boldsymbol{\beta} X_{ij} + \boldsymbol{\gamma} Y_{ij})} \tag{7}$$

Conditional Logit Model

McFadden (1973) introduced the conditional logit model, which is in many ways a generalization of the binary logistic regression to multinomial choices. Respondents are given different scenarios before choosing among the presented alternatives. In this data format, each observation corresponds to one alternative available to the respondent, and the dependent variable is binary, represented by 1 when the respondent selects that alternative and 0 if the person does not choose it. Here the respondents' choice is influenced by two broad variables; these variables include decision-maker variables such as age, employment status, income, the highest level of education, etc. as well as attributes of the choice alternatives such as the visibility of the installation, size of solar installation, changes in the price of electricity, setback, probability of residential development. The decision-maker variables cannot be included directly in the model but are integrated into the conditional logit model by interacting them with alternative-specific constants. This model considers how different characteristics of the solar siting choice impact the utility of choosing different alternatives; and it is based on the assumption that all else equal, changing an attribute will have the same marginal impact on utility for any of the other alternatives of that attribute. The probability that respondent *i* selects or chooses alternative *j* is under the conditional logit model is given as:

$$\Pr(Y_i = j) = \frac{\exp(\beta X_{ij})}{\sum_{j=1}^{J} \exp(\beta X_{ij})} \tag{8}$$

From the model, the indirect utility of the different attributes of the proposed development plan (size of a solar installation; visibility of solar panels; changes in the price of electricity; setback; the probability of residential development) is estimated as:

$$V_{ij} = \beta_1 Price + \beta_2 Full\_Vis + \beta_3 Part\_Vis + \beta_4 Set + \beta_5 Acres + \beta_6 Prob + \beta_7 Dev \tag{9}$$

Mixed Logit Model

Unlike the conditional logit model, the mixed or random parameter logit model relaxes the independence of irrelevant alternatives (IIA) assumption. It allows for preference heterogeneity and also heterogeneity in the scale parameter by including a random parameter that constitutes how each respondent's preference differs from the population mean. Equation (10) below shows the utility of respondent *i* for the chosen alternative (j).

$$U_{ij} = X_{ij}(\beta + \eta_i) + \varepsilon_{ij} \tag{10}$$

Here X_{ij} = observed attributes, β = vector of mean preference parameters, and η_i = vector of individual specific deviation from the mean preference parameter.

Calculating WTP for Marginal Changes and Compensating Variation for a specified project

Compensating variation, or total WTP, is estimated by equating the indirect utility of a specific selected development plan with the status quo plan.

Utility of development:

$$V_{ij} = \beta_1 Price + \beta_2 Full\_Vis + \beta_3 Part\_Vis + \beta_4 Set + \beta_5 Acres + \beta_6 Prob + \beta_7 Dev$$

Where Dev = Alternative specific constant for alternatives that are development plan

Utility of status quo: In V_{SQ}, all of the attribute values are zero (except Prob).

$$V_{SQ} = \beta_6 Prob$$

Equating the two plans: $V_1 = V_{SQ}$

$$\text{WTP} = \frac{-(V_1 - V_{SQ})}{\beta_1}$$

Where V_1 in this case is the utility of the non-price attributes of the specified program.

Calculating Marginal WTP

To understand the logic behind marginal WTP estimates, consider comparing the indirect utility of a development plan to another similar plan with a marginal difference in only one attribute (in this example, setback). Such a comparison yields:

$$V_{1A} = \beta_1 Price + \beta_2 Full\_Vis + \beta_3 Part\_Vis + \beta_4 Set + \beta_5 Acres + \beta_6 Prob + \beta_7 Dev$$

$$V_{1B} = \beta_1 [Price + MWTP] + \beta_2 Full\_Vis + \beta_3 Part\_Vis + \beta 4[Set + 1] + \beta_5 Acres + \beta_6 Prob + \beta_7 Dev$$

$$V_{1A} = V_{1B}$$

Setting these equal and solving for $MWTP$ yields:

$$MWTP_{set} = -\frac{\beta_4}{\beta_1}$$

Interacting Land Use Types

Dummies for land use cannot be directly included in the model but can interact with the alternative specific constants ASCs and these interactions are expected to yield different utility levels at different prices as represented by Figure 1.4.

$$\sum_{i=1}^{4} ASC_{SQ} * LU_i \tag{11}$$

Including the interactions of land use with the ASC, and the ASC is a dummy variable for whether an alternative is a development program, and the interaction is denoted as Land Use_Dev.

$$V_{ij} = \beta_1 Price + \beta_2 Full\_Vis + \beta_3 Part\_Vis + \beta_4 Set + \beta_5 Acres + \beta_6 Prob + \beta_7 Farm\_Dev + \beta_8 Forest\_Dev + \beta_9 Commercial\_Dev + \beta_{10} Brownfield\_Dev \tag{12}$$

Calculating Compensating Variation /Total WTP for Different Land Use Types

$$V_{LU(A)} = \beta_1 [WTP] + \beta_2 Full\_Vis + \beta_3 Part\_Vis + \beta_4 Set + \beta_5 Acres + \beta_6 Prob + \beta_7 Farm\_Dev + \beta_8 Forest\_Dev + \beta_9 Commercial\_Dev + \beta_{10} Brownfield\_Dev$$

Calculating the willingness to pay for a specific land use type is given as:

$$V_{LU(A)} = V_{SQ}$$

$$WTP_{LU(A)} = \frac{(V_{SQ} - V_{LU(A)})}{\beta_1}$$

Also, six distinct comparisons can be made for the difference in WTP for the four land-use types. A single general example of WTP to move from land-use *A* to land-use *B* is calculated as follows:

$$WTP_{LU(A)} = WTP_{LU(B)}$$

$$\frac{(V_{SQ} - V_{LU(A)})}{\beta_1} - \frac{(V_{SQ} - V_{LU(B)})}{\beta_1}$$

$$= \frac{(V_{LU(B)} - V_{LU(A)})}{\beta_1}$$

Results

Summary Statistics

Table 1.3 displays the distribution of summary statistics of all survey respondents. The average age of our final sample is 54 years with over 56% of respondents aged 55 and above. Also, the average household income of respondents was estimated between $75,000 to $99,999. 70% of respondents earned an annual household income of $75,000 and more. About 56% of respondents are employed full time and 67% of the respondents had a college degree or more. The majority of respondents representing 52% were female compared to the RI 2010 census data gender distribution which reported females as 52% of the total population. Also, 34.8% and 19.2% of our sample respondents were affiliated with Democrat and Republican political parties respectively. The average number of years respondents have lived in their current residence is 11 to 15 years. The majority of respondents (65%) lived in suburban communities and the smallest percentage of respondents (15.1%) lived in urban communities.

Logit Regression Models

Table 1.4 displays three conditional logit (CL) regression models and one mixed logit (ML) model. The first and second columns contain basic model outputs with only solar siting attributes and no land interactions for the CL and ML models respectively. The third column contains the output of the conditional logit model of solar attributes with land use (brownfield, commercial, farm, and forest) interacted with the *Dev* alternative-specific constant; and the fourth column is the output of the conditional logit model with land use interacted with both and the *Dev* alternative-specific and cost.

Attributes

Results from basic models for ML and CL regression modes are similar for all attributes of our discrete choice experiment. All models (basic and interaction models) show that attribute *Acres* is positive and statistically significant at a 1% significance level, meaning respondents prefer larger solar installations. Both *Partially Visible* and *Fully Visible* attributes were negative and statistically significant at 1% and 5% significance levels respectively, implying that respondents do not like to have solar installations to be visible to them. Models that include land interactions showed that the coefficient for *Setback* is positive and significant at the 10% level. This means a higher *Setback* slightly increases the chance for a respondent to select a solar siting program. However, in the basic model with no land interaction, *Setback* has a negative but statistically insignificant coefficient meaning *Setback* has no impact on the respondent solar siting decision. Thus, evidence that respondents care about panel setbacks is weak and mixed at best.

The *Probability of Development* attribute contains non-zero values for only status quo choices. Here, the land-use interaction model shows that the coefficient of the probability of development attribute is negative and highly significant means that respondents are less likely to choose the status quo (and more likely to choose a solar development option) when the probability of development is high. This implies respondents prefer the solar siting program if there is a high chance the forest or farmland will be converted to residential development in the next 10 years. Also, in the basic model, *Dev* is negative and statistically insignificant. Meaning the proposed solar siting program has no impact on respondents' choices if there is no specific type of land proposed for their installation.

Finally, the Cost attribute is negative and highly significant across all models. Implying that the higher cost of the program reduces respondents' decision to select the specified solar siting program.

Current Land Use Interactions

Coefficients of all current land use type interactions with the solar program ASC are highly significant at a 1% significance level, but they do not share the same sign. The *Brownfield*Dev* and *Commercial*Dev* coefficients were positive, implying respondents are highly likely to choose a solar siting program if the current land use is a brownfield or commercial land type. Conversely, coefficients of the *Farm*Dev* and *Forest*Dev* interactions were negative, implying respondents are less likely to choose a solar siting program if the current land use is farm or forest land. These results conform to our expectations, that individuals prefer large utility-scale solar siting on brownfields and commercial lands instead of farm and forest land types.

Cost Interactions

In the cost interaction model, all current land-use types and cost interaction are negative and highly significant at a 1% significance level. However, *Commercial* Cost* has a higher coefficient followed by *Brownfield*Cost* implying that respondents are more sensitive to price changes on commercial and brownfield solar development plans than on farm and forest solar development plans. This is likely due at least in part to the different values price (represented by changes in monthly electric bill) for commercial/brownfield and farm/forest. The commercial/brownfield price range is almost all positive (losses), while farm/forest is equally split between positive (losses) and negative (gains). If people are loss averse, you'd expect the pattern we see here (respondents are actually loss averse in our data). Also, *Farm*Cost* has a higher coefficient than *Forest*Cost* implying that respondents are more sensitive to price changes on farm than forest solar development plans.

Welfare Estimates

Table 1.5 displays the welfare estimates of our choice experiment. The first panel presents the marginal willingness to pay estimates of the solar siting attributes (acres, partial visibility, full visibility, setback, probability of development, cost) and the second panel presents compensating variation/total WTP estimates of current land use type (brownfield, commercial, farm, forest lands) respectively.

Marginal WTP

Marginal WTP results are presented in panel A, on average respondents are willing to pay \$0.31 each month for an additional acre of land proposed for solar installation where no current land use is specified. However, when current land use is specified, respondents are willing to pay a reduced average of \$0.25 for an additional acre of (brownfields, commercial, farm, or forest) land for solar installation. Compared to no visibility of solar installation, respondents are willing to be paid/compensated an amount of \$3.67 and \$3.06 to allow for partial visibility of solar panels when current land use is not specified and is specified respectively. Also, on average respondents must be paid more (\$10.99 and \$8.91) to allow for full visibility of solar installation if current land use is not specified and when specified respectively.

The MWTP estimate for *Setback* is insignificant in our basic model but slightly significant at 10% in the current land use specified model implying respondents' decision to choose a solar siting program is largely unaffected by the setback of solar panels from property lines. The *Probability of development* MWTP in the basic model is positive and highly significant implying that respondents are willing to pay an average of \$0.52 more for each percentage increase in the probability of development. When current land use is specified as farm or forest land respondents are willing to accept a very little compensation of \$0.20 when the chances of the forest and farmland being converted for residential development increases.

Compensating Variation (CV)/ Total WTP

Panel C presents CV results for the basic model and all current land-use types. To calculate the CV estimates of solar installation for all 4 current land use types (brownfield, commercial, farm, and forest) we assume a completely visible solar installation, 10 acres of solar installation, a setback of 100 feet from property lines, and a 0% probability of residential development if the solar installation is not built.

Generally, respondents are opposed to a solar development plan with the conditions mentioned above and require to be compensated \$10.82 to agree to solar installations when no current land use is specified. However, when current land use is specified, observe a more nuanced story. Also, respondents are willing to pay and average monthly fee of \$13.02 and \$18.04 for brownfields and commercial to be converted for solar installation respectively. However, respondents require an average monthly compensation of \$26.60 and \$43.15 for farm and forest land conversion to solar installations based on the conditions of the solar program mentioned above.

From the cost interaction model, respondents are willing to have an average monthly increase of \$11.54 and \$15.03 in monthly electric bills to allow solar installation on brownfields and commercial lands respectively. On the other hand, respondents expect an average monthly decrease of \$28.34 and \$54.09 in monthly electric bills to allow for solar installation on farm and forest lands respectively.

Economic Interpretation of CV Estimates

The assumed solar program with completely visible solar installation, 10 acres of solar installation, setback of 100 feet from property lines, and a 0% probability of solar installation yield different CV estimates for each land type. 1 acre of solar installation produces enough power for 22 homes in RI, this implies 10 acres of solar installation will provide power for 220 homes. For brownfields, the 220 homes are willing to pay a monthly average total of

($13.02*220 homes) = $2,864.40 which translates to an average annual total of $34,372.80 if this solar program is built on a brownfield. Also, when the solar program is built on commercial land, the 220 homes are willing to pay an average monthly total of ($18.04*220 homes) = $3,968.80 which translates to an annual average total of $47,626.60. However, when the assumed solar program is proposed on farmland, the 220 homes require an average monthly total compensation of (-$26.60*220 homes) = -$5,852.00 which translates to an average annual total of -$70,224.00. Solar program proposed on forest land requires the greatest average monthly total compensation of (-$43.15*220 homes) = -$9,493.00 which translates to an average annual total of -$113,916.00.

Comparing WTP Premia Based on Current Land-use Types

Table 1.6 compares the difference in WTP for 6 distinct pairs of current land-use types. As expected, the difference between the most (commercial) and least (forest) popular land-use types were the highest. The difference between the two most popular (brownfield and commercial) was the least. The difference between the two least popular land choices for solar installation (farm and forest) is much larger. This implies that respondents' dislike for forest land conversion is much larger even than their aversion for their second-least liked land use conversion.

Conclusion

This study quantified perceived externalities from large utility-scale solar installations based on different solar siting attributes, including current land use types (brownfield, commercial, farm, and forest). Both online and mail versions of a survey with a solar siting DCE were sent to 3,000 RI residents with a final sample of 656 representing a 21.9% response rate.

The conditional logit regression model was used to estimate respondents' WTP for the various solar siting attributes; solar siting attributes such as the Visibility of solar panels and cost (change in electric bill) significantly reduce respondents' preference for solar siting program in RI. Respondents needed to be compensated \$3 -\$11 to allow for partial and complete visibility of solar panels. The probability of residential development attribute had a negative coefficient in preferred model, however, the increase in its magnitude increases the preference for solar development.   Respondents also preferred the solar program if there was a higher likelihood for farm or forest land to be converted for residential development. However, respondents preferred solar siting on large parcels and hence were willing to pay \$0.25 for an additional acre of installation.

To calculate the total WTP (CV) for the different land types, we specified a 10-acre installation, fully visible panels, and a setback of 100 feet as well as a 0% probability of residential development in the next 10 years. We found a highly significant difference in the CV of the various land types. Respondents were willing to pay an average of \$13.02 and \$18.04 each month for solar siting on brownfields and commercial lands respectively, this translates to an annual average total WTP of \$34,372.80 and \$47,626.60 for 220 homes for the proposed solar installation on brownfields and commercial land type. However, respondents need to be compensated an average of \$26.60 and \$43.15 each month and translates to an annual average total of -\$70,224.00 and -\$113,916.00 for 220 homes for solar installation on farm and forest land respectively. This makes forest land the least preferred or unpopular choice for utility-scale solar siting while commercial lands are the most preferred or popular for their siting. In total, we estimate that residents would be willing to pay \$161,542 per year to move a proposed solar installation from forest land to commercial land. It is worth noting that this is the most conservative estimate that assumes the only affected residents are those who receive the power. It is more likely that all nearby residents are affected, in which case the WTP estimate may be an order of magnitude higher.

Finally, as different US states seek to increase energy generation from renewable sources and meet their renewable energy targets, how different attributes warrant residents' disapproval or approval of solar siting in their communities are specified. Results also show that residents will be less opposed to utility-scale solar siting programs if installations are made on lands considered degraded or having fewer ecosystem benefits (such as commercial and brownfields) with larger acreage and if the panels can be made completely not visible to residents' homes or frequently traveled roads. Though development on commercial and brownfield land is costly, if state policymakers can subsidize their cost to solar developers, this action will receive larger support from the public for their conversion to solar installation. Also, farm and forest land that is nearer to already developed residential and commercial areas (and so likely has a higher probability of being converted to residential land in the near term) is more likely to receive support for solar development than similar farm and forest land with a low probability of residential development.

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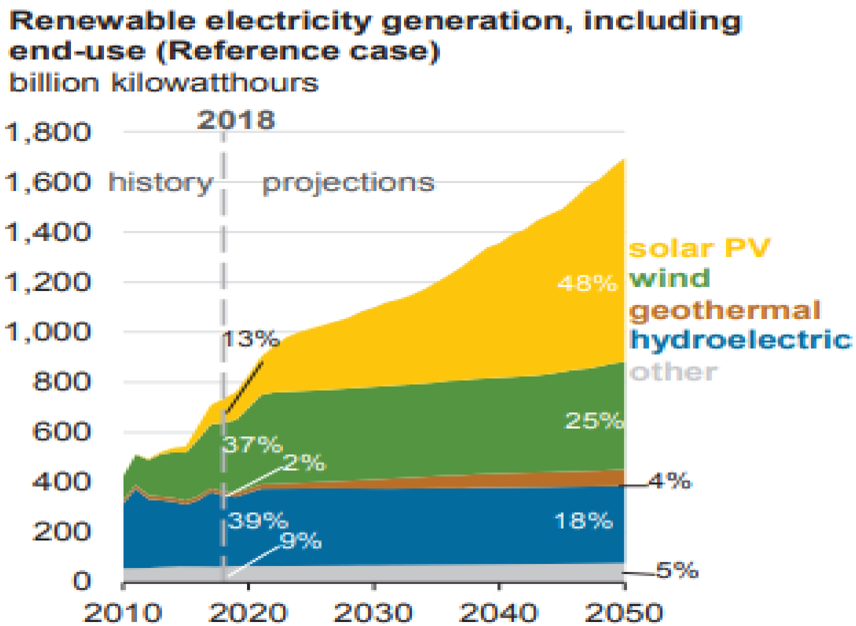

Figure 1. 1: US Renewable Energy Generation and Projections

(US Energy Information Administration, EIA 2019)

Table 1. 1: Average Construction Cost ($/kilowatts) by Energy Source

Year	Natural gas	Solar photovoltaic	Wind	Biomass	Hydroelectric	Petroleum liquids
2013	965	3,705	1,895	3,495	2,294	765
2014	1,017	3,492	1,754	1,987	1,221	1,226
2015	812	2,921	1,661	1,531	580	1,021
2016	895	2,434	1,630	2,198	5,312	1,672
2017	920	2,343	1,647	4,116	-	856
2018	837	1,848	1,382	-	-	687
2019	1,078	1,796	1,391	2,904	-	1,149
2020	1,116	1,655	1,498	2,886	1,415	795

(US Energy Information Administration, EIA 2019

https://www.eia.gov/electricity/generatorcosts/)

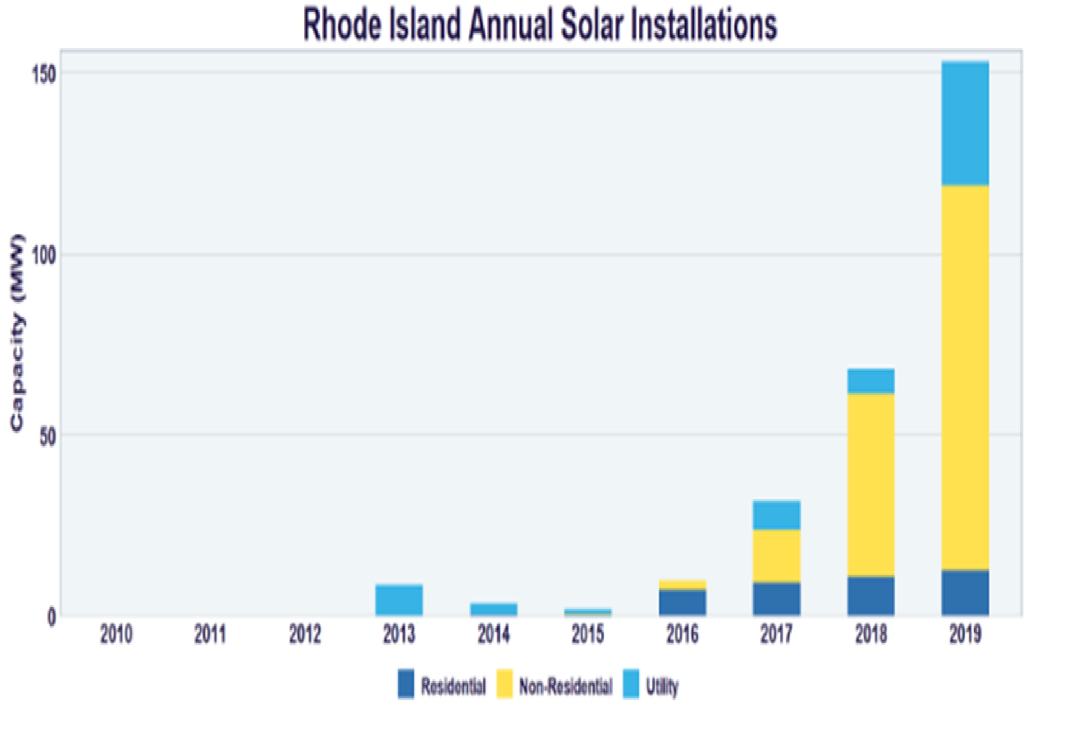

Figure 1. 2: Rhode Island Annual Solar Installation

(Solar Energy Industries Association, 2020

Table 1. 2: Discrete Choice Experiment Attributes and Definitions

Attribute	Definition	Levels
Change in electricity bill	The dollar increase or decrease in a respondent's monthly electricity bill if the parcel is converted to solar power generation.	-$30, -$20, -$10, -$5, $5, $10, $20, $30
Current land use		
Farmland	This land is currently used to grow agricultural crops. In this case, solar installations would be built on the ground.	
Forest	The land is currently privately-owned forest land. In this case, trees will be clear cut and solar installations would be built on the ground.	
Brownfield	A former industrial or commercial site where future use is affected by real or perceived environmental contamination. These include capped landfills and quarries. In this case, solar installations would be built on the ground.	
Commercial	The land is currently used for business activities, including buildings and parking lots, or undeveloped land that is zoned for commercial purposes. In this case, solar installation could be built on the ground, on building rooftops, or as parking lot canopy	
Probability of residential development	The likelihood that the land being considered will be developed into residential housing in the next ten years if a solar installation is not built.	0%, 25%, 50%
Setback	Minimum distance of the solar panels from the property line.	0, 50, 100, 250
Size of installation	The size of the solar installation in acres.	10, 20, 30, 40, 50
Visibility	Visibility of a solar installation from a respondent's house or from regularly traveled roads.	Not visible, Partially visible, Completely visible

	CHOICE A	CHOICE B	CHOICE C
Size of installation	20 acres (generates enough power for 640 homes)	50 acres (generates enough power for 1600 homes)	NO SOLAR PANELS
Visibility	Completely visible	Partially visible	
Setback	100 ft	250 ft	
Probability of residential development	0%	0%	0%
Change in monthly electricity bill (annual)	$5 increase ($60 annual ↑)	$20 increase ($240 annual ↑)	No change

Figure 1. 3: Discrete Choice Experiment on Attributes of Solar Siting

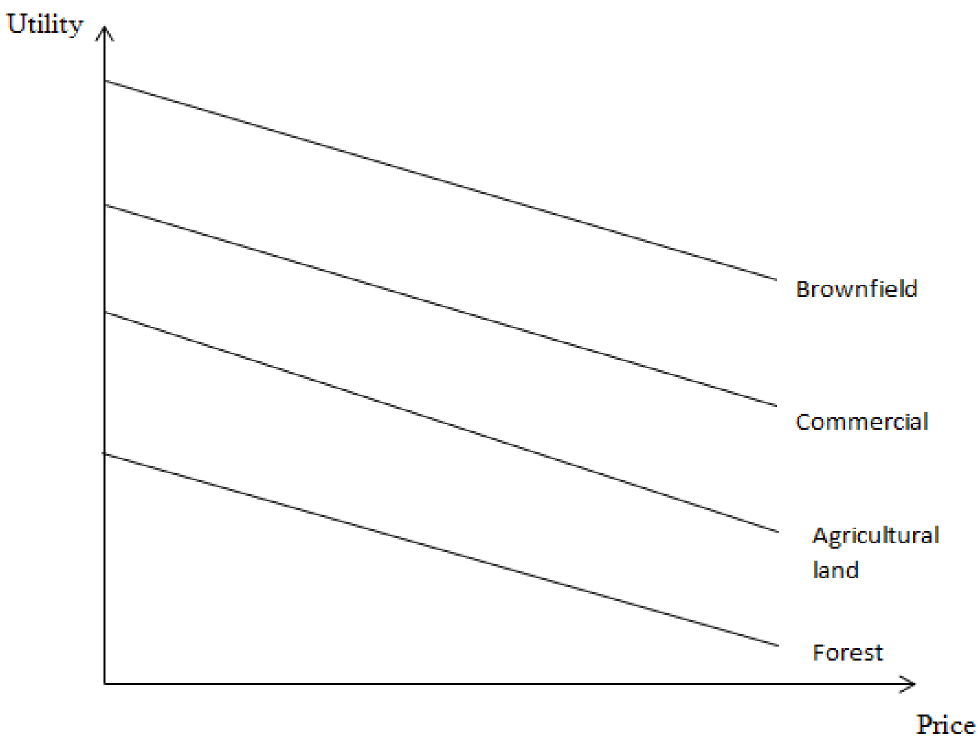

Figure 1. 4: Solar Siting Utility vs Price Current Land Use Type Graph

Table 1. 3: Summary Statistics of Respondents Distribution by Age, Educational Level, Employment Status, Household Income Level

Variables	Percentage (%) Distribution
Age	
18-29	8.69
30-44	16.92
45-54	18.14
55-64	23.32
65 and Older	32.93
Educational Level	
Less than 12 years, no high school diploma	0.31
High school graduate	8.01
Some college or associate's degree	24.04
Bachelor's degree	35.44
Graduate/professional degree	32.2
Employment Status	
Full-time student	0.92
Employed part time (fewer than 30 hours per week)	6.77
Employed full time (30 or more hours per week)	56.62
Unemployed	2.92
Retired	27.69
Other	5.08
Household Total Income	
Less than $30,000	4.83
$30,000 to $49,999	9.82
$50,000 to $74,999	14.81
$75,000 to $99,999	18.64
$100,000 to $149,999	23.63
$150,000 or more	28.29
Community	
Urban	15.1
Suburban	64.87
Rural	20.03
Political Party	
Democrat	34.76
Republican	19.21
Neither (Independent)	46.04
Gender	
Male	46.02
Female	52.73

Other	1.25
Current Residence Years	
0 – 5 years	13.82
6 – 10 years	12.60
11 – 15 years	12.44
More than 15 years	61.14
Total number of Respondents	656

Table 1. 4: Conditional and Mixed Logit Regression Basic Models, Conditional Logit Regression for Models with Land use Interactions and Cost Interactions

	Basic Models		Conditional Logit Interaction Models	
Variables	Conditional Logit	Mixed logit	Land Interactions	Cost Interactions
Acres of Installations	0.001***	0.010***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Partial Visibility	-0.115**	-0.116**	-0.129**	-0.131**
	(0.055)	(0.055)	(0.057)	(0.058)
Fully Visibility	-0.345***	-0.350***	-0.375***	-0.394***
	(0.060)	(0.061)	(0.063)	(0.065)
Setback	-0.011	0.010	0.055*	0.056*
	(0.028)	(0.029)	(0.028)	(0.029)
Probability of dev	0.016***	0.016***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Dev	-0.081	-0.093		
	(0.086)	(0.097)		
Land use Interactions				
Brownfield*Dev			0.761***	0.928***
			(0.113)	(0.125)
Commercial*Dev			0.973***	1.164***
			(0.114)	(0.128)
Farm*Dev			-0.904***	-0.908***
			(0.119)	(0.119)
Forest*Dev			-1.599***	-1.550***
			(0.117)	(0.116)
Cost	-0.031***	-0.033***	-0.042***	
	(0.002)	(0.002)	(0.002)	
Cost Interactions				
Brownfield*Cost				-0.061***
				(0.006)
Commercial*Cost				-0.063***
				(0.006)
Farm*Cost				-0.040***
				(0.003)
Forest*Cost				-0.033***
				(0.003)

Number of Choices	11,808	11,808	11,808	11,808
Number of Respondents	656	656	656	656

, **, * represents 10%, 5%, and 1% significance levels. Standard Errors are presented in parenthesis.*

Table 1. 5: Welfare Estimates for Solar Siting Attributes and Current land use Types

Attributes	Basic Model no Land Interactions	Model with Land Interactions	Model with Cost Interactions
	Panel A: Marginal WTP		
Acres of Installations			
	$0.312***	$0.251***	
	(0.189, 0.435)	(0.156, 0.347)	
Partial Visibility			
	$-3.668**	-$3.059**	
	(-7.121, -0.214)	(-5.720, -0.399)	
Fully Visibility			
	-$10.998***	-$8.913***	
	(-14.964, -7.032)	(-11.974, -5.852)	
Setback			
	$0.361	$1.297*	
	(-2.091, 1.369)	(-0.040, 2.634)	
Probability of development			
	-$0.515***	$0.196***	
	(-$0.398, -$0.631)	($0.297, $0.096)	
	Panel B: Total WTP		
	-$10.82***		
	(-$15.94, -$5.71)		
Brownfield		$13.02***	$11.54***
		($8.02, $18.01)	($8.03, $15.05)
Commercial		$18.04***	$15.03***
		($12.86, $23.22)	($11.44, $18.61)
Farm		-$26.60***	-$28.34***
		(-$32.17, -$21.03)	(-$34.64, -$22.03)
Forest		-$43.15***	-$54.09***
		(-$49.14, -$37.15)	(-$64.84, -$43.34)

, **, * represents 10%, 5%, and 1% significance levels. Confidence interval in parenthesis. To estimate the CV, we specify a completely visible solar installation, 10 acres of solar installation, setback of 100 feet from property lines, and a 0% probability of solar installation*

Table 1. 6: Comparing WTP Premia for Current Land Use Type

Premia	WTP ($)
Brownfield-Commercial	5.02**
	(0.27, 9.77)
Brownfield –Farm	-39.61***
	(-45.89, -33.34)
Brownfield- Forest	-56.16***
	(-63.09, -49.23)
Commercial-Farm	-44.64***
	(-51.35, -37.92)
Commercial-Forest	61.18***
	(-68.76, -53.60)
Farm – Forest	-16.54***
	(-20.54, -12.54)

CHAPTER 2: PROXIMITY TO UTILITY-SCALE ELECTRICITY GENERATORS AND HOUSING PRICES: A HEDONIC ANALYSIS OF DIFFERENT FUEL TYPES

Abstract

The study investigates one critical reason residents oppose the siting of utility-scale energy generators in their vicinity: the potential of these generators to impact nearby property values. This study uses the spatial difference-in-difference hedonic price method to estimate the dis-amenity value of proximity to utility-scale generators on nearby property values using data from Georgia, North Carolina, Rhode Island, and South Carolina by combining Zillow ZTRAX housing transactions data with utility-scale generator data from the US Energy Information Administration and estimating the distance from each property to the closest energy generator installations. Our study also tests whether the estimated treatment effect varies by the fuel type of the generator. Results show negative treatment effects for properties within 1 mile of utility-scale energy generators (natural gas, petroleum, hydroelectric, biomass, solar, and wind). However, these negative treatment effects are greater for properties in proximity to fossil fuel generators such as natural gas and petroleum relative to renewable energy generators. Also, non-landfill biomass energy generators have larger negative impacts on nearby property values relative to landfill biomass energy generator.

Introduction

Total US energy consumption is projected to increase through 2050. Most of this increase is expected to be from fossil fuel sources, though renewable energy sources are expected to expand more rapidly (US Department of Energy, 2010a, 2010b; AEO, 2022). In 2021, the US Energy Information Administration (EIA) reported that the nation's total primary energy consumption was 97 quads (quadrillion British thermal units), and 79% of it was from fossil fuel energy sources (Elum and Momodu, 2017). Petroleum provided the highest energy source from fossil fuel (35 quads). This was followed by natural gas with 31.3 quads and coal consumption of 1033 quads. However, coal energy generation began to decline significantly from 2005, with a historical decline of 0.819 quads, representing a drop of 16% in 2019 due to increased energy output from natural gas and wind energy sources. Other non-fossil fuel sources include renewable energy sources as well as hydroelectricity and nuclear energy, which accounted for 21% of total energy consumption in 2021(EIA Outlook, 2021).

Global demand for energy from renewable sources such as geothermal, solar, tidal, wind, biomass, etc., have been on an upward trend due to the desire to reduce the effects of fossil fuel emissions (from non-renewable energy sources) on the climate and overall health of their inhabitants. Renewable energy sources are energy from sources that are not exhaustible. However, most of the renewable energy sources such as solar, wind, and geothermal are considered free of carbon dioxide generation thus providing 'greener' atmospheric conditions; whereas most non-renewable energy sources are fossil fuels, which produce about 21 billion tons of carbon dioxide every year, leading to critical environmental issues like global warming and ocean acidification (Ackermann and Söder, 2002; Apergis et al. 2018; Dogan and Seker 2016; Manwell, McGowan, and Rogers, 2009; US Department of Energy, 2007). Additionally, Zhang

(2019) finds that fossil fuel emissions are the leading cause of air pollution deaths. There has been a global rise in renewable (clean) energy investment and the World Bank also recorded a global increase of 8% in the use of renewable energy sources in 2018 (World Bank IEA, 2019). The emergence of renewable energy standards for many US states has led to a significant increase in renewable energy investment and generation. In 2021 about 20% of the total utility-scale energy generated (4,116 billion kWh) was from renewable energy sources. Fossil fuels and nuclear energy also accounted for 61% and 19% respectively of the total energy generated. Figure 2.1 thus illustrates US energy generation from fossil, non-fossil fuel, and renewable energy sources from 1950 to 2021 (EIA Monthly Energy Review, 2022).

Despite the environmental advantages of large utility-scale renewable energy sources, they face many challenges including finding appropriate siting locations that don't fact resistance from residents living close to the generators (Kim, Kim, and Yoo, 2023). For instance, many residents view wind turbines as a visual dis-amenity and a source of noise pollution in their community (Heintzelman and Tuttle, 2012). Another reason for opposition is the potential for wind turbines to kill birds that fly close to them. Further, headaches, insomnia, nausea, panic attack, and rapid heartbeat are among health issues attributed to the presence of wind energy generation in a community (Chapman and Crichton, 2017). Utility-scale generation of solar and wind energy also requires a large spatial footprint of the generators, which may lead to loss of habitat for some plant or animal species and may also compete with current land use. Geothermal plants can emit harmful gases such as hydrogen sulfide and nitrogen oxides into the atmosphere. Some geothermal plants also emit mercury into underground water systems, which poses a health risk to humans and animals that eat fish from contaminated water bodies (Kagel, Bates, and Gawell, 2005). For its part, hydropower generation may alter the flow of water bodies and destroy the habitat of some animals and even humans whose homes, farms, businesses, etc. may be flooded due to the overflow of hydropower dams (Kumar et al. 2022). Likewise, necessary siting components of non-renewable and renewable energy generation, such as substations and transmission lines, face opposition; Gregory and von Winterfeld's (1996) study showed that there is a perception among the public that proximity to electricity transmission lines increases the risk of cancers such as leukemia and brain cancer.

These perceived negative impacts of different energy sources (both renewable and non-renewable) have raised major concerns that their siting near communities has the potential of impacting nearby property values. Most property owners show strong opposition to the siting of these large utility-scale energy sources near their properties and this public opposition is termed 'Not In My Backyard' or NIMBYism (Carlisle et al. 2016; van der Horst, 2007; Wolsink, 2007; Gregory and von Winterfeld’s, 1996). This research, therefore, aims to estimate the dis-amenity values associated with generator proximity to different fuel types.

Literature Review

Hedonic Models have been used to explore the effects of a wide range of non-market dis-amenities. Studies examining the housing price impacts of waste stations (Eshet, et al. 2007; Kohlhase, 1991), landfills (Bouvier, et al., 2000; Hite, et al., 2001; Reichert, Small, and Mohanty, 1992; Batalhone, Nogueira, and Mueller, 2002; Ready, 2010), point-source pollution (Brasington and Hite, 2004), sewage treatment plants (Batalhone, Nogueira, and Mueller, 2002), and incinerators (Zhao, Simons, and Fen, 2016; Kiel and McClain's, 1995) all show that proximity to a variety of dis-amenities have adverse economic impacts through reductions in property values. Narrowing the focus to aspects of energy infrastructure, previous work has examined the impact of proximity to substations (Hwang, Jeong, and Lee, 2015) and transmission lines (Jackson and Pitts, 2010; Des Rosiers, 2002; Hamilton and Schwann, 1995; Sims and Dent, 2005; Wyman and Mothorpe, 2018; Gregory and von Winterfeld, 1996; Elliott and Wadley, 2002; Chalmers and Voorvaart, 2009). While these studies are tangentially related, for this study the majority of our literature review is on the dis-amenities of utility-scale energy generators on nearby property values.

Valuing Fossil Fuel Energy Generation Plants Impact on Residential Properties

Davis (2011) used hedonic models to assess the impact of non-cogeneration fossil fuel powerplants (plants producing only electricity) with a production capacity of 100MW or more opened from 1993 to 2000 on local housing prices and rents. He found housing prices and rents within 2 miles of a fossil fuel power plant decreased in value by 3% to 7% compared to housing properties with similar characteristics beyond 2 miles of the plant. Khezr, Nepal, and Ganegodage (2021) examined the impact of fossil fuel powerplants (coal-fired, gas turbine, and gas reciprocal) on housing properties in New South Wales, Australia, finding that houses within 9.32 miles of coal and gas generators reduced housing values by 12.1 and 8.1%, respectively. Kim, Kim, and Yoo (2023) also used the hedonic price method to estimate the impact of a natural gas plant on 2,291 nearby apartment prices in Gyeonggi-do, South Korea. They found that apartments within 0.62 miles of the natural gas plant had an average reduction in price of 0.7% relative to similar apartments much further from the plant.

Valuing Nuclear Energy Generation Plants on Housing Properties

Several studies have focused on the loss of housing value due to their proximity to nuclear powerplants, though the majority of these studies identify the effect of nuclear disasters (Fukushima or Three Mile Island) on housing values near other nuclear generators rather than estimating an effect relative to the absence of a nuclear generator (Tanaka and Zabel 2018; Bauer, Braun, and Kvasnicka 2017; Boes, Nüesch, and Wüthrich 2015); Nelson 1981; Gamble and Downing 1982; Clark, et al. 1997). For instance, Tanaka and Zabel (2018) assessed property values close to a nuclear power generating plant after the Fukushima nuclear disaster, an extreme nuclear accident that occurred in Japan in 2011. The authors obtained data on US residential property prices before and after the disaster to estimate the Fukushima nuclear disaster impact on property prices. They found that after the disaster, properties within 2km of nuclear plants decreased in prices by 10% to 20% and properties between 1.24 miles to 2.49 miles away from a nuclear plant decrease housing prices by about 3% to 5% but the decrease in prices was only temporary influenced by the Fukushima nuclear disaster and property prices return to their original level about one year after the disaster. Bauer, Braun, and Kvasnicka (2017) employed a difference-in-difference approach to estimate how the Fukushima nuclear power plant disaster impacted housing prices in Germany. They compared housing prices closer to a nuclear power plant and housing prices far away from nuclear plants before and after the disaster. They found that properties close to these plants were reduced by about 5% before the disaster and housing properties close to nuclear plants that were shut down after the disaster fell by about 10%. Boes, Nüesch, and Wüthrich (2015) estimated the impact of the Fukushima disaster on rents of apartments in Switzerland close to nuclear powerplants by using a difference-in-difference approach to analyze rental prices over 12 years spanning from before and after the disaster. Apartments close to nuclear plants decreased by 2.3% in rent after the disaster.

Some studies on the impact of nuclear plant disasters on property prices found no decline in their values attributable to the disaster. For instance, Nelson (1981) examined the impact of a nuclear plant disaster (Three Mile Island, TMI) on residential housing properties. The first section of the paper uses a hedonic pricing method to estimate property prices within 4 miles of the nuclear plant while the second section uses a comparison of multi-listing housing sales from 1978 to 1979 within 5 miles of a nuclear plant with quarterly mean housing prices. The study showed neither a decrease nor an increase in property values. Gamble and Downing (1982) examine the economic impact of the TMI nuclear plant accident in 1979 on residential property prices by using county assessment property and multiple listing service data before and after the accident using visibility and distance to nuclear plants to assess the impact on property prices. The study concluded that the TMI accident had no significant impact on property prices. Clark et al. (1997) used both the hedonic method and geographic information systems (GIS) to find the influence of two nuclear plants on nearby housing prices in California. They also find no significant decrease in housing prices.

Hedonic Pricing Method Valuation of Renewable Energy Generation Impact on Nearby Residential Properties

The literature on the impact of renewable energy sources on property values focuses mainly on wind energy generation and these studies do not show uniform results. Most of these studies find a negative impact or decrease in housing prices attributable to nearby wind energy generation sources. For instance, Sims and Dent (2007) used hedonic pricing and a comparative analysis sales model to find the impact of two wind farms on the housing values of over 1,000 housing properties in Cornwall, UK. The study found proximity to the wind farm reduces the value of properties in the same neighborhood. Laposa and Mueller (2010) estimated the effect of a proposed wind farm siting on a ranch in northern Colorado on property prices of adjacent parcels. They examined property prices before and post an announcement of this proposed project using standard OLS regression of the hedonic pricing model and found that the announcement of the proposed project significantly reduced property prices. However, they noted that this significant impact could be due to the emergence of a national housing crisis and not the announcement of the proposed project.

Heintzelman and Tuttle (2011) also estimated the impact of wind energy installations on property values in three counties of New York using about 11,000 property transactions over nine years. They accounted for endogeneity biases in the model by using fixed effects and found that wind energy installations cause a significant reduction in property prices in two of the three counties selected for the study. They found that property value could decrease by 7.73% to 14.87% for a distance decrease of one mile of property to the wind farm. Further, Sunak and Madlener (2012) used a hedonic pricing model to estimate the visual and shadowing impacts of wind farms on property prices in western Germany and compared the results with OLS regression. The global OLS regression results implied that wind farms decrease property prices whereas the geologically weighted hedonic pricing shows that the proximity, visibility, and shadowing variables were spatially non-stationary across the area of study and found that closeness to the wind farm and shadowing negatively impact local property prices.

Krueger, Parsons, and Firestone (2011) used a stated preference choice model to assess the cost of the dis-amenity of visibility of offshore wind turbines to Delaware residents. The study showed the external cost of the turbines was much greater for residents who lived near the ocean. Also, Lutzeyer, Phaneuf, and Taylor (2018) used a choice experiment to examine the impact of offshore wind farms on coastal NC beach home rental prices. They found that visibility of utility-scale wind farms reduces beach homes rental value by 10% if wind farm is located within 8 miles of the shore.

However, Hoen et al. (2011) used a large amount of housing price data from nine states within 10 miles of wind energy generation sources. The housing price data included property prices before and after the installation of wind turbines. They employed spatial difference-in-difference hedonic models as well as ordinary least squares and found that property values were not impacted by the installation of wind turbines. Similarly, Sims, Dent, and Oskrochi (2008) went further to find the impact of the visual and aural presence of wind farms on housing sales prices of properties within a half-mile of a wind turbine in Cornwall, UK. From their hedonic pricing analysis, they estimated no significant impacts of a wind farm on property prices. They, however, found that noise pollution and flicker from the blades of the turbine as well as its visibility may affect the prices of certain properties closer to the turbines.

A few studies have also valued the impact of other renewable energy sources on housing prices. Al-Hamoodah, et al. (2018) examined how utility-scale solar installations impact housing prices by employing geospatial analysis and a survey of residential property assessors. The study showed that few respondents who lived close to large utility-scale solar installations viewed the facility as producing a negative impact on their community while most residents said the facility did not economically impact housing prices. Also, Abashidze and Taylor (2022) used the hedonic price method to assess the impact of ground-mounted, utility-scale solar installations on nearby farmland prices. They found no direct impact of solar installations on nearby farmland values.

A study close to this study was done by Gaur and Lang (2023). They employed a difference-in-difference approach of the Hedonic Price Modeling to estimate the economic impact of solar facilities on housing property values in Massachusetts and Rhode Island. They found that housing property values within one mile of a solar facility decrease in housing economic value by 1.7% as compared to housing properties between one to three miles of a solar facility, however, to the best of our knowledge, no study has examined the differential impact of multiple energy sources on adjacent property prices. Thus, this study is unique because it explores how multiple energy-generating sources, whether clean (e.g. solar) or dirty (e.g. coal), impact residential housing prices across several states in the eastern US.

Data

Two data sets were integrated to implement our hedonic analysis. Data on spatial location and characteristics of utility-scale generators were obtained from the US Energy Information Administration (EIA) form EIA-860, which reports the status of utility-scale (capacity of 1MW and above) electric generator plants in the US. EIA data files include the prime fuel source for each generator (as well as any additional fuel types), the total capacity of the generator (measured in MW), the total capacity of all fuel types for the generator, the operating year of the generator, and location attributes of plants (longitude and latitude). We constrain our focus to generators in our four states of interest (GA, NC, RI, and SC) that began operation between January 2000 and December 2020. Also, only new generators (meaning new generation sites), not just capacity increases to existing generation sites, were included in our study; this is because a new boiler added to an existing generator during this study period is not adding a new dis-amenity.

Data on housing transactions were obtained from the Zillow ZTRAX database (http://www.zillow.com/data). Housing transaction data consists of structural attributes and location of single-family housing properties of four states: GA, NC, RI, and SC. The ZTRAX database contains a variety of transactions, from commercial property to agricultural land to residential property. The housing data include structural attributes (the number of bedrooms, number of bathrooms, lot size and building area, etc.), sales price, date of property sale, and location attributes of the property (latitude and longitude of property), is obtained by merging the ZTRANS (containing the transaction information such as sales price amount, sales year, etc), and ZASMT (structural attributes of the properties) for each state using their FIPS code number (Petrolia et al., 2023).

The generator data and property transactions data are combined in Geographic Information System (GIS) by identifying proximity to generators using 0.5-mile bins for each fuel type. These bins extend from 0.5 miles from the generator to 10 miles from the generator. Our analysis focuses on arms-length transactions of single-family residential properties occurring from January 2000 to December 2020. Initial data cleaning included eliminating transactions that did not meet the above restrictions, transactions that were missing sales price or vital structural information, observations with outlier values in structural attributes, and any property more than 10 miles from a generator. Additionally, we included a restriction to ensure no observation is treated by multiple generators by dropping any observation that was in one of the treatment buffers for multiple fuel-type generators. After this cleaning, we were left with 382,726 transactions. [1]

Methodological Framework

Rosen (1974) was the first to use the hedonic pricing theory and illustrated that attributes of an item can be used to find its monetary value. The hedonic pricing model is based on hedonic pricing theory, which states that the market price of a good is related to its attributes or characteristics, both market and nonmarket. This is most often used to put a monetary value on amenities that impact the price of housing properties. This method can combine many attributes into one dimension and is also able to illustrate the marginal tradeoffs of both those who demand and supply.

In the spirit of Rosen (1974), we estimate the nonmarket value of proximity to utility-scale electricity generators from the implicit prices revealed in property transactions. To estimate a causal impact of utility-scale generator location on housing prices, we employ a spatial difference-in-differences (DID) estimator where the distinction between treated and control transactions is based on spatial proximity to the generator. We explore models for a variety of

[1] The data comprise 93,767 GA housing transactions, 66,359 NC housing transactions, 136,148 RI housing transactions, and 86,452 SC housing transactions. The four states were selected because they are located on the US East Coast and have multiple electricity generators of different fuel types.

[1] Specifically, we drop all properties with fewer than one or more than ten bedrooms, fewer than 0.5 or more than 10 bathrooms, properties with lot size less than 200sqft (the minimum square feet of a residential property) or greater than 100,000 sqft, structure square footage of less than 120 sqft (the minimum square feet of any residential property) or greater than 5,000 sqft, and transaction prices less than $10,000 or greater than $1,000,000.

treated groups ranging from one[2] mile to five miles from the generator while keeping our control group constant (properties between five and ten miles from a generator).

In general, the hedonic price function is a reduced-form model without theoretical underpinnings regarding the correct functional form. Cropper et al. (1988) found that in the presence of unobserved attributes linear functional forms outperform more flexible functions such as Box-Cox regressions in estimating the hedonic price gradient. Following this logic, the hedonic price regression model in our application is given as:

$$ln(P_{ijt}) = S_{it}\alpha + \rho Treat_i + \delta Post_{jt} + \beta Treat_i * Post_{jt} + N_j + T_t + \mu_{ijt} \quad (1)$$

Here P_{ijt} represents the arm's length transaction price of property *i* in neighborhood *j* at time *t*, and *S* represents a vector of structural characteristics of the property. A standard DID is performed by comparing single-family housing prices before and after the construction of the generator for houses near the generator (within 1, 2, 3, 4, and 5 miles, depending on the specification) versus a control group of properties between 5 and 10 miles from the nearest energy generator (Davis, 2011; Gaur and Lang, 2023). As such, *Treat* is an indicator for whether the transaction is in the treatment proximity band (1-5 miles depending on specification), *Post* is an indicator for whether the transaction occurred after the establishment of the nearby generator, and *Treat*Post* is the interaction of these indicators. The estimated coefficient β is our key parameter of interest measuring the average treatment effect on the treated (ATT) or the average willingness to accept for being located within proximity of a power generator.

[2] Though fuel type bins created are from 0.5 miles, treatment groups used in the analysis start from 1 mile, because not enough pre and post observations were found for all fuel types within the 0.5-mile bins.

Finally, equation (1) also includes neighborhood fixed-effects N_j (identifying each electricity plant and their matched treatment and control households within a 10-mile radius) and year-by-month fixed effects Tt to control for unobserved time-invariant spatial characteristics and time-varying macro shocks, respectively. These are vital, as the siting of fuel plants is not randomly distributed across the landscape; thus, spatial FEs control for unobserved attributes of the specific location that may be correlated with generator siting. Similarly, temporal FEs control for macroeconomic factors within treatment and control groups across the region of study that change over time. Equation (1) also includes a random error component, μ_{ijt}. To investigate the potentially heterogeneous impact of various fuel types on nearby property values and estimate a DID that allows for heterogeneity in different fuel/treatment types, treatment effects for each fuel type are estimated using separate DID models and compared with their control groups. Fuel types included in this study are Biomass, Hydroelectric, Petroleum, Natural gas, Solar, and Wind.

Results

Summary Statistics

Table 2.1 presents summary statistics of the structural attributes of housing properties for the individual states GA, NC, RI, and SC as well as the combined dataset. The combined data show that the average selling price of a single-family housing property is approximately $209,053 with minimum and maximum housing prices of $10,000 and $1,000,000 respectively. The average age of the house is 46 years. The average number of bedrooms is 3, and the average bathroom number is 2. Also, the average lot size and the building area are approximately 16,055 sqft and

1,754 sqft respectively. RI had the highest average single-family housing price of approximately $245,912 while NC had the lowest price of $169,628. RI also recorded the highest average age of housing properties (70 years) while SC recorded the lowest average housing age of 27 years. SC had the largest lot area size of 20,007 sqft whereas RI had the smallest of 12,254 sqft; SC had the largest average building area size of 1,831 sqft and NC recorded the smallest average of 1,594 sqft.

Table 2.2 displays the distribution of the structural attributes by each treatment group and control group. A comparison is made between the 5 treatment groups: treatment group 1 (properties within a mile of a generator), treatment group 2 (properties within 2 miles of a generator), treatment group 3 (properties within 3 miles of a generator), treatment group 4 (properties within 4 miles of a generator), treatment group 5 (properties within less than 5 miles of a generator) and the control group which comprises of properties within 5 to 10 miles of a generator. Here, the average values of the structural estimates for the treatment groups are similar and closely comparable to the average values for the control group. Also, the control group's average values for the structural attributes are similar to the average values of the total data used in our study.

Also, Table 2.3 breaks down of number of observations for each fuel type by pre (properties sold before energy installation), post (properties sold after energy installation).Properties sold before solar fuel installation have the most observations for each treatment group, while those sold before petroleum installation had the least observations for treatment group 1 and 2. Also, properties sold before hydroelectric fuel installation had the least number of observations for treatment groups 3, 4, and 5. Also, properties sold after solar fuel installation have the most observations for each treatment group, while those sold after hydroelectric installation had the least observations for each treatment group.

Treatment Effects by Fuel Type

Table 2.4 presents the preferred models, which estimate individual fuel type treatment effects on nearby property values using plant code and month-year fixed effects. Outputs are from log-linear or semi log models and hence results are interpreted as a percentage change in housing pricing.

Biomass (landfill and non-landfill types)

Model 1a, 2a, and 3a predict that properties within 1, 2, and 3 miles of a housing property sold after the construction of a biomass power plant had decreases of about 9.1%, 7.0%, and 5.3% in housing price respectively and all treatment effects are statistically significant. Properties further away from biomass plants, that is, 4 and 5 miles had small positive treatment effects, however, this positive treatment effect is only statistically significant at 10% for properties within 5 miles of a biomass plant.

Hydroelectric

Treatment effects of properties within 1, 2, 3, 4, and 5 miles of hydroelectric plants were negative. Specifically, models 1a, 2a, 3a, 4a, and 5a predict that properties within 1, 2, 3, 4, and 5 miles of a hydroelectric generator fuel type reduce in property price by 15.4%, 12.9%, 29.8%, and 32.9%, and 28.2%% respectively, but only property value reductions within 4 miles of a hydroelectric plant are statistically significant at 10% alpha value.

Natural Gas

Treatment effects of properties within 5 miles of a natural gas plant were negative. Specifically, models 1a, 2a, 3a, 4a, and 5a predict that properties within 1, 2, 3, 4, and 5 miles of a natural gas generator fuel type reduce in property price by 23.0%, 24.7%, 18.4%, 15.9% and 14.6% respectively, and all reductions are highly statistically significant at 1% alpha value.

Petroleum

Only treatment effects of properties within 1 miles of a petroleum plant were consistently negative. Our estimated effects are noisy and this is evidenced by the enormous variation in point estimates by treatment band and the high standard errors associated with all estimates. Specifically, model 1a, predict that properties within 1 mile of a petroleum generator fuel type reduce in property price by 75.1%but this reduction is not statistically significant even at 10% alpha value. However, models 2a, 3a, 4a, and 5a predict that properties within 2, 3, 4, and 5 miles of a petroleum generator fuel type increase nearby property prices.

Solar

Treatment effects of properties within 5 miles of a solar plant were negative. Specifically, models 1a, 2a, 3a, 4a, and 5a predict that properties within 1, 2, 3, 4, and 5 miles of a solar generator fuel type reduce in property price by 10.1%, 6.7%, 3.0%, 3.4% and 3.2%, and only reductions at 2, 4, and 5 miles are statistically significant even at 10% alpha value.

Wind

Treatment effects of properties within 5 miles of a wind plant were negative. Specifically, models 1a, 2a, 3a, 4a, and 5a predict that properties within 1, 2, 3, 4, and 5 miles of a wind generator fuel type reduce in property price by 8.4%, 5.5%, 6.5%, 6.9%, and 6.5% respectively, however, only price reductions of properties within 3, 4, and 5 miles of a wind generator are statistically significant at 10% alpha value.

Biomass Decomposition (landfill and non-landfill)

Table 2.4.1 also presents the separate treatment effects of biomass fuel types in two main groups: landfill and non-landfill biomass energy on nearby property values using plant code and month-year fixed effects. Biomass energy is decomposed into two main groups: landfill and non-landfill biomass energy. Landfill biomass energy is generated from existing landfill waste sources hence I expect that energy generation from them would have less impact on nearby property values. The majority of their impact on nearby property values is attributable to the landfill waste dump itself, and in most or all cases the landfill exists before energy is generated from them. The non-landfill biomass energy comprises all biomass generator sources such as wood waste, bio waste, etc. excluding only landfill biomass generator sources. I expect non-landfill biomass energy sources to have a higher impact on nearby property values since this waste often does not already exist in the communities where the biomass plants are built.

Landfill Biomass

Models $1a_{\_1}$, $2a_{\_1}$, and $3a_{\_1}$ have negative treatment effects and models $4a_{\_1}$ and $5a_{\_1}$ have modest positive treatment effects. All models were highly statistically significant. Specifically, properties within 1, 2, and 3 miles of a landfill biomass generator decrease in value by 6.0%, 4.0%, and 2.4% respectively. Whereas properties within 4 and 5 miles of a landfill biomass generator increase in property value by 2.3% and 2.4% respectively.

Non-landfill biomass

Models $1a_{\_1}$, $2a_{\_1}$, $3a_{\_1}$, $4a_{\_1}$, and $5a_{\_1}$ show that properties within 1, 2, 3, 4, and 5 miles of non-landfill biomass generators have highly statistically significant negative treatment effects. Specifically, properties within 1, 2, 3, 4, and 5 miles of non-landfill biomass generator decrease in value by 45.9%, 30.2%, 24.9%, 13.8%, and 9.1% respectively, and statistically significant at a 1% significance level. Further, a post-estimation test to investigate if the treatment effects of landfill and non-landfill biomass-type generator sources were statistically different was conducted which revealed that treatment effects for landfill biomass and non-landfill biomass sources were statistically different for each treatment group.

Robustness Checks: County, Zip Code, and Census Tract Fixed Effects

Tables 2.5 and 2.6 present individual fuel type treatment effects on nearby property values using county, zip code, census tract, and month-year fixed effects.

Hydroelectric

County, zip code, and census tract fixed effects models produce negative treatment effects for hydroelectric energy types, however county and zip code fixed effects models produce similar outputs. . Specifically, the county and zip code models predict that properties within 1, 2, 3, 4, and 5 miles of a hydroelectric generator fuel type reduce in property price by 15%, 13%, 30%, 33%, and 28% respectively, however, only price reductions of properties within 4 miles of a hydroelectric generator are statistically significant at 10% alpha value. Also, the census tract fixed effects models (1c, 2c, 3c, 4c, and 5c) predict, that properties within 1, 2, 3, 4, and 5 miles of a hydroelectric generator fuel type reduce in property price by 20.7%, 4.4%, 15.4%, 22.1%, and 18.7% respectively, and all reductions are not statistically significant even at 10% alpha value.

Natural Gas

County and zip code fixed effects models produce similar outputs for natural gas energy type fixed effects models that show that natural gas generator plants have negative treatment effects on all properties within 5 miles of the plant. Specifically, models predict that properties within 1, 2, 3, 4, and 5 miles of a natural gas generator fuel type reduce in property price by about 23%, 24%, 18%, 16%, and 14% respectively, and all reductions are highly statistically significant at 1% alpha value. However, census tract fixed effects models (1c, 2c, 3c, 4c, and 5c) predict only positive treatment effects which are all not statistically significant at a 10% significance level., Specifically, properties within 1, 2, 3, 4, and 5 miles increase in property value by 4.4%, 2.9%, 3.0%, 5.2%, and 5.6%.

Petroleum

County and zip code fixed effects models produce similar outputs for petroleum energy type fixed effects. Models predict negative treatment effects for properties within 1 mile of a petroleum generator. Properties within 1 mile decrease in property value by 75.1% which is not statistically significant even at a 10% alpha value. Properties within 2, 3, 4, and 5 miles increase in property value by 47.7%, 66.1%, 65.9%, and 67.2% and this increase is not statistically significant for properties within 2 miles of a petroleum plant. Census tract fixed effects predict a statistically significant negative treatment effect. Properties within 1, 2, 3, 4, and 5 miles of a petroleum generator reduce in property price by 50.5%, 21.3%, 20.2%, 18.9%, and 18.5% respectively, and all reductions are statistically significant.

Solar

Zip code fixed effects predict negative treatment effects for properties within 5 miles of a utility-scale solar generator. Properties within 1, 2, 3, 4, and 5 miles of a solar generator decrease in property value by 10.1%, 6.7%, 3.0%, 3.4%, and 3.2% respectively, however, these reductions are only statistically significant for properties within 2, 4, and 5 miles of a solar plant. County fixed effects predict negative treatment effects for properties within 5 miles of a utility-scale solar generator. Properties within 1, 2, 3, 4, and 5 miles of a solar generator decrease in property value by 8.2%, 4.7%, 2.2%, 3.6%, and 3.4% respectively, but reductions are only statistically significant for properties within 4 and 5 miles of a solar generator. Census tract fixed effects predict positive treatment effects for all properties within 5 miles of a solar generator.

Wind

Zip code fixed effects predict negative treatment effects for properties within 5 miles of a wind generator. Properties within 1, 2, 3, 4, and 5 miles of a wind generator decrease in property value by 8.4%, 5.5%, 6.5%, 6.9%, and 6.5% respectively, and property price reductions at 4 and 5 miles are statistically significant at 5% whereas those within 3 miles of a solar generator are statistically significant at 1% alpha level. County fixed effects predict negative treatment effects for properties within 5 miles of a wind generator. Properties within 1, 2, 3, 4, and 5 miles of a wind generator decrease in property value by 13%, 9.4%, 10.5%, 10.6%, and 10.3% respectively. These reductions are all statistically significant except for properties within 4 miles of a wind generator.

Biomass (landfill and non-landfill)

Zip code fixed effects predict that properties within 1, 2, 3, 4, and 5 miles of a biomass generator plant decrease in value by 9.1%, 7.0%, 5.3%, 0.03%, and 1.2% respectively and all treatment effects are statistically significant except for properties within 4 miles of a biomass generator. County fixed effects predict that properties within 1, 2, 3, 4, and 5 miles of a biomass generator plant decrease in value by 11.3%, 9.8%, 8.5%, 2.4% and 1.8% respectively and all treatment effects are statistically significant at a 1% significance level. Also, census tract fixed effects predict that treatment effects of properties within 1mile of a biomass generator plant decrease in value by 4.4% at a 10% significance level.

Biomass Decomposition (landfill and others)

Table 2.5.1 and 2.6.1 also presents the separate treatment effects of two main biomass fuel types: landfill and non-landfill biomass types (wood, waste) on nearby property values as well the difference in treatment effects between them using county, zip code, census tract, and month-year fixed effects. Here, 'non-landfill biomass' refers to all biomass generator sources excluding landfill biomass generator sources.

Landfill Biomass

Zip code fixed effects models predict that properties within 1, 2, 3, and 5 miles of a landfill biomass generator decrease in value by 5.7%, 3.7%, 1.8%, and 3.0% respectively, and these reductions are statistically significant. Also, county fixed effect models have negative treatment effects for all models, however, are statistically significant for property value reductions for 1, 2, and 3 miles of landfill energy generators at 8.1%, 6.9%, and 5.6% respectively. However, census tract fixed effects models predict that properties 1, 2, 3, 4, and 5 miles increase in value by 4.1%, 19.7%, 19.7%, 12.5%, and 9.1% respectively and these increases are all statistically significant at 1% except properties within 1 mile of a landfill biomass generator plant which is only significant at 10%.

Non-landfill biomass

As expected, other (non-landfill) energy generators have greater impacts (reductions) on nearby property values compared to the impact of landfill energy generators. Zip Code fixed effects models predict that properties within 1, 2, 3, 4, and 5 miles of a landfill biomass generator decrease in value by 40.6%, 30.0%, 25.5%, 14.5%, and 9.8% respectively and these reductions are statistically significant at 1% significance level. County fixed effects models predict that properties within 1, 2, 3, 4, and 5 miles of a landfill biomass generator decrease in value by 45.0%, 29.9%, 24.2%, 13.3%, and 8.7% respectively and these reductions are statistically significant at 1% significance level. Also, census tract fixed effects models predict that properties 1, 2, 3, 4, and 5 miles decrease in value by 51.3%, 51.1%, 62.7%, 58.5%, and 50.9% respectively and these increases are all statistically significant at 1% significance level.

Again, a post-estimation test to investigate if the treatment effects of landfill and non-landfill biomass-type generator sources were statistically different for each fixed effect model was conducted which revealed that treatment effects for landfill biomass and non-landfill biomass sources were statistically different for each treatment group.

Conclusion

This research estimates the dis-amenity value of proximity to utility-scale generators using Zillow ZTRAX housing transactions data combined with utility-scale generator data from the US Energy Information Administration for four coastal regions of eastern US states: Georgia, North Carolina, Rhode Island, and South Carolina. The study employed Geographic Information Systems (GIS) to estimate the distance from each property to the closest energy generator installations and further used spatial difference-in-differences hedonic model to estimate these dis-amenities. The study also assessed how the different technologies of biomass energy sources such as landfill, waste/wood, etc. individually impact nearby property values. Negative treatment effect was found for properties within 5 miles of utility-scale energy generators in our study (natural gas, petroleum, hydroelectric, biomass, solar, and wind) for different fixed effects models (county, zip, census tract, and plant code). However, fossil fuel energy generators such as natural gas had greater negative impacts on nearby property values relative to clean renewable energy sources such as hydroelectric, solar, and wind. Biomass generators, while renewable energy sources, are not 'green' in the sense of producing low emissions; we find significant negative impacts of these biomass generators on nearby property values. Further, non-landfill biomass energy generators such as wood and waste have higher negative impacts on nearby property values relative to landfill biomass energy generators. This could be due to the fact that non-landfill biomass generates new emissions that would otherwise not exist, while landfill biomass burns existing emissions from a landfill to generate energy.

Energy generation and consumption is expected to increase in the coming years due to expected population increase. This work is therefore useful in that it provides empirical evidence to policy makers about which fuel type generators are considered by residents to have the highest dis-amenity to their environment, specifically property values to provide more insight to the increasing siting decisions they will make in the future.

Potential future extensions of this work will use Woodridge dynamic treatment effects to understand heterogeneity of treatment effects across different time periods. The study employed varying treatment bands in estimating impacts of nearby fuel generators on housing prices, thus future work can explore exact treatment bands for each fuel type at which treatment effects equal to zero. Finally, treatment effects can be examined for different capacities or installation sizes.

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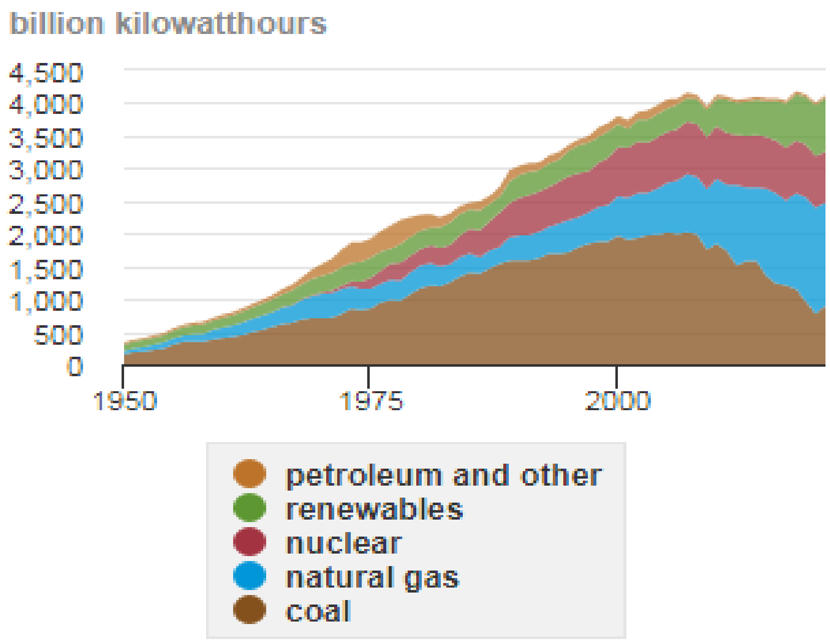

Figure 2. 1: US Energy Generation by Major Energy Source, 1950-2020

(US EIA Monthly Energy Review, January 2022)

Table 2. 1: Summary Statistics of Structural Attributes of States Housing Properties

State	Statistics	Price ($)	Age	Bedrooms	Bathrooms	Lot size sqft	Building area sqft
GA	mean	242,692	38.6	3	2	18,216	1,829
	sd	172,919	27.9	1	1	16,533	907.9
	min	10,000	1	1	1	400.8	120
	max	1,000,000	200	10	8	99,752	4,997
NC	mean	241,625	35.3	3	1	15,623	1,676
	sd	125,604	25.7	1	1	14,082	726.7
	min	10,000	2	1	1	435.6	120
	max	999,128	172	8	7	99,752	4,996
RI	mean	327,181	70.5	3	2	12,054	1,800
	sd	160,532	34.8	1	1	15,184	1,048
	min	10,605	1	1	1	401	120
	max	1,000,000	219	10	10	99,887	5,000
SC	mean	248,919	27.6	3	2	19,998	1,917
	sd	143,732	21.5	1	1	16,642	885.6
	min	10,000	1	1	1	217.8	120
	max	999,917	195	10	10	99,752	5,000
Total	mean	273,969	46.9	3	2	15,977	1,812
	sd	159,577	34.1	1	1	16,010	931.3
	min	10,000	1	1	1	217.8	120
	max	1,000,000	219	10	10	99,887	5,000

Table 2. 2: Distribution of Structural Attributes by Treatment and Control Groups

Groups	Statistics	Price ($)	Age	Bedrooms	Bathrooms	Lot size sqft	Building area sqft
Treatment Group 1	Mean	262,261	66.9	4	2	11,011	1,839
	Sd	144,623	39.1	2	0.5	14,185	1,010
	Min	10,605	1	1	1	435.6	120
	Max	1,000,000	219	10	2	99,752	5,000
Treatment Group 2	Mean	276,987	66.4	4	2	11631	1,828
	Sd	159,564	37.5	1	0.5	14,008	983.9
	Min	10,000	1	1	1	435.6	120
	Max	1,000,000	219	10	2	99,887	5,000
Treatment Group 3	Mean	269,987	55.8	3	2	13,329	1,751
	Sd	151,569	35.7	1	0.4	14,460	914.9
	Min	10,000	1	1	1	435.6	120
	Max	1,000,000	219	10	2	99,887	5,000
Treatment Group 4	Mean	270,782	54	3	1	13,996	1,754
	Sd	154,889	35	1	0.5	14,814	926.6
	Min	10,000	1	1	1	217.8	120
	Max	1,000,000	219	10	2	99,887	5,000
Treatment Group 5	Mean	270,662	53.2	3	1	14,311	1,755
	Sd	155,321	34.8	1	0.5	14,962	929.1
	Min	10,000	1	1	1	217.8	120
	Max	1,000,000	219	10	2	99,887	5,000
Control Group	Mean	270,782	54	3	1	13,996	1,754
	Sd	154,889	35	1	0.5	14,814	926.6
	Min	10,000	1	1	1	217.8	120
	Max	1,000,000	219	10	2	99,887	5,000

Treatment group 1 (properties within a mile of a generator), Treatment group 2 (properties within 2 miles of a generator), Treatment group 3 (properties within 3 miles of a generator), Treatment group 4 (properties within 4 miles of a generator), Treatment group 5 (properties within less than 5 miles of a generator) and the Control group which comprises of properties within 5 to 10 miles of a generator.

Table 2. 3: Breakdown of Fuel Type by Pre/Post and Treatment/Control

Fuel Type	Group	Pre (sold before fuel installation)	Post (sold after fuel installation)
Biomass	Treatment 1	1,267	2,353
	Treatment 2	6,184	7,216
	Treatment 3	17,533	14,966
	Treatment 4	39,523	31,050
	Treatment 5	53,231	40,634
	Control Group	153,000	163,589
Hydro	Treatment 1	191	495
	Treatment 2	1,038	2,051
	Treatment 3	2,914	5,069
	Treatment 4	5,840	8,350
	Treatment 5	7,065	10,120
	Control Group	199,166	183,194
Ngas	Treatment 1	7,446	2,576
	Treatment 2	28,909	10,220
	Treatment 3	57,337	21,258
	Treatment 4	67,621	27,108
	Treatment 5	70,676	29,725
	Control Group	135,555	163,589
Petro	Treatment 1	157	868
	Treatment 2	575	5,998
	Treatment 3	46,619	36,911
	Treatment 4	48,933	44,070
	Treatment 5	50,455	45,996
	Control Group	155,776	147,318
Solar	Treatment 1	8,312	3,692
	Treatment 2	29,161	16,286
	Treatment 3	60,776	42,022
	Treatment 4	88,843	65,896
	Treatment 5	99,687	75,028
	Control Group	106,544	118,286
Wind	Treatment 1	1,666	736
	Treatment 2	14,355	6,726
	Treatment 3	28,160	12,524
	Treatment 4	49,412	20,237
	Treatment 5	56,770	23,428
	Control Group	149,461	169,886

Table 2. 4: Treatment Effects with Plant Code and Month-year Fixed Effects

Variables	Treatment 1mile	Treatment 2mile	Treatment 3mile	Treatment 4mile	Treatment 5mile
	Model 1a	Model 2a	Model 3a	Model 4a	Model 5a
Hydroelectric	-0.154	-0.129	-0.298	-0.329*	-0.282
	(0.271)	(0.261)	(0.212)	(0.190)	(0.191)
Natural Gas	-0.230***	-0.247***	-0.184***	-0.159***	-0.146***
	(0.044)	(0.027)	(0.019)	(0.017)	(0.015)
Petroleum	-0.751	0.477	0.661**	0.659**	0.672**
	(0.475)	(0.319)	(0.318)	(0.312)	(0.317)
Solar	-0.101	-0.067*	-0.030	-0.034**	-0.032**
	(0.074)	(0.035)	(0.023)	(0.016)	(0.015)
Wind	-0.084	-0.055	0.065*	-0.069**	-0.065**
	(0.061)	(0.041)	(0.034)	(0.031)	(0.031)
Biomass (landfill and non-landfill)	-0.091***	-0.070***	-0.053***	0.003	0.009*
	(.019)	(0.010)	(0.007)	(0.005)	(0.005)
Fixed Effects					
Month Year	Y	Y	Y	Y	Y
Plant Code	Y	Y	Y	Y	Y

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 2. 5.1: Biomass Decomposition Treatment Effects with Plant Code and Month-year Fixed Effects

Variables	Treatment 1mile	Treatment 2mile	Treatment 3mile	Treatment 4mile	Treatment 5mile
	Model 1a_1	Model 2a_1	Model 3a_1	Model 4a_1	Model 5a_1
Landfill Biomass	-0.060***	-0.040	-0.024***	0.023***	0.024***
	(0.019)	(0.011)	(0.007)	(0.005)	(0.005)
Non-landfill Biomass	-0.459***	-0.302***	-0.249***	-0.138***	-0.091***
	(0.042)	(0.023)	(0.014)	(0.010)	(0.008)
Fixed Effects					
Month Year	Y	Y	Y	Y	Y
Plant Code	Y	Y	Y	Y	Y

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p

Table 2. 6: Treatment Effects with Zip Code, County, Census Tract and Month-year Fixed Effects

Variables	Treatment 1 mile			Treatment 2 mile			Treatment 3 mile		
	Model 1b	Model 1c	Model 1d	Model 2b	Model 2c	Model 2d	Model 3b	Model 3c	Model 3d
Hydroelectric	-0.154	-0.153	-0.207	-0.139	-0.129	-0.044	-0.298	-0.298	-0.154
	(0.271)	(.271)	(0.295)	(0.261)	(261)	(0.296)	(0.212)	(.213)	(0.239)
Natural Gas	-0.230***	-.223***	0.044	-0.247***	-0.242***	0.029	-0.184***	-0.178***	0.030
	(0.044)	(.044)	(0.058)	(0.027)	(.027)	(.045)	(0.019)	(.019)	(0.041)
Petroleum	-0.751	-0.751	-0.505**	0.477	0.477	-0.213**	0.661	0.661**	-0.202***
	(0.475)	(.475)	(.234)	(0.319)	(.319)	(0.098)	(0.318)	(.318)	(0.070)
Solar	-0.101	-0.082	0.012	-0.067*	-0.047	0.042	-0.030	-0.022	0.063**
	(0.075)	(0.070)	(0.088)	(0.035)	(0.034)	(0.047)	(0.023)	(0.023)	(0.030)
Wind	-0.084	-0.130**	-	-0.055	-0.094**	-	-0.065*	-0.105***	-
	(0.061)	(0.059)	-	(0.041)	(0.040)	-	(0.034)	(0.033)	-
Biomass (landfill and non-landfill)	-0.091***	-0.113***	-0.044*	-0.070***	-0.098***	0.041**	-0.053***	-0.085***	0.003
	(0.019)	(.019)	(0.024)	(0.010)	(0.011)	(0.017)	(0.007)	(0.007)	(0.014)
Fixed Effects									
Month Year	Y	Y	Y	Y	Y	Y	Y	Y	Y
Zip Code	Y			Y			Y		
County		Y			Y			Y	
Census Tract			Y			Y			Y

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 2. 6: Treatment Effects with Zip Code, County, Census Tract and Month-year Fixed Effects

Variables	Treatment 4 mile			Treatment 5 mile		
	Model 4b	Model 4c	Model 4d	Model 5b	Model 5c	Model 5d
Hydroelectric	-0.329*	-.329*	-0.221	-0.282	-.283	-0.187
	(0.190)	(.191)	(0.216)	(0.191)	(.192)	(0.213)
Natural Gas	-0.159***	-0.156***	0.052	-0.146***	-0.143***	.056
	(0.017)	(0.017)	(0.040)	(0.015)	(.015)	(.039)
Petroleum	0.659**	.659**	-.189***	0.672*	.672	.185***
	(0.312)	(.312)	(.058)	(0.317)	(.317)	(0.054)
Solar	-0.034**	-0.036**	0.036	-0.032**	-.034**	0.028
	(.016)	(0.017)	(0.022)	(0.015)	(.016)	(0.020)
Wind	-0.069**	-0.106	-	-0.065**	-0.103***	-
	(0.031)	(0.031)	(-)	(0.031)	(0.030)	(-)
Biomass (landfill and non-landfill)	0.003	-0.024***	.026***	0.009*	-0.018***	0.012
	(0.005)	(.005)	(0.010)	(0.005)	(.005)	(0.008)
Fixed Effects						
Month Year	Y	Y	Y	Y		
Zip Code	Y			Y		
County		Y			Y	
Census Tract			Y			Y

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 2. 7.1: Biomass Decomposition Treatment Effects with Zip Code, County, Census Tract and Month-year Fixed Effects

Variables	Treatment 1 mile			Treatment 2 mile			Treatment 3 mile		
	Model 1b_1	Model 1c_1	Model 1d_1	Model 2b_1	Model 2c_1	Model 2d_1	Model 3b_1	Model 3c_1	Model 3d_1
Landfill	-0.057***	-0.081***	0.041*	-0.037***	-0.069***	.197***	-0.018**	-0.056***	.197***
	(0.019)	(0.019)	(0.023)	(0.011)	(0.011)	(.017)	(0.007)	(0.007)	(.014)
Non-landfill	-0.406***	-0.450***	-0.507***	-0.308***	-0.299***	-.481***	-0.255***	-0.242***	-0.605**
	(0.040)	(0.042)	(0.093)	(.023)	(0.023)	(0.041)	(0.014)	(0.014)	(0.034)
Fixed Effects									
Month Year	Y	Y	Y	Y	Y	Y	Y	Y	Y
Zip Code	Y			Y			Y		
County		Y			Y			Y	
Census Tract			Y			Y			Y

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 2. 6.1: Biomass Decomposition Treatment Effects with Zip Code, County, Census Tract and Month-year Fixed Effects

Variables	Treatment 4 mile			Treatment 5 mile		
	Model 4b	Model 4c	Model 4d	Model 5b	Model 5c	Model 5d
Landfill	0.029***	-0.003	0.125***	-0.030***	-0.003	0.091***
	(0.005)	(0.005)	(0.009)	(0.005)	(0.005)	(0.008)
Non-landfill	-0.145***	0.133***	-0.549***	-0.098***	-0.087***	-.479***
	(0.009)	(0.009)	(0.031)	(0.008)	(0.008)	(.027)
Fixed Effects						
Month Year	Y	Y	Y	Y		
Zip Code	Y			Y		
County		Y			Y	
Census Tract			Y			Y

Robust standard errors in parentheses *** p<0.0

CHAPTER 3: FLOOD RESILIENCE OF POWERPLANTS AND SUBSTATIONS IN COASTAL COUNTIES AND DIFFERENT ECONOMIC TIERS IN NORTH CAROLINA

Abstract

Site selection decisions for utility-scale energy infrastructure have essential ramifications for the surrounding community. This is especially true in coastal regions, where land is often scarce due to high population densities. Despite the benefits coastal communities provide, coastal communities and their energy infrastructure face many risks such as hurricanes, coastal floods, storm surges, heatwaves, rising temperatures, and rising sea levels that threaten their existence. This study uses North Carolina powerplant and substation data from the US Energy Information Administration and spatially explicit data on flood risk with various measures from First Street Foundation's Flood Lab to assess the flood risk of coastal community energy infrastructure and the resilience faced by these energy infrastructures. The study examines the relationship between socio-economic attributes (coastal proximity and economic development) and energy infrastructure flood resilience across coastal communities. It compares the present and predicted future flood resilience of these energy infrastructures. Results show that expected future flood damage to both powerplants and substations is greater than past expected flood damages. However, expected flood damages are much smaller for substations than for powerplants. Coastal substations have greater expected flood damages relative to non-coastal substations; however, the reverse is true for coastal powerplants. Finally, substations in the lesser economically stressed counties (Tier 2) had the highest expected flood damages, while powerplants in the most economically stressed (Tier 1) had the highest expected flood damages.

Introduction

Extreme weather event flooding may impact communities differently depending on many factors. Relevant factors include socio-economic and geographic factors such as proximity to water bodies, population size changes, economic development, and flood adaptation protection. Also, flood-prone areas such as coastal communities are experiencing a rapid increase in population size and economic growth and hence face greater exposure to flood loss even apart from changes in flood frequency expected from climate changes (Bouwer, 2011; Kundzewicz, et al., 2013).

Coastal Community Flood Vulnerability

Coastal communities served as home to about 23% of the world's population globally as of 2004 and this share is projected to increase to about 50% of the world's population by 2030 (Adger et al., 2005). In the US, coastal communities are home to four out of every ten Americans and are an economic hub for many businesses nationwide. Coastal communities contribute significantly to the US economy; for instance, in 2011, coastal communities contributed $6.6 trillion to the nation's Gross Domestic Product (GDP); (NOAA, 2012; NOAA, 2014).

Despite the benefits coastal communities provide, their infrastructure faces many risks that threaten them, including hurricanes, coastal floods, storm surges, heat waves, rising temperatures, rising sea levels, etc. (Sutton-Grier, Wowk, Bamford, 2015). Coastal flooding and typhoons affect about 10 million people annually and given expected population increases, about 50 million people are expected to be affected by 2080 (Nicholls, 2004).

Coastal Energy Infrastructure Vulnerability

The US Global Change Research Program (USGCRP) asserts that energy system infrastructures are vulnerable to rapidly changing climate conditions, especially those infrastructures located in areas with harsher weather conditions. Energy infrastructure is impacted by both severe and long-term climate changes (GAO 2014). The United States has substantial energy generation infrastructure near the coast. Extreme weather conditions such as coastal flooding storm surges, and sea-level rise threaten these coastal energy generation infrastructures. For instance, the Department of Energy asserts that flooding from storm surge impacts aboveground fuel storage tanks (DOE 2015a; DOE 2015b GAO 2014). The US Global Climate Research Program (2014) projects that coastal energy generation infrastructure is more exposed to damage due to rising sea levels and extreme storm events, especially as coastal populations increase over time.

As the negative impacts from extreme weather events soar, the generation, distribution, and transmission of energy are affected due to the exposure of the coastal energy generation infrastructure to these events. The US Government Accountability Office (2014) stipulates that climate change, extreme weather conditions, coastal floods, and hurricanes are expected to impact and cause energy disruptions within four main infrastructures of the energy sector which are:

- Infrastructure for extracting and processing resources (oil platforms, refineries, processing plants, etc.)
- Infrastructure for transportation and storage (storage tanks, pipelines, etc.)
- Infrastructure for electricity generation (powerplants)

- Infrastructure for transmission and distribution of electricity (electricity substations, power lines, etc.)

The four sections of energy infrastructure are connected and form the supply chain as illustrated in Figure 3.1.

In the face of these extreme weather conditions confronting coastal areas, the US Department of Energy (DoE) seeks to find efficient ways to develop measures to ensure the resilience of coastal energy generation infrastructure through private-public partnerships, energy technologies, etc. Also, the development of natural and built infrastructures such as dunes, wetlands, barrier islands, sea walls, bulkheads, culverts, etc. along the coast are part of the measures to protect US shorelines (Spalding et al., 2014). Coastal energy infrastructure can be costly and serve critical purposes; hence finding ways to make them adaptive and ultimately resilient to these harsh and uncertain conditions and disasters is of great necessity. Therefore, this chapter seeks to answer the following questions:

1. Which coastal communities face the largest risk of disruptions to their power infrastructure and potentially stranded assets?
2. What aspects of energy infrastructure (generation-powerplants, distribution-substations, etc.) are most vulnerable to flooding?
3. What is the present and future expected flood damage by year and return period to powerplants and substations?
4. Are there systematic differences in flood risk for powerplants and substations based on socio-economic and spatial differences?

Related Studies

Disruptions in energy generation and transmission affect many sectors of the economy such as agriculture, education, health, manufacturing, transportation, etc. (GAO, 2014). Coastal winds also threaten power lines whereas storms and coastal flooding weaken coastal energy generation infrastructure foundations (US Climate Resilience Toolkit). Figure 3.2 shows a flood vulnerability assessment map of the eastern US coast. It also displays an overlay of energy infrastructure locations and New York flood hazard zones.

The location of energy infrastructure impacts its vulnerability. Energy infrastructure for generation, refining, processing, and transportation located offshore or close to the coast will often be more vulnerable to extreme weather conditions, storm surges, hurricanes, sea-level rise as well as coastal floods (USGCRP, DoE 2015). For instance, the Gulf Coast has a rapidly rising sea level and a projection of one to five inches of sea level rise each decade. This sea level rise and Gulf Coast land subsidence are huge threats to the about 187 large energy generation facilities at or less than four feet above sea level in the region (NOAA, 2009; USGCRP, 2014; US Department of Energy, 2015).

Impact of Extreme Weather Conditions on Coastal Energy Infrastructure

Hurricane Katrina reduced about 1.4 million barrels per day of oil production in the Gulf of Mexico and damaged four natural gas facilities on the Gulf Coast. The Minerals Management Service announced that about 8.3 billion cubic feet of natural gas generation was shut down daily by Hurricane Katrina (EIA, 2005). The 2005 coastal hurricanes led to total damages of about $160 billion (NCDC, 2013). Also, in 2004, Hurricane Ivan impacted oil production facilities in the Gulf of Mexico, and Hurricane Sandy in 2012 caused about 377 deaths and infrastructure damage of about $110 billion. These damages significantly impacted the power generation infrastructure, disrupting in the supply and transmission of energy in the region (Zamudaa et al., 2018; Zamudaa et al., 2019). Table 3.1 illustrates how some hurricanes caused damage to the electric grid and the number of customers whose power was disrupted as a result of energy infrastructure damages.

Definition of Coastal Resilience

The DoE suggests two main solutions to the impact of climate change on energy infrastructure: hardening and resilience. They define hardening as "*physical changes to infrastructure to make it less susceptible to storm damage, such as high winds, flooding, or flying debris"* and resiliency as "*the ability to recover quickly from damage to facilities' components or to any of the external systems on which they depend*". Both solutions they described are adaptive measures that tend to reduce the impacts of climate change on energy infrastructure.

Resilience, however, has many definitions based on the particular field of study. A federal Executive Order in 2013 defined resilience as *"the ability to anticipate, prepare for and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions"* (The White House, 2013). Many studies from the field of disaster research have also defined resilience in different ways; some of these definitions are captured in Table 3.2. All the definitions of resilience above reflect the strength of a system to take in negative impacts, adapt to changes, and recover from the effects mainly through negative feedback. Klein et al. (1998) stipulated that the resilience of the coast has three main parts: morphological or physical resilience; ecological resilience; and socio-economic resilience (Klein et al., 2003). The National Oceanic and Atmospheric Administration (NOAA) also assert that coastal resilience has three main components: society, economy, and environment. Adger et al. (2005) defined resilience as *"the capacity of linked social-ecological systems to absorb recurrent disturbances such as hurricanes or floods to retain essential structures, processes, and feedback."* Their study focused on how coastal areas' vulnerability to extreme weather and climate conditions can be reduced and their resilience can be enhanced by using the connection between anthropological societies and ecosystems. They stipulated that government involvement, policies, incentives, and strategies as well as cooperation with society can help coastal ecosystems withstand extreme weather and climate conditions. Thus, multilevel systems adopted by the government are essential to building the resilience of coastal ecosystems.

Brown, Tompkins, and Adger (2002) assert that coastal zone management, in increasing the resilience of such communities to extreme weather and climate uncertainties, should include diversified systems, meaning physical-biological as well as anthropological. They stipulated that coastal public-private partnerships where ownership rights that assign coastal resources to private or public partners help in building the resilience of coastal ecosystems.

Berkes (2007) sought to understand uncertainty and ways of curbing vulnerability caused by natural hazards and asserted that the resilience of a system can also reveal the vulnerability of the system to hazards. The study stipulated that resilience is connected to the vulnerability of a system in four main ways which are: the ability to accommodate changes and unexpected disruptions in a system; accommodating diverse disciplines to ensure multiple source solutions to the vulnerability of a system; diversifying knowledge for building the resilience of the system and ensuring systems have the chance to self-organize. Brody et al. (2008) examined flood damages in Texas and the role or effects of different natural and build infrastructures such as wetland alterations dams etc. in protecting coastlines. They used the amount of damage to assess the impact of 423 flood events. They found that natural wetlands help to significantly reduce flood damage.

Data

This study combines powerplant and substation data from the US Energy Information Administration with flood risk data from the First Street Foundation's Flood Lab dataset to understand the resilience of NC energy infrastructure in the face of flooding.

Energy Information Administration (EIA) Data

EIA utility-scale power plant data and shapefiles were employed for the universe of utility-scale generators in North Carolina. They consisted of the following attributes:

- Location attributes: longitudes, latitudes, county, city, zip code, street address.
- Generator characteristics: primary fuel source (biomass, coal, hydroelectric, natural gas, nuclear, petroleum, solar, or wind) and generator capacity measured in megawatts.

EIA substations data and shapefiles similarly contain the universe of energy substations in North Carolina. This dataset includes:

- Location attributes: longitudes, latitudes, county, city, zip code, street address.
- Substation characteristics: Maximum and minimum voltage and the number of lines.

First Street Foundation Flood Lab Data

First Street Foundation's Flood Lab provides spatially explicit data on flood risk using a variety of measures. The First Street Flood Lab data contains a variety of different flood data attribute packages; this study focuses on location and inundation depth products. The location product consists of location summary and location detail:

1. Location Summary: provides location attributes, flood factor, future risk direction, historic, and environmental risk information of the property.
    a. Location attributes include state, county, zip, city, street number, and FSID, which refers to the First Street unique identification number for each property.
    b. Flood factor: ranging from 1 to 10 with 1 associated with minimal flood risk and 10 associated with extreme flood risk to building footprint. Flood risk is calculated as the cumulative risk over 30 years. Figure 3.3 represents the flood factor rankings with color codes and meanings by First Street Foundation.
    c. Risk direction: measures the change in flood risk of the property for 30 years, which is from 2020 to 2050. Represented by -1, 0, and 1 for decrease, stationary, and increase in flood risk respectively over the period.
    d. Environmental risk: represents the type of environmental risks that affect the property. It is =1 for precipitation risk only; = 2 for precipitation and sea level rise; and = 3 for precipitation, sea level rise, and hurricane storm surge.

Also, inundation depth measures were employed. Inundation/ flood depth measure is the depth from the lowest elevation of the property footprint with three attributes: storm return period, year, and climate model.

a. Inundation/ flood depth is categorized into three climate model groups: low, mid, and high.
b. Storm return period: 2, 5, 10, 20,50, 100, 250, and 500 years.
c. Year: 2020, 2025, 2030, 2035, 2040, 2045, and 2050.

The First Street Foundation provided API Access in Python to extract flood data products. Using the EIA longitudes and latitudes information for powerplants and substations and codes for the location detail Python script were used to extract the FSIDs of each property. With the available property FSIDs, other sets of Python scripts were developed to extract the location summary and flood risk information of each property. This was then merged with the full EIA powerplant and substation datasets.

Results

Powerplants Flood Data Summary Statistics

The total number of powerplants is 712 with 547 solar, 42 petroleum, 41 hydroelectric, 34 biomass, 26 natural gas, 11 coal, 8 nuclear, 1 wind, 1 pumped storage, and 1 'other'. A total of 600 (84%) powerplants had a flood factor of 1 (minimal flood risk), while the next most frequent value, at 34 (4.8%) powerplants was a flood factor of 10 (extreme flood risk). The full flood factor distribution of powerplants is represented in Figure 3.4. Here, 621 (87.2%) powerplants were in locations with no future risk direction, which means estimated risk remains stationary over the 30 years period of 2020-2050. 86 (12.1%) powerplants are predicted to experience an increase in future flood risk while 5 (0.7%) powerplants had a decrease in future flood risk. Also, 679 (95.4%) powerplants were in locations with 1 environmental risk (that is precipitation risk only); and 33 (4.6%) powerplants were in locations with 3 environmental risks (that is, precipitation, sea level rise, and hurricane storm surge). Further, 709 (99.6%) powerplants were in locations with no past flooding event, and 3 (0.4%) powerplants were in locations with 1 past flooding event.

Coastal Versus Non-Coastal Counties Powerplant Summary Statistics

Out of the 100 counties in NC, 18 of them are located in coastal locations within the coastal plain and termed generally as NC coastal counties: Beaufort, Brunswick, Camden, Carteret, Chowan, Craven, Currituck, Dare, Hyde, Jones, New Hanover, Onslow, Pamlico, Pasquotank, Pender, Perquimans, Tyrrell, and Washington. 62 out of 712 powerplants are in these coastal counties.

Figure 3.5 shows the breakdown of powerplants located in NC coastal counties by fuel type. Rather than using raw number of generators, these and all subsequent measures for powerplants are weighted by megawatt (MW) capacity. Solar powerplants were more numerous but produce smaller capacity compared to natural gas powerplants which produces about half (48%) of MW of generating capacity located in coastal counties followed by solar plants (28%) and the least number of coastal counties' powerplants were wind and petroleum (at 1% each). Similarly, figure 3.6 represents the distribution of MW weighted powerplants in non-coastal counties. More than half (61%) of MW weighted powerplants located in non-coastal counties were natural gas plants followed by hydroelectric plants (18%) and the least number of coastal counties' powerplants were biomass and petroleum (at 2% each).

In all, 66% of powerplants in coastal counties have a minimal flood factor of 1, this was followed by 12.9% of powerplants which faced a major flood factor of 6. Only 3.23% of NC coastal counties' powerplants faced the extreme flood factor of 9, and Figure 3.7 shows the flood factor distribution of NC coastal counties' powerplants. A total of 650 powerplants were in non-coastal NC counties. 86% of these powerplants have a minimal flood factor of 1, this was followed by 5.2% and 2.15% of powerplants which faced extreme flood factors of 10 and 9 respectively. Figure 3.8 shows the flood factor distribution of NC non-coastal counties' powerplants.

Substations Flood Data Summary Statistics

The total number of substations in NC is 2,666. 2,189 (82.1%) of the total substations had a flood factor of 1 (minimal flood factor) followed by 111 (4.2%) substations with a flood factor of 9 (extreme flood factor). The full flood factor distribution of substations is represented in Figure 3.9. Also, 2,263 (84.9%) substations were in locations with no future risk direction, that is risk remains stationary over 30 years period. 379 (14.2%) substations had an increase in future flood risk while 24 (0.9) substations had a decrease in future flood risk. 2,517 (94.4%) substations were in locations with 1 environmental risk (precipitation risk only) and 150 (5.6%) substations were in locations with 3 environmental risks (precipitation, sea level rise, and hurricane storm surge). Also, 2,634 (98.8%) substations were in locations with no past flooding event and 11 (0.4%) substations were in locations with 1 past flooding event, and 11 (0.8%) substations with 2 past flooding events.

68% of substations in coastal counties have a minimal flood factor of 1, this was followed by 8.4% of substations that faced an extreme flood factor of 9. Also, 1.24% of substations in coastal counties each had flood factors of 2, 7, and 10 respectively and Figure 3.10 shows the flood factor distribution of NC coastal counties substations. 84.1% of substations in non-coastal counties have a minimal flood factor of 1, this was followed by 3.6% of substations that faced an extreme flood factor of 9. Also, 3.0% of substations in non-coastal counties had extreme flood factor 10, and Figure 3.11 shows the flood factor distribution of NC non-coastal counties substations.

Calculating Expected Flood Damages

As mentioned previously, the Flood Lab data include inundation depth estimates for eight different return periods ranging from 2 to 500 years. Expected damage is calculated as a summation of the probability of each storm event (based on the return period) multiplied by flood damage for each return period storm. Flood damage is calculated as a function of inundation depth or depth of flooding in feet[2] based on the FEMA functionality thresholds and damage functions of the Energy Infrastructure table (FEMA, Hazus-MH Flood Technical Manual) as shown in Table 3.3. As these values (in FEMA functionality thresholds and damage functions of the Energy Infrastructure) are discrete at integer levels of inundation depth while our estimates for the inundation depths for NC powerplants and substations are fairly continuous, the values in this table were used to develop a 4th-order polynomial to allow for a continuous function of damages by inundation depth.

The estimated numbers for the polynomial estimation of damages by flood depth (in feet) are as follows.

Powerplants: $2.214x + 0.246x^2 – 0.060x^3 + 0.004x^4$

Substations: $2.746x – 0.408x^2 + 0.042x^3 - 0.001x^4$

Where x = inundation depth for each year and return period

Expected damage in year t is calculated in Equation 1 below

$$E(Damage_t) = \sum_{k=0}^{8} Pr(Return\_period_{kt}) * Damage_{kt} \qquad (1)$$

Where, $Damage_{kt} = F(inundation\ depth_{kt})$

k represents return periods for the various climate model (2, 5, 10, 20, 50, 100, 250, 500); t = years for which inundation depths are predicted.

Powerplants Expected Flood Damage

Table 3.4 presents capacity-weighted current (2020) and future expected flood damages of NC powerplants based on flood inundation climate model depths from First Street Flood Lab climate models (low, mid, and high). 2020 expected damage from the mid-climate model predicts an annual average of 0.48% flood damage, this means we expect annual damages from flooding equal to 0.48% of the value of the generator. As expected, the percentage of expected flood damage increases slightly respectively for low, mid, and high climate models as the model projects further into the future. Thus, future expected flood damages are slightly greater than 2020 expected flood damages for the three climate model depths.

Expected Flood Damage of Powerplants by Fuel Types

Table 3.5 represents the expected flood damage to NC powerplants by fuel type. Petroleum powerplants recorded the highest present and future damage due to flooding across all climate models. This was followed by hydroelectric and wind powerplants expected flood damages respectively. All other fuel types have generally very low expected damages, with coal and natural gas powerplants facing the least present and future expected flood damages.

Expected Flood Damage of Powerplants by Counties

These relatively low and stable (across time) expected damages for the entire state conceal remarkably large between-county variability in infrastructure risk. All three climate models (low, mid, and high) predict that 32[3] NC counties have expected flood damages of 0, while several counties have annual expected damages of more than 40% of infrastructure value. Table 3.6 presents the five highest MW weighted expected flood damage of NC powerplants county-by-county.

Coastal Vs Non-Coastal Counties

Expected flood damages of powerplants weighted by capacity are examined for coastal and non-coastal counties in Table 3.7. 73% of powerplant capacity is in non-coastal counties and 27% is in coastal counties. Surprisingly, expected flood damages were much lesser for powerplants in coastal counties than non-coastal counties for each inundation climate model depth per year.

Powerplant Expected Flood Damage by Economic Tier

NC counties are classified into three tiers based on economic well-being by the state's Department of Commerce. Tier 1 counties are the most economically distressed counties followed by Tier 2 counties and the least economically stressed counties are classified as Tier 3. The economic Tiers were calculated based on four factors: average unemployment rate, median household income, percentage growth in population, and adjusted property tax base per capita. The NC economic county tiers are represented in Figure 3.12.

370 (51.9%), 203 (28.5%), and 139 (19.5%) of powerplants are in Tier 1, 2, and 3 counties respectively. Table 3.8 shows the expected flood damage of powerplants based on the three NC economic regions. Powerplants located in the most economically stressed counties (Tier 1) have the highest expected flood damages for the entire 30-year period compared to

[3] 32 NC counties with zero expected damages: Bertie, Caswell, Columbus, Davidson, Davie, Forsyth, Franklin, Gates, Granville, Greene, Guilford, Harnett, Henderson, Hertford, Hoke, Jones, Moore, Onslow, Orange, Pasquotank, Person, Randolph, Richmond, Sampson, Stanly, Stokes, Union, Vance, Wake, Warren, Yadkin.

powerplants in the two less economically stressed counties. The expected damage of powerplants due to flooding ranges between 0.95% and 0.88% for Tier 1 counties. However, powerplants located in the least economically stressed counties (Tier 3) had the lowest expected flood damages for the entire 30-year period relative to powerplants in Tier 1 and 2 counties. The expected damage of powerplants due to flooding ranges between 0.17% and 0.37% for Tier 3 counties.

Substations Expected Flood Damage

Table 3.9 shows most past and future expected damages to NC substations due to inundation depth calculated based on the return period and year of flooding. As expected, the percentage of expected flood damage increases slightly respectively for low, mid, and high inundation depths as the model projects further into the future. However, these increases are very small, and in general the expected flood damages are much smaller for the substations than powerplants.

Expected Flood Damage of Substations by Counties

All three climate models (low, mid, and high) predicted zero expected annual damages for substations within 12 NC counties[4]. Table 3.10 presents the five highest expected flood damage of NC substations county-by-county.

Coastal Vs Non-Coastal Counties

Table 3.9 shows most past and future expected damages to NC substations due to flooding. Expected flood damages of substations are examined for 2 communities' coastal and non-coastal counties in Table 3.11. 2,345 (87.9%) substations were in non-coastal counties and 322 (12.1%) were in coastal counties. The expected flood damages were roughly double for substations in

[4] 12 NC counties with zero expected damages for substations: Caswell, Clay, Gates, Graham, Granville, Greene, Mitchell, Northampton, Person, Stokes, Warren, and Yadkin.

coastal counties than non-coastal counties for each climate model. However, it is worth emphasizing that this doubling is from a very low level.

Economic Tier Substations Expected Flood Damage

809 (30.3%), 909 (34.1%), and 949 (35.6%) substations are in Tier 1, 2, and 3 counties respectively. Table 3.12 shows the expected flood damage of substations based on the three NC economic Tier regions. Substations located in the most economically stressed counties (Tier 1) have the lowest expected flood damages for the entire 30-year period compared to substations in two less economically stressed counties. The expected damage of substations due to flooding ranges between 0.09% and 0.25% for Tier 1 counties. However, substations located in the next economically stressed counties (Tier 2) have the highest expected flood damages for the entire 30-year period compared to substations in Tier 1 and 3 counties. The expected damage of substations due to flooding ranges between 0.19% and 0.42% for Tier 2 counties.

Conclusion

Flooding from extreme weather events affects communities' energy infrastructure differently based on diverse factors especially the location or siting of the energy infrastructure. Therefore, this study set out to examine how flooding impact powerplants and substations in different communities.

Results showed that weighted by megawatts capacity, natural gas accounted for the majority of powerplants in both coastal and non-coastal counties while petroleum had the least in both communities. On average powerplants have greater current and future expected flood damages hence more vulnerable to flooding relative to substations' expected flood damages. The average 2020 expected flood damage to powerplants (weighted by megawatts) was 0.46% and for substations was 0.13%. We hypothesized that energy infrastructure would face higher risks in counties on the coast and in less economically developed counties. Our hypothesis related to coastal counties was confirmed for substations, while powerplants within non-coastal counties surprisingly had higher expected flood damage relative to those located in coastal counties. Conversely, our theory about economically developed counties was confirmed for powerplants, as those located in the most stressed economic counties (Tier 1) had the highest average expected flood damages; however, the same pattern was not found with substations whose average expected flood damages were highest in Tier 2 (less economically stressed) counties relative to Tier 1 and 3 counties.

It is reasonable to ask why we would see these patterns. We would suggest two phenomena explain these patterns, one related to the spatial necessity of the infrastructure and one related to the economic impact of infrastructure siting. First, by spatial necessity we mean whether the infrastructure must be sited near where the electricity is used. This is much truer for substations than for generators. As a result, while the greatest flood risk in NC is at the coast, it is likely we see the expected higher coastal risk in the infrastructure that is less mobile (substations) than in infrastructure that has more freedom in siting (generators). With regard to the economic impact pattern we expected, Chapter 2 highlighted the negative economic impact of generator siting (especially for fossil fuel generators). We suspect that there is a correlation between economic disadvantage and inland flood risk, specifically that high-risk areas that lack the amenities of the coast are more likely to be economically disadvantaged. Thus, an explanation for our finding that generators in Tier 1 counties are at higher risk than other counties is that disadvantaged inland counties tend to have higher flood risk. This is supported anecdotally in Figure 3.12, where one can observe that the Tier 1 counties are clustered in the coastal plain but typically not at the coast.

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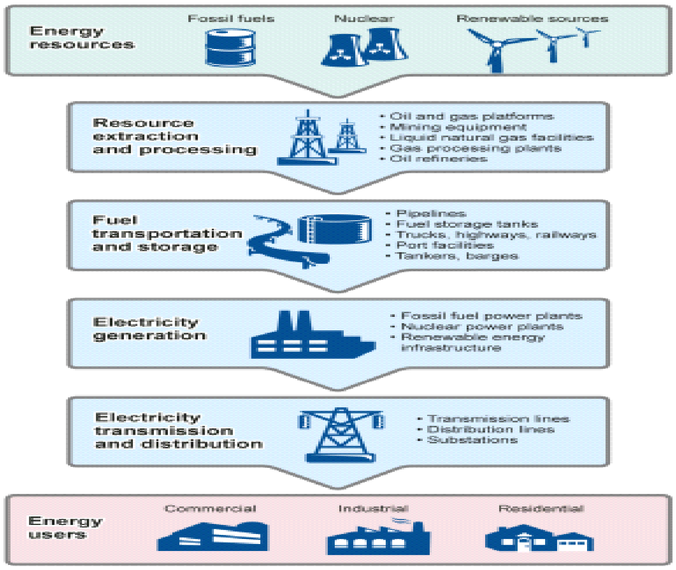

Figure 3. 1: Illustration of US Energy Supply Chain

(GAO, 2014)

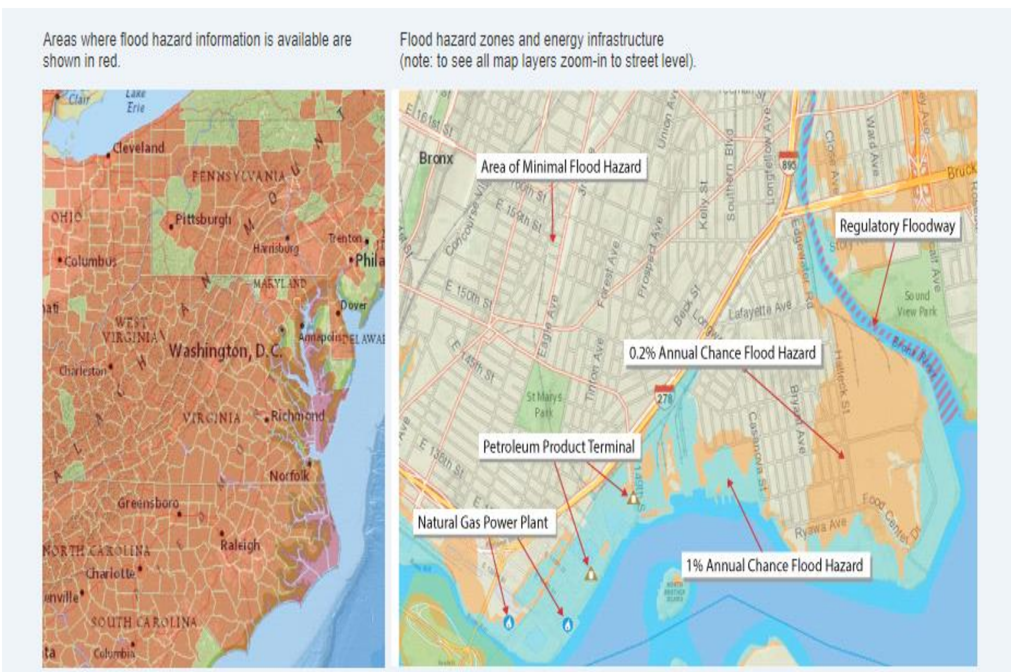

Figure 3. 2: EIA Flood Vulnerability Assessment Map

Table 3. 1: Damage to Electric Grid from Hurricanes

	Katrina (2005)	Rita (2005)	Wilma (2005)	Gustav (2008)	Ike (2008)
Customers Affected (in millions)	2.7	1.5	3.5	1.1	3.9
Utility Poles Destroyed	72,447	14,817	14,000	11,478	10,300
Transformers Damaged	8,281	3,580	NA	4,349	2,900
Transmission Structures Damaged	1,515	3,550	NA	241	238
Substations Offline	300	508	241	368	283

(Department of Energy, 2009)

Table 3. 1: Some Definitions of Resilience from the Field of Disasters and Hazards

Source	**Definition**
Timmerman (1981)	Resilience is the measure of a system's or part of the system's capacity to absorb and recover from occurrence of a hazardous event.
Wildavsky (1991)	Resilience is the capacity to cope with unanticipated dangers after they have become manifest, learning to bounce back.
Buckle (1998)	Resilience is the capacity that people or groups may possess to withstand or recover from the emergencies and which can stand as a counterbalance to vulnerability.
EMA (1998)	Resilience is a measure of how quickly a system recovers from failures.
Mileti (1999)	Local resiliency means that a locale is able to withstand an extreme natural event without suffering devastating losses, damage, diminished productivity, or quality of life without a large amount of assistance from outside the community.
Comfort et al. (1999)	The capacity to adapt existing resources and skills to new systems and operating conditions.
Adger (2000)	Social resilience is the ability of groups or communities to cope with external stresses and disturbances as a result of social, political, and environmental change.
Buckle et al. (2000)	… the quality of people, communities, agencies, and infrastructure that reduce vulnerability. Not just the absence of vulnerability rather the capacity to prevent or mitigate loss and then secondly, if damage does occur to maintain normal condition as far as possible, and thirdly to manage recovery from the impact.
Klein, Nicholls, and Thomalla (2003)	…the amount of disturbance a system can absorb and still remain within the same state…the degree to which the system is capable of self-organization (p. 35)…the degree to which the system can build and increase the capacity for learning and adaptation (p. 40).

(Peacock et al. 2010)

Figure 3. 3: Flood Factor Rankings by First Street Foundation

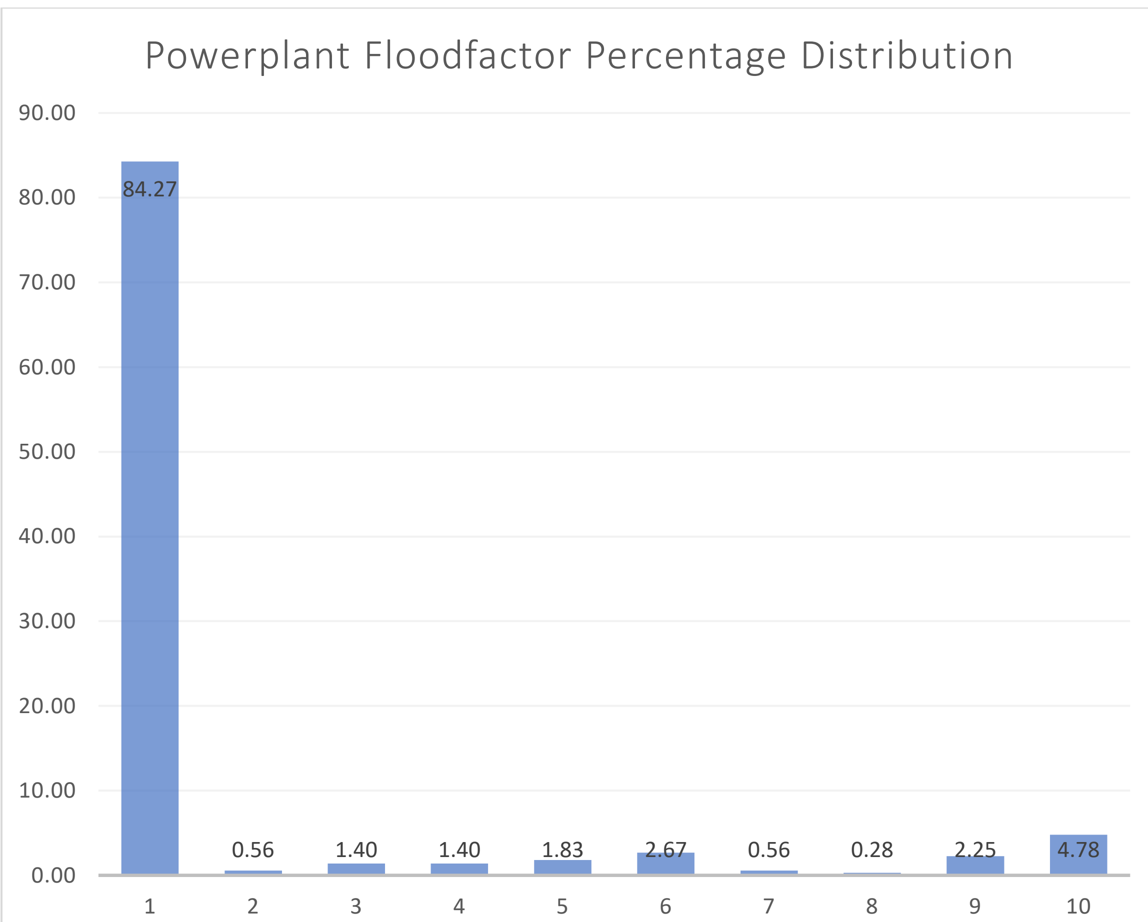

Figure 3. 4: NC Powerplants Flood Factor Percentage Distribution

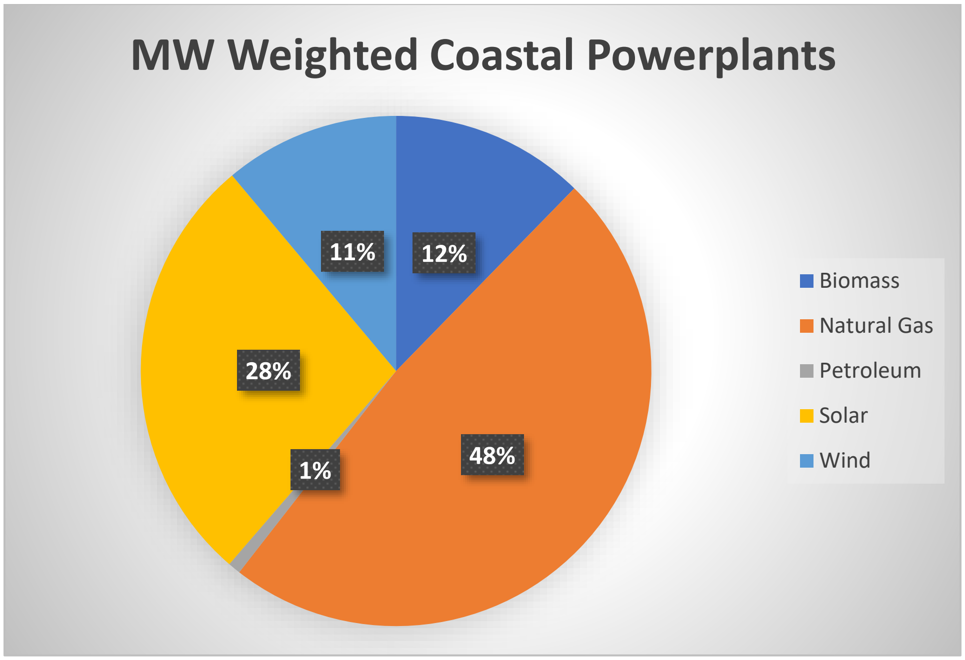

Figure 3. 5: Coastal Powerplants Weighted by MW Distribution

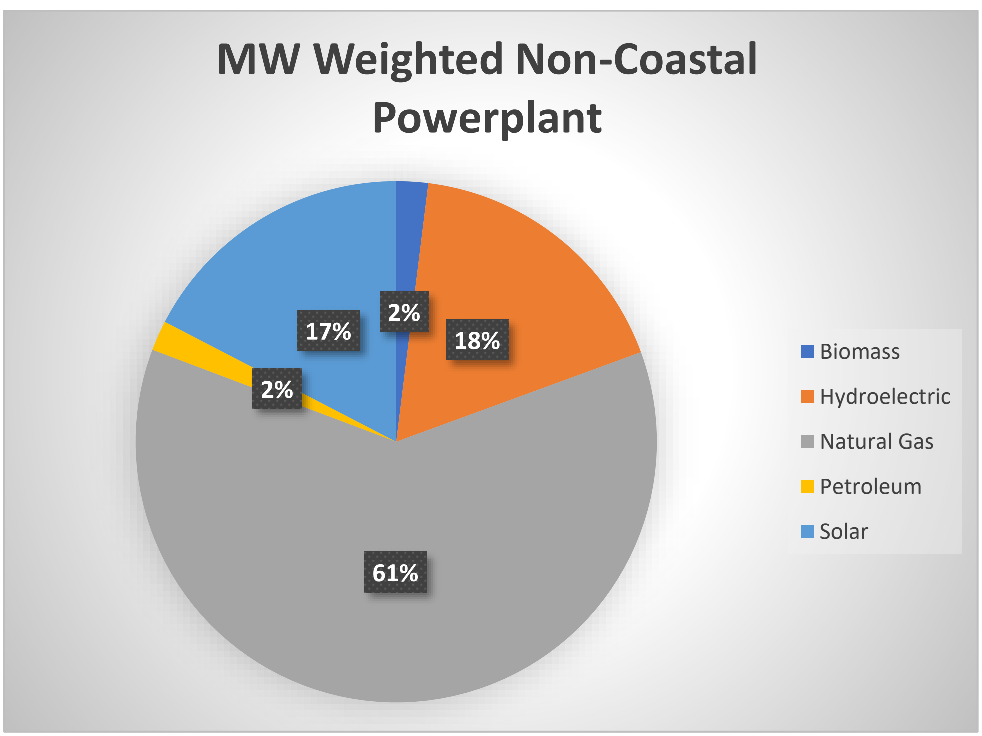

Figure 3. 6: Non-Coastal Powerplants Weighted by MW Distribution

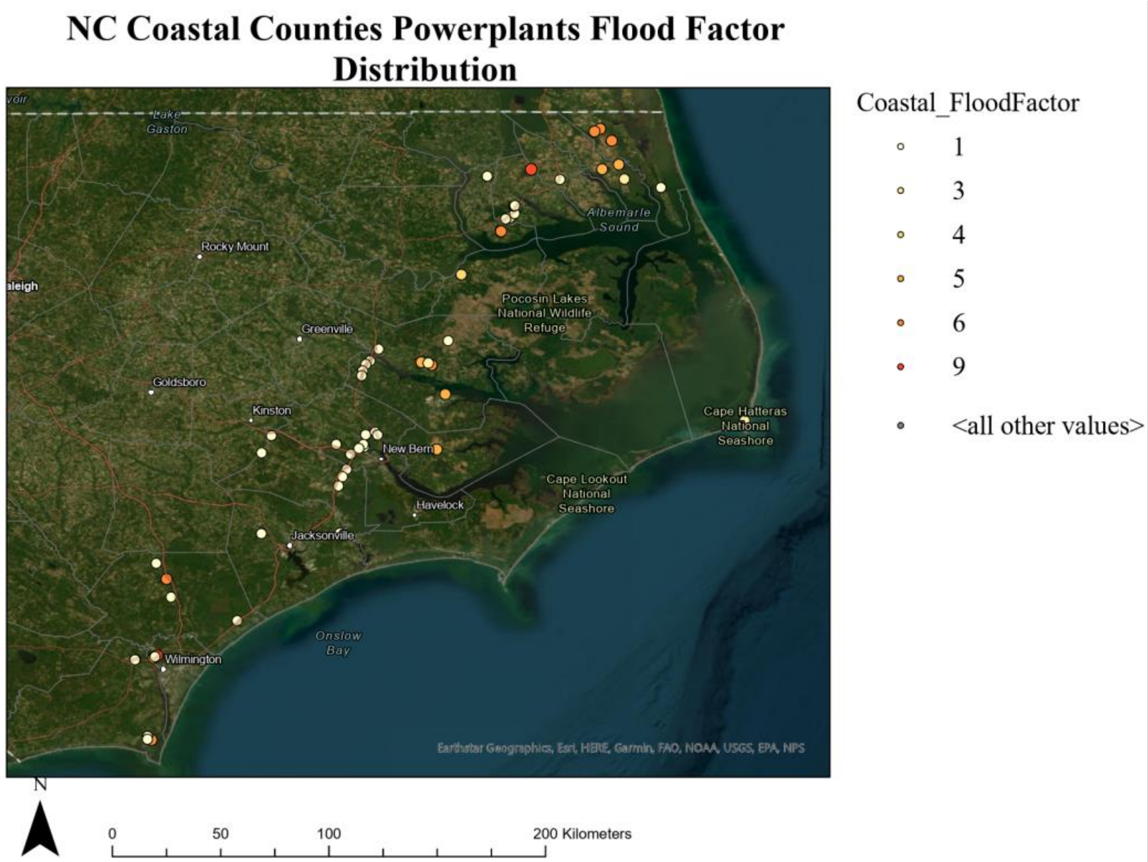

Figure 3. 7: NC Coastal Counties Powerplants Flood Factor Distribution

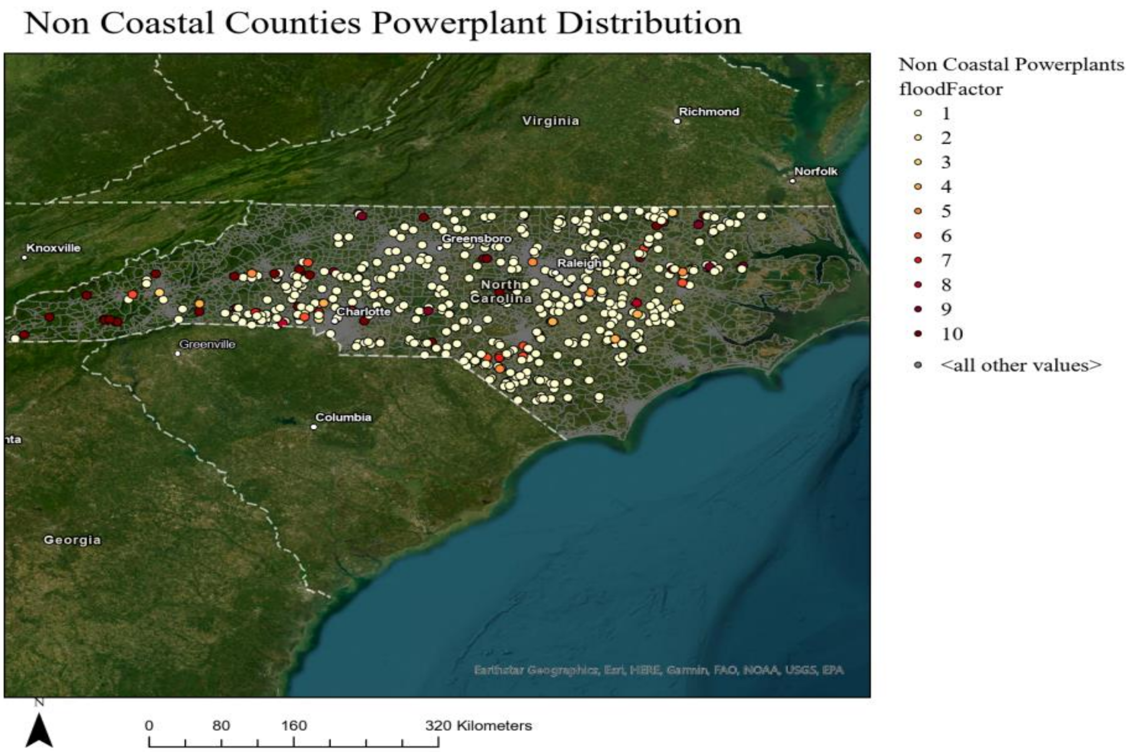

Figure 3. 8: NC Non-Coastal Powerplant Flood Factor Distribution

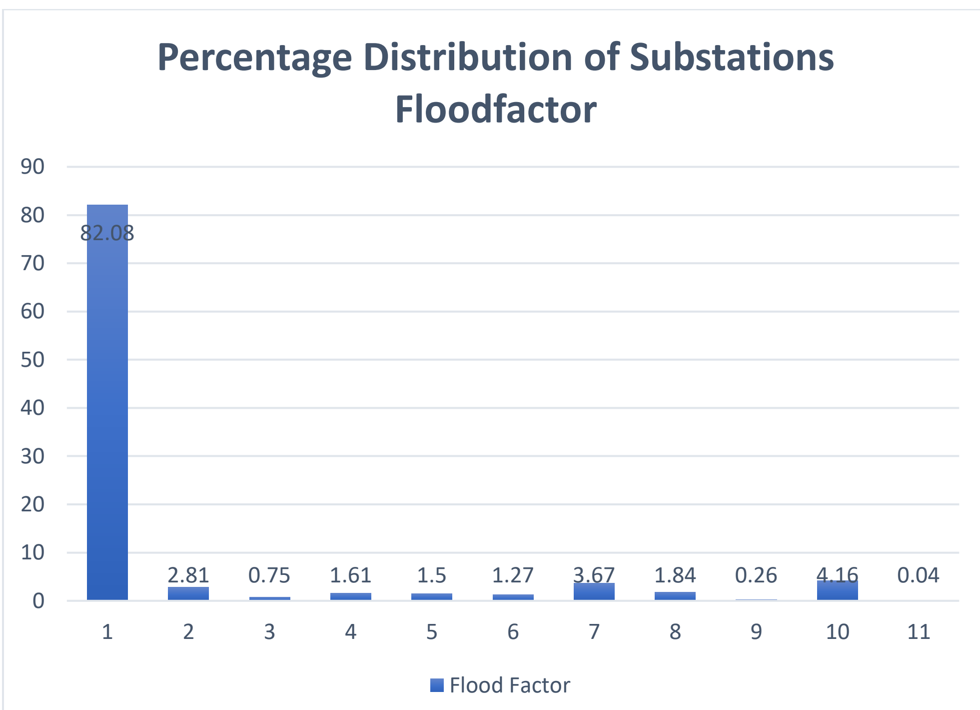

Figure 3. 9: NC Substations Flood Factor Percentage Distribution

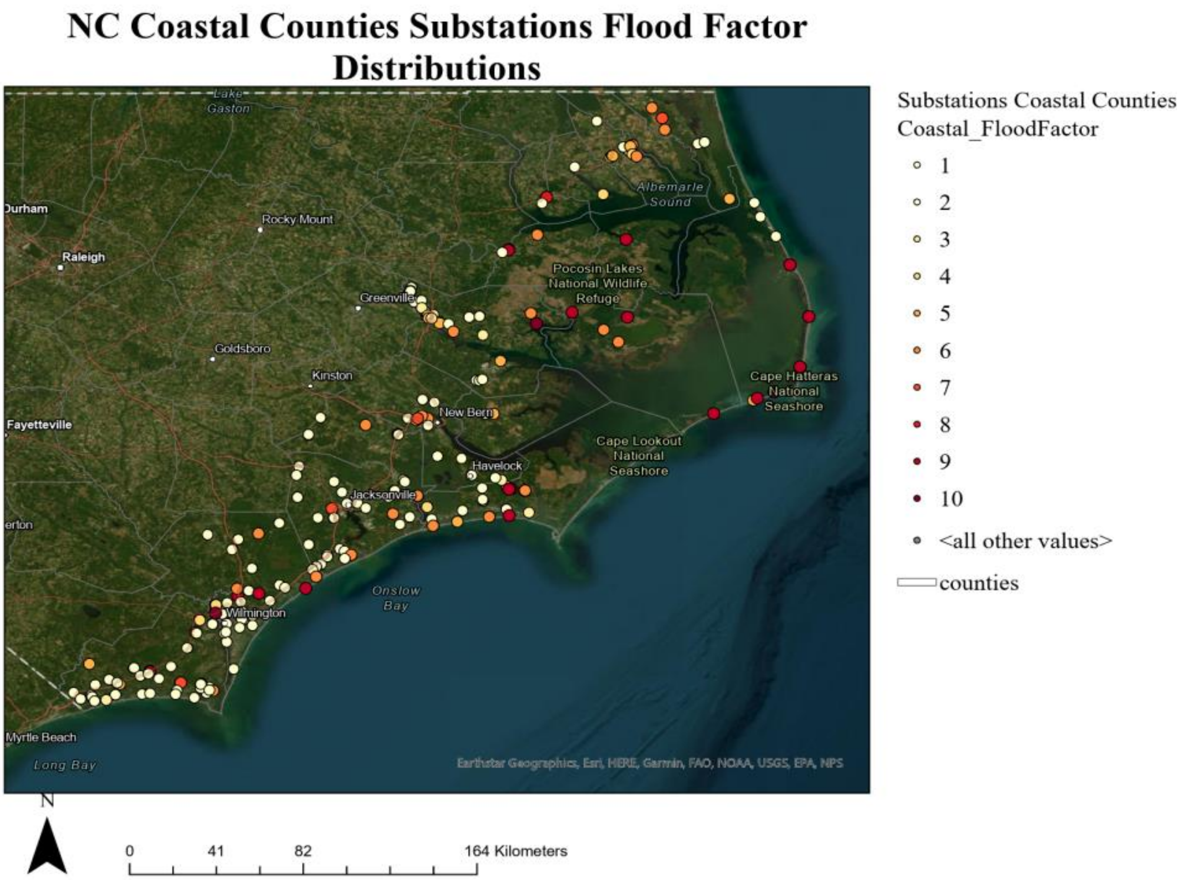

Figure 3. 10: NC Coastal Counties Substations Flood Factor Distribution

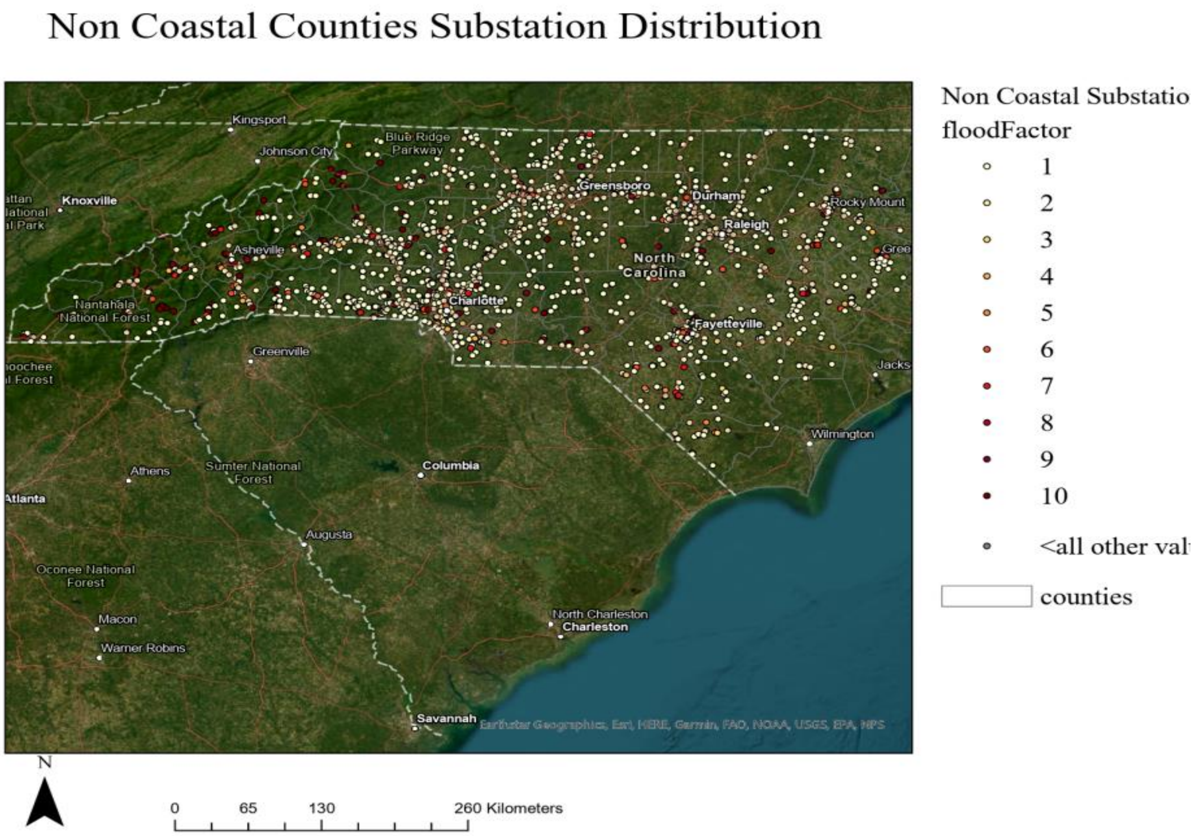

Figure 3. 11: NC Non-Coastal Substations Flood Factor Distribution

Table 3. 2: FEMA Electric Power Classifications, Functionality Thresholds, and Damage Functions

Specific Occupancy	Functionality Threshold Depth	Percent Damage by depth of flooding in feet2										
		0	1	2	3	4	5	6	7	8	9	10
Low Voltage Substation	4	0	2	4	6	7	8	9	10	12	14	15
Medium Voltage Substation	4	0	2	4	6	7	8	9	10	12	14	15
High Voltage Substation	4	0	2	4	6	7	8	9	10	12	14	15
Small Powerplants	4	0	2.5	5	7.5	10	12.5	15	17.5	20	25	30
Small Powerplants	4	0	2.5	5	7.5	10	12.5	15	17.5	20	25	30
Small Powerplants	4	0	2.5	5	7.5	10	12.5	15	17.5	20	25	30

Table 3. 3: MW Weighted Powerplants Expected Average Flood Damage Based on Flood Climate Models

Variables	Year	Weights	Climate Model	Mean	Std Dev.	Min	Max
Past Expected Damages							
Expected Damage 2020_mid_ft	2020	52384.9	Mid	0.48	4.38	0	100
Future Expected Damages							
Expected Damage 2035_low_ft	2035	52384.9	Low	0.46	4.29	0	100
Expected Damage 2035_mid_ft	2035	52384.9	Mid	0.49	4.41	0	100
Expected Damage 2035_high_ft	2035	52384.9	High	0.55	4.69	0	100
Expected Damage 2050_low_ft	2050	52384.9	Low	0.46	4.28	0	100
Expected Damage 2050_mid_ft	2050	52384.9	Mid	0.51	4.46	0	100
Expected Damage 2050_high_ft	2050	52384.9	High	0.55	4.66	0	100

Table 3. 4: Distribution of MW Weighted Powerplants Expected Average Flood Damage by Fuel Type

Variable	No. of Observations	Weight	Mean	Std. Dev.	Min	Max
Biomass						
Expected Damage 2020_mid_ft	34	645.6	0.346	1.455	0	6.763
Expected Damage 2035_low_ft	34	645.6	0.611	1.483	0	6.682
Expected Damage 2035_mid_ft	34	645.6	0.627	1.539	0	6.972
Expected Damage 2035_high_ft	34	645.6	0.733	1.676	0	7.443
Expected Damage 2050_low_ft	34	645.6	0.899	1.758	0	6.854
Expected Damage 2050_mid_ft	34	645.6	0.916	1.808	0	7.163
Expected Damage 2050_high_ft	34	645.6	1.008	1.963	0	7.664
Coal						
Expected Damage 2020_mid_ft	11	13794.8	0.002	0.040	0	0.644
Expected Damage 2035_low_ft	11	13794.8	0.002	0.039	0	0.640
Expected Damage 2035_mid_ft	11	13794.8	0.003	0.041	0	0.662
Expected Damage 2035_high_ft	11	13794.8	0.003	0.041	0	0.670
Expected Damage 2050_low_ft	11	13794.8	0.002	0.040	0	0.646
Expected Damage 2050_mid_ft	11	13794.8	0.003	0.042	0	0.676
Expected Damage 2050_high_ft	11	13794.8	0.004	0.042	0	0.686
Hydroelectric						
Expected Damage 2020_mid_ft	41	3679.5	3.487	11.811	0	100
Expected Damage 2035_low_ft	41	3679.5	3.212	11.521	0	100
Expected Damage 2035_mid_ft	41	3679.5	3.607	11.962	0	100
Expected Damage 2035_high_ft	41	3679.5	4.401	12.993	0	100
Expected Damage 2050_low_ft	41	3679.5	3.160	11.514	0	100

Expected Damage 2050_mid_ft	41	3679.5	3.762	12.146	0	100
Expected Damage 2050_high_ft	41	3679.5	4.161	12.798	0	100
			Natural Gas			
Expected Damage 2020_mid_ft	26	13835.2	0.026	0.124	0	0.636
Expected Damage 2035_low_ft	26	13835.2	0.025	0.123	0	0.634
Expected Damage 2035_mid_ft	26	13835.2	0.027	0.124	0	0.637
Expected Damage 2035_high_ft	26	13835.2	0.028	0.125	0	0.645
Expected Damage 2050_low_ft	26	13835.2	0.026	0.124	0	0.636
Expected Damage 2050_mid_ft	26	13835.2	0.028	0.124	0	0.639
Expected Damage 2050_high_ft	26	13835.2	0.030	0.126	0	0.645
			Petroleum			
Expected Damage 2020_mid_ft	42	408.4	9.495	17.298	0	40.961
Expected Damage 2035_low_ft	42	408.4	9.457	17.221	0	40.783
Expected Damage 2035_mid_ft	42	408.4	9.528	17.343	0	41.076
Expected Damage 2035_high_ft	42	408.4	9.685	17.624	0	41.744
Expected Damage 2050_low_ft	42	408.4	9.450	17.196	0	40.730
Expected Damage 2050_mid_ft	42	408.4	9.562	17.390	0	41.194
Expected Damage 2050_high_ft	42	408.4	9.725	17.679	0	41.884
			Solar			
Expected Damage 2020_mid_ft	547	4183.1	0.083	0.448	0	6.411
Expected Damage 2035_low_ft	547	4183.1	0.097	0.461	0	6.334
Expected Damage 2035_mid_ft	547	4183.1	0.102	0.478	0	6.422
Expected Damage 2035_high_ft	547	4183.1	0.109	0.506	0	6.611
Expected Damage 2050_low_ft	547	4183.1	0.117	0.509	0	6.291

Expected Damage 2050_mid_ft	547	4183.1	0.121	0.528	0	6.417
Expected Damage 2050_high_ft	547	4183.1	0.129	0.560	0	6.696
			Wind			
Expected Damage 2020_mid_ft	1	208	1.018	.	1.018	1.018
Expected Damage 2035_low_ft	1	208	0.975	.	0.975	0.975
Expected Damage 2035_mid_ft	1	208	1.036	.	1.036	1.036
Expected Damage 2035_high_ft	1	208	1.095	.	1.095	1.095
Expected Damage 2050_low_ft	1	208	0.998	.	0.998	0.998
Expected Damage 2050_mid_ft	1	208	1.051	.	1.051	1.051
Expected Damage 2050_high_ft	1	208	1.111	.	1.111	1.111

Table 3. 6: Powerplants Expected Flood Damage by Counties

Table 3. 5: Powerplants Expected Flood Damage by Counties

Variables	No. of Observations	Weights	Mean	Std Dev.	Min	Max
Highest Powerplants Expected Flood Damage by Counties						
Caldwell						
Expected_Damage_20_mid_ft	2	27.7	69.643	20.836	0.000	75.652
Expected_Damage_35_low_ft	2	27.7	67.810	20.287	0.000	73.660
Expected_Damage_35_mid_ft	2	27.7	70.338	21.043	0.000	76.406
Expected_Damage_35_high_ft	2	27.7	74.623	22.325	0.000	81.061
Expected_Damage_50_low_ft	2	27.7	68.476	20.486	0.000	74.384
Expected_Damage_50_mid_ft	2	27.7	71.043	21.254	0.000	77.173
Expected_Damage_50_high_ft	2	27.7	76.397	22.856	0.000	82.988
Jackson						
Expected_Damage_20_mid_ft	5	55.2	50.357	26.412	12.823	100.000
Expected_Damage_35_low_ft	5	55.2	50.022	26.414	12.843	100.000
Expected_Damage_35_mid_ft	5	55.2	50.572	26.389	12.893	100.000
Expected_Damage_35_high_ft	5	55.2	51.719	26.378	12.933	100.000
Expected_Damage_50_low_ft	5	55.2	49.767	26.414	12.855	100.000
Expected_Damage_50_mid_ft	5	55.2	50.787	26.373	12.941	100.000
Expected_Damage_50_high_ft	5	55.2	51.319	26.342	13.000	100.000
Rockingham						
Expected_Damage_20_mid_ft	1	1.2	41.565	.	41.565	41.565
Expected_Damage_35_low_ft	1	1.2	45.577	.	45.577	45.577
Expected_Damage_35_mid_ft	1	1.2	46.216	.	46.216	46.216
Expected_Damage_35_high_ft	1	1.2	46.932	.	46.932	46.932
Expected_Damage_50_low_ft	1	1.2	44.979	.	44.979	44.979
Expected_Damage_50_mid_ft	1	1.2	45.608	.	45.608	45.608
Expected_Damage_50_high_ft	1	1.2	46.315	.	46.315	46.315
Cherokee						
Expected_Damage_20_mid_ft	4	168.6	41.523	5.332	0.000	42.236
Expected_Damage_35_low_ft	4	168.6	41.039	5.270	0.000	41.744
Expected_Damage_35_mid_ft	4	168.6	41.542	5.334	0.000	42.255
Expected_Damage_35_high_ft	4	168.6	42.471	5.452	0.000	43.200
Expected_Damage_50_low_ft	4	168.6	40.888	5.252	0.000	41.591
Expected_Damage_50_mid_ft	4	168.6	41.542	5.335	0.000	42.255
Expected_Damage_50_high_ft	4	168.6	42.792	5.492	0.000	43.527
Clay						
Expected_Damage_20_mid_ft	1	1.8	40.730	.	40.730	40.730
Expected_Damage_35_low_ft	1	1.8	40.479	.	40.479	40.479

Expected_Damage_35_mid_ft	1	1.8	40.810	.	40.810	40.810
Expected_Damage_35_high_ft	1	1.8	41.061	.	41.061	41.061
Expected_Damage_50_low_ft	1	1.8	40.467	.	40.467	40.467
Expected_Damage_50_mid_ft	1	1.8	40.892	.	40.892	40.892
Expected_Damage_50_high_ft	1	1.8	41.240	.	41.240	41.240

Table 3. 6: Coastal and Non-Coastal MW Weighted Powerplants Average Expected Flood Damage

Variables	Coastal Counties	No. of Observation	Weight	Mean	Std Dev.	Min	Max
Expected Damage 2020_mid_ft							
	0	650	38438.2	0.64	5.10	0.00	100.00
	1	62	13946.7	0.02	0.12	0.00	1.18
Expected Damage 2035_low_ft							
	0	650	38438.2	0.62	5.00	0.00	100.00
	1	62	13946.7	0.02	0.13	0.00	1.18
Expected Damage 2035_mid_ft							
	0	650	38438.2	0.66	5.14	0.00	100.00
	1	62	13946.7	0.02	0.14	0.00	1.18
Expected Damage 2035_high_ft							
	0	650	38438.2	0.75	5.47	0.00	100.00
	1	62	13946.7	0.03	0.14	0.00	1.19
Expected Damage 2050_low_ft							
	0	650	38438.2	0.62	4.99	0.00	100.00
	1	62	13946.7	0.03	0.16	0.00	1.34
Expected Damage 2050_mid_ft							
	0	650	38438.2	0.68	5.19	0.00	100.00
	1	62	13946.7	0.03	0.16	0.00	1.34
Expected Damage 2050_high_ft							
	0	650	38438.2	0.73	5.42	0.00	100.00
	1	62	13946.7	0.03	0.17	0.00	1.34

NC Economic County Tiers

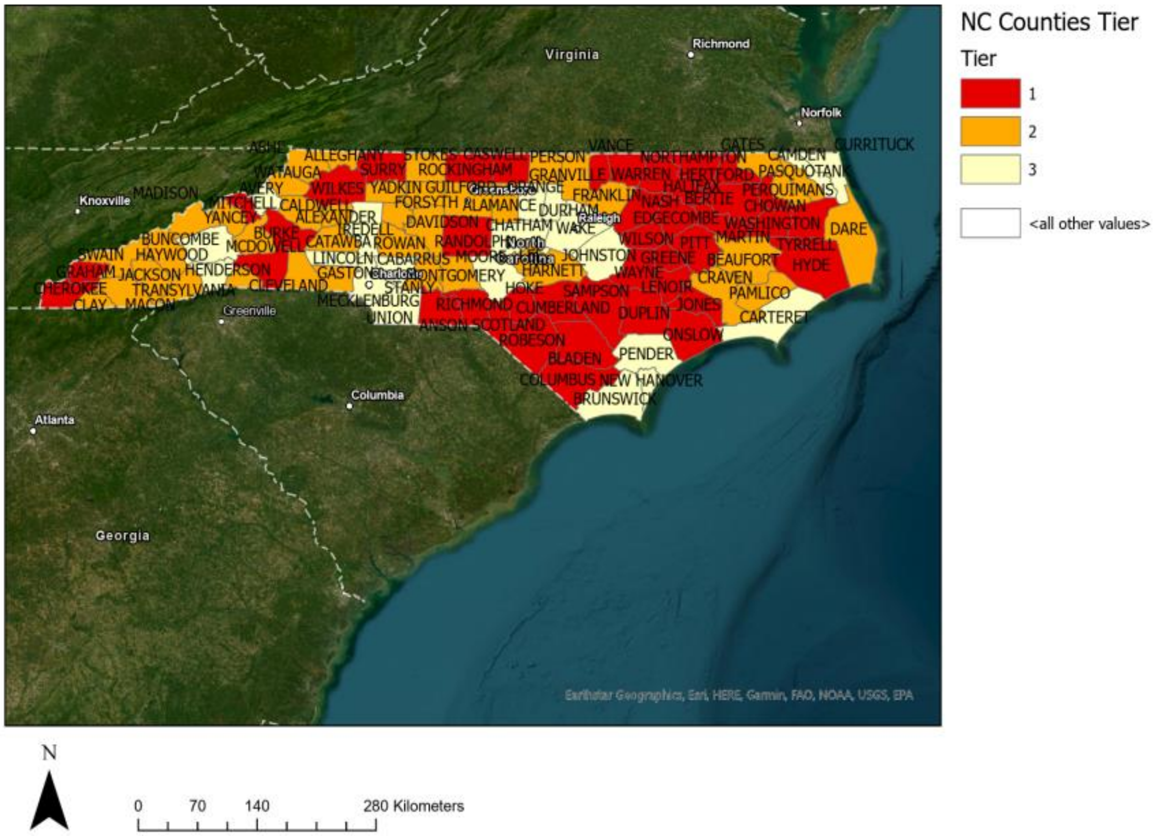

Figure 3. 12: NC Counties Economic Tiers

Table 3. 7: NC Economic Tiers MW Weighted Expected Powerplant Average Flood Damage

Variables	Economic Tiers	No. of Observation	Weight	Mean	Std Dev.	Min	Max
Expected Damage 2020_mid_ft							
	1	370	13348.1	0.88	5.82	0	42.24
	2	203	18444.4	0.47	5.17	0	100.00
	3	139	20592.4	0.22	1.61	0	44.08
Expected Damage 2035_low_ft							
	1	370	13348.1	0.89	5.77	0	45.58
	2	203	18444.4	0.46	5.10	0	100.00
	3	139	20592.4	0.18	1.30	0	43.80
Expected Damage 2035_mid_ft							
	1	370	13348.1	0.90	5.84	0	46.22
	2	203	18444.4	0.47	5.20	0	100.00
	3	139	20592.4	0.24	1.75	0	44.18
Expected Damage 2035_high_ft							
	1	370	13348.1	0.93	5.96	0	46.93
	2	203	18444.4	0.49	5.37	0	100.00
	3	139	20592.4	0.37	2.65	0	44.69
Expected Damage 2050_low_ft							
	1	370	13348.1	0.90	5.76	0	44.98
	2	203	18444.4	0.46	5.11	0	100.00
	3	139	20592.4	0.17	1.23	0	43.87
Expected Damage 2050_mid_ft							
	1	370	13348.1	0.91	5.85	0	45.61
	2	203	18444.4	0.48	5.23	0	100.00
	3	139	20592.4	0.27	1.93	0	44.28
Expected Damage 2050_high_ft							
	1	370	13348.1	0.95	6.00	0	46.32
	2	203	18444.4	0.49	5.42	0	100.00

3	139	20592.4	0.33	2.32	0	44.81

Table 3. 8: Expected Average Damage to Substations Based on Flooding Depth in Feet

Variables	Climate Models	No. of Observations	Mean	Std. Dev.	Min	Max
			Present			
Expected Damage 2020_mid_ft	Mid	2667	0.13	0.60	0	8.16
			Future			
Expected Damage 2035_low_ft	Low	2667	0.14	0.62	0	8.15
Expected Damage 2035_mid_ft	Mid	2667	0.14	0.63	0	8.15
Expected Damage 2035_high_ft	High	2667	0.15	0.64	0	8.17
Expected Damage 2050_low_ft	Low	2667	0.15	0.66	0	8.14
Expected Damage 2050_mid_ft	Mid	2667	0.16	0.67	0	8.14
Expected Damage 2050_high_ft	High	2667	0.17	0.68	0	8.16

Table 3. 9: Substations Expected Flood Damage by Counties

Variables	No. of Observations	Mean	Std Dev.	Min	Max
Highest Substations Expected Flood Damage Counties					
Dare					
Expected_Damage_20_mid_ft	18	1.292	0.984	0	2.118
Expected_Damage_35_low_ft	18	1.923	1.275	0	3.020
Expected_Damage_35_mid_ft	18	1.986	1.295	0	3.095
Expected_Damage_35_high_ft	18	2.053	1.306	0	3.149
Expected_Damage_50_low_ft	18	2.473	1.572	0	4.215
Expected_Damage_50_mid_ft	18	2.591	1.609	0	4.367
Expected_Damage_50_high_ft	18	2.700	1.649	0	4.427
Hyde					
Expected_Damage_20_mid_ft	5	0.689	0.503	0.149	1.274
Expected_Damage_35_low_ft	5	1.143	0.926	0.202	2.400
Expected_Damage_35_mid_ft	5	1.281	0.931	0.324	2.490
Expected_Damage_35_high_ft	5	1.463	0.733	0.744	2.491
Expected_Damage_50_low_ft	5	1.259	1.405	0.203	3.342
Expected_Damage_50_mid_ft	5	1.470	1.366	0.434	3.527
Expected_Damage_50_high_ft	5	1.724	1.159	0.712	3.527
Watauga					
Expected_Damage_20_mid_ft	8	1.731	1.669	0	4.259
Expected_Damage_35_low_ft	8	1.862	1.649	0	4.413
Expected_Damage_35_mid_ft	8	1.881	1.672	0	4.471
Expected_Damage_35_high_ft	8	1.890	1.681	0	4.488
Expected_Damage_50_low_ft	8	1.972	1.698	0	4.62
Expected_Damage_50_mid_ft	8	1.996	1.727	0	4.694
Expected_Damage_50_high_ft	8	2.008	1.736	0	4.707
Yacey					
Expected_Damage_20_mid_ft	9	1.108	2.437	0	7.246
Expected_Damage_35_low_ft	9	1.107	2.438	0	7.233
Expected_Damage_35_mid_ft	9	1.111	2.446	0	7.260
Expected_Damage_35_high_ft	9	1.116	2.458	0	7.297
Expected_Damage_50_low_ft	9	1.108	2.440	0	7.229
Expected_Damage_50_mid_ft	9	1.114	2.455	0	7.274
Expected_Damage_50_high_ft	9	1.120	2.469	0	7.321
Haywood					
Expected_Damage_20_mid_ft	18	0.843	1.806	0	6.930
Expected_Damage_35_low_ft	18	0.858	1.806	0	6.962
Expected_Damage_35_mid_ft	18	0.879	1.829	0	7.015

Expected_Damage_35_high_ft	18	0.896	1.849	0	7.047
Expected_Damage_50_low_ft	18	0.885	1.824	0	7.031
Expected_Damage_50_mid_ft	18	0.914	1.856	0	7.099
Expected_Damage_50_high_ft	18	0.932	1.878	0	7.134

Table 3. 10: Expected Average Flood Damage to Substations of Coastal and Non-Coastal Counties

Coastal Counties	Coastal Counties	No. of Observation	Mean	Std. Dev.
Expected Damage 2020_mid_ft				
	0	2,345	0.13	0.61
	1	322	0.15	0.49
Expected Damage 2035_low_ft				
	0	2,345	0.13	0.62
	1	322	0.22	0.66
Expected Damage 2035_mid_ft				
	0	2,345	0.13	0.62
	1	322	0.23	0.69
Expected Damage 2035_high_ft				
	0	2,345	0.14	0.63
	1	322	0.26	0.71
Expected Damage 2050_low_ft				
	0	2,345	0.13	0.63
	1	322	0.27	0.82
Expected Damage 2050_mid_ft				
	0	2,345	0.14	0.64
	1	322	0.29	0.86
Expected Damage 2050_high_ft				
	0	2,345	0.14	0.65
	1	322	0.33	0.90

Table 3. 11: Expected Average Flood Damage to Substation by NC Economic Tier Counties

Expected Damage	Tiers	No. of Observation	Mean	Std. Dev.
Expected Damage 2020_mid_ft				
	1	809	0.09	0.52
	2	909	0.19	0.75
	3	949	0.10	0.48
Expected Damage 2035_low_ft				
	1	809	0.10	0.53
	2	909	0.21	0.80
	3	949	0.11	0.48
Expected Damage 2035_mid_ft				
	1	809	0.10	0.54
	2	909	0.21	0.81
	3	949	0.11	0.49
Expected Damage 2035_high_ft				
	1	809	0.11	0.55
	2	909	0.22	0.82
	3	949	0.12	0.50
Expected Damage 2050_low_ft				
	1	809	0.11	0.55
	2	909	0.22	0.85
	3	949	0.11	0.50
Expected Damage 2050_mid_ft				
	1	809	0.11	0.56
	2	909	0.23	0.87
	3	949	0.12	0.51
Expected Damage 2050_high_ft				
	1	809	0.12	0.57
	2	909	0.24	0.89
	3	949	0.13	0.53

CONCLUSION

Energy infrastructure siting decisions face a variety of challenges, especially in coastal areas where land is often scarce and has more rapid population growth. Also, perceived and actual dis-amenities to lands, water bodies, human health, the environment, negative aesthetic effects, and the potential impact of energy infrastructures on nearby property prices raise opposition of residents to their siting in many communities. This dissertation explores different aspects of site selection and fuel choice for large-scale energy infrastructure in three different papers:

Chapter 1 used a designed discrete choice experiment to quantify perceived externalities of public preferences for where utility-scale solar energy should be sited in RI. The DCE tests different levels of six solar siting attributes, most notably current land use (brownfields, commercial, farm, or forest). Conditional and mixed logit regression models were used to estimate respondents' WTP for the various solar siting attributes and current land use types proposed for their installation. Both models predicted similar outputs. Respondents preferred a larger size of installation. They disliked full and partial visibility of the panels from their homes or most traveled roads. Also, respondents prefer solar siting on commercial and brownfields and are willing to pay a monthly fee for their installation. However, respondents dislike solar installation on farm and forest land and require monthly compensation to allow their installation on them. A proposed solar program with an installation size of 10 acres, fully visible panels, and a setback of 100 feet as well as a 0% probability of residential development in the next 10 years. 220 households are proposed to be powered by the proposed solar installation. The 220 households are willing to pay an annual average of $47,627 for their installation on commercial land and $34,373 for their installation on brownfields. However, the 220 households are willing to be compensated an annual total average of $113,916 and $70,224 for its installation on forest and farmlands respectively.

Chapter 2 used the hedonic pricing method to estimate the dis-amenity value of proximity to multiple utility-scale generators using Zillow ZTRAX housing transaction data for four East Coastal US states, GA, NC, RI, SC, and energy data from US Energy Information Administration. The spatial difference-in-difference hedonic model was used to estimate the dis-amenity by measuring the impact of 6 energy generator types (biomass, hydroelectric, natural gas, petroleum, solar, and wind) on nearby property values. Employing spatial (county, zip, census tract) and temporal (month-year) fixed effects, similar treatment effects were estimated for the different fixed effect models which yielded negative treatment effects for properties within 1 mile of an energy generator. Dirtier energy sources (fossil fuels natural gas and petroleum as well as biomass) have a greater negative impact on nearby property values relative to cleaner energy sources (solar and wind). Also, non-landfill biomass generators have greater negative impacts on nearby property value relative to landfill biomass generators.

Finally, Chapter 3 used data from Energy Information Administration (EIA) and spatially explicit data on flood risk with a variety of measures from First Street Foundation's Flood Lab to assess the resilience of coastal community energy infrastructure and the flood risk faced by renewable energy infrastructure in North Carolina by specifically by examining how flooding impact powerplants and substations in different communities. Powerplants have higher present and future expected flood damages relative to substations. Also, petroleum and hydroelectric powerplants had higher present and future expected flood damages relative to all other NC utility-scale generators (biomass, coal, natural gas, nuclear, solar, wind). Also, substations in coastal counties have higher present and future expected flood damages relative to those in non-coastal counties. Further, powerplants in most economically stressed counties have higher present and future expected flood damages.

US Department of Energy asserts that total US energy consumption will continue to rise in the coming years. Much land area is projected to be required for the utility-scale generation of electricity. Hence, continual disapproval of the public of the generator siting is expected to rise for both non-renewable (including fossil fuel sources) and renewable sources. It is therefore imperative that policymakers know the actual and perceived dis-amenities residents assert that different energy infrastructure choices have on their health, environment, property values, aesthetic effects, etc. Knowing how individuals and markets respond to different infrastructure siting choices can help policy makers make wiser, more informed choices. Also, coastal flooding is projected to rise due to factors such as hurricanes, coastal floods, storm surges, rising sea levels, etc. It is important for policymakers and energy developers to understand how siting of the energy infrastructure in different communities may be impacted by present and future flooding events. This information can help planners identify areas where current energy infrastructure is at the greatest risk and adopt and build more resilient energy infrastructure in these more flood-prone communities moving forward.