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The Spatial Economics of Clean Energy in New Jersey

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THE SPATIAL ECONOMICS OF CLEAN ENERGY IN NEW JERSEY

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Abstract

THE SPATIAL ECONOMICS OF CLEAN ENERGY IN NEW JERSEY

by Anthony Bevacqua

Clean energy policy is critically important in driving reductions of greenhouse gases and mitigating climate change. As clean energy technologies improve over time and interact with social systems and broader energy markets, there is a need for innovative environmental management that supports development of new clean energy policy. Understanding where these technologies may be deployed, quantifying the anticipated benefits, and mitigating risks are required for successful policy optimization. With these considerations in mind, this dissertation explores geothermal heat pumps (GHP), solar photovoltaics, and the Regional Greenhouse Gas Initiative (RGGI). We call upon spatial economics to investigate these topics by incorporating the biophysical environment, socioeconomic factors, and economic considerations in our methodology to approach this problem from a holistic environmental management perspective.

Reducing energy end use is a climate mitigation strategy that can be applied across the building, industry, and transportation sectors. Increasing energy efficiency, particularly in the building sector, is a promising means to reduce energy end use. In the second chapter of this dissertation, we perform a place-based investigation of GHP systems in New Jersey. In doing so we provide new baseline information on which building sectors this technology is most used and identify areas of significant clustering. Both of which provide insights for new energy efficiency policy within the study area. In the third chapter, we conduct a life cycle assessment of geothermal heat pumps to assess the cradle-to-grave environmental and human health impacts throughout the lifetime of a system operating in New Jersey. The results of this section highlight

lower environmental and human impacts associated with GHP systems operating within New Jersey compared to the rest of the United States. We also conclude that GHP systems are significantly less impactful throughout their lifetime and operation as compared to other heating and cooling configurations that are common in the state.

A combination of renewable energy technologies such as wind and solar photovoltaics will be an integral part of the clean energy electric generation portfolio of the future. Understanding where these systems are best located and how the public values their benefits can support smart policy decisions. In the fourth chapter, we evaluate solar photovoltaic potential using hosting capacity interpolation, multi-market suitability models, and remote sensing. The findings show hosting capacity of potential solar siting locations varies within each electric distribution company (EDC) territory. The results of the suitability models highlight areas for targeted local investigations of project suitability and community solar off-taker potential. Our municipal remote sensing analysis yield valuable local scale information of roof geometry, flood hazards, and solar radiation potential which can be used to streamline system siting and design. In the fifth chapter, we conduct a consumer willingness to pay survey for potential community solar customers in New Jersey. Evaluating the responses of over six-hundred residents underscores the common barriers to traditional residential net metering, such as home ownership and financial requirement. It also illuminates consumers' willingness to participate in community solar projects that improve environmental quality and are sited in commercial settings and landfills.

Reducing the carbon dioxide emissions associated with the electric generation sector will be crucial in mitigating future climate change. Emission trading schemes (ETS) are a regulatory approach that forces emitters to internalize the negative externalities of carbon dioxide with the goal of driving emission efficiency improvements and creating funding mechanisms to support other climate mitigation and adaptation efforts. In the sixth chapter, we perform a qualitative policy analysis of the Regional Greenhouse Gas Initiative (RGGI) ETS in the context of generation shifting mitigation. We identify the best mitigation approaches as the program expands to be a combination of increased monitoring and modeling, promoting load reductions through efficiency, and expanding the RGGI program to states within distribution systems that have partial state participation.

In New Jersey, successful climate mitigation and clean energy transitions are a function of policy, available technology, and energy markets. Historically, stringent air quality regulations and inexpensive natural gas have led to efficient fossil generation within the state. Additionally, early progressive solar policies have led to a robust solar industry and resulting overall in-state solar photovoltaic capacity ranking high in the nation. Although low-hanging fruit may be relatively sparse, current political environments in the state have been supportive of improved climate action and sparked increased potential for academic research to make tangible contributions to new clean energy policy. As the state continues to transition towards a clean energy future, government administrations, regulatory agencies, grid operators, research institutions, and stakeholders must work alongside each other to develop new policies that support increased climate mitigation

Currently in New Jersey, the potential of clean energy has not been adequately researched, particularly on local and regional scales. The goal of this research is to address this gap by contributing to the body of knowledge in our applied subject areas. The spatial economic approach can be used effectively in clean energy investigations because energy is inherently influenced by economics and geography. We anticipate the overall findings of this work to be

applied within the study area to increase clean energy generation and access, promote the clean energy economy, and conserve valuable landscapes.

Keywords: clean energy, climate change mitigation, energy efficiency, renewable energy

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I dedicate this work to my family. Without the unwavering support of my wife, my parents and siblings, and I would not be the person I am today.

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List of Abbreviations

GHG: Greenhouse Gases
GHP: Geothermal Heat Pump
GSHP: Ground Source Heat Pump
SCREC: Solar Renewable Energy Credit
PV: Photovoltaics
U.S.EPA: United States Environmental Protection Agency
NJDEP: New Jersey Department of Environmental Protection
NJBPU: New Jersey Board of Public Utilities
NJEDA: New Jersey Economic Development Agency
GIS: Geographic Information System
IDW: Inverse Distance Weighted Interpolation
RGGI: Regional Greenhouse Gas Initiative
U.S. EIA: United States Energy Information Administration
LCA: Life Cycle Assessment
LCIA: Life Cycle Impact Assessment
MMTCO2e: Million Metric Tons of Carbon Dioxide Equivalent
E.U. ETS: European Union Emission Trading Scheme
RGGI: Regional Greenhouse Gas Initiative

1 Introduction

1.1 Climate Change Mitigation & Clean Energy

Increasing greenhouse gas (GHG) concentrations in the atmosphere as a result of human activities are the main driver of climate change (Rosenweig, 2008; Barnett, 2001; Oreskes, 2004). These gases include carbon dioxide, methane, nitrous oxide, hydrofluorocarbons, perfluorocarbons, and hexafluoride, and vary in their ability to absorb energy and stay aloft in the atmosphere. Primarily found in the lower atmosphere, GHG's alter the Earth's radiation budget, creating radiative forcing that warms the troposphere and the Earth's surface (Lashof, 1990). Additionally, there are both positive and negative feedbacks associated with climate change and GHG's, demonstrated by decreased albedo of the cryosphere, and release of methane from reduced permafrost, which can further enhance warming effects (Hall, 2004).

The environmental, social, and ecological ramifications of anthropogenic climate change are vast and occur over several spatial and temporal scales (Houghton, 1995; Stern, 2006; Patwardhan et al, 2007; Parmesan, 2003). Impacts of climate change have been observed through various indicators across the hydrosphere, cryosphere, lithosphere, and atmosphere (Hall, 2004). Climate change disrupts natural systems and can diminish environmental quality and ecosystem services and can displace or destroy species habitat (Montoya, 2010). Climate change also impacts human health by increasing exposure to natural hazards such as extreme weather events, vector borne diseases, and food systems disruption (Martens, 1995; Lal, 2004; Downing, 2013). Additionally, the impacts of climate change pose significant economic threats to global trade, transportation infrastructure, and national security (Tol, 2002). Furthermore, studies in environmental justice show not all communities face the social and economic burdens of the impacts of climate change equally across national and global scales (Adger, 2001). Impacts and future risks are heightened in impoverished communities and countries of the developing world (Ikeme, 2003).

As society is faced with current and future conditions under the influence of climate change, strategies moving forward will include adaptation and mitigation. Climate change adaptation refers to measures taken to reduce vulnerability to the negative effects of climate change (Lobell, 2008). Examples of climate adaptation include retreat from coastal areas to reduce exposure to sea level rise and increased frequency of coastal hazards (Dolan, 2006); changes in terrestrial and marine species geographic ranges due to changing conditions (Fitzpatrick, 2009); and shifts in crop selection and additional use of fertilizers and pesticides in agriculture, due to decreased yields (Brown, 2008). As the effects of climate change compound over time, adaptation actions are likely to become more disruptive to society with additional social and economic costs and losses (Tol, 2002).

Mitigation strategies are centered on reducing the concentration of greenhouse gases in the atmosphere. The overarching goal of mitigation is to avoid anthropogenic influence on the climate system in order to dampen future climate change impacts. This is achieved by reducing emission sources and enhancing sinks that store greenhouse gases (Oreskes, 2004). Fossil fuel use in the electricity generation, heating, and transportation sectors are the largest sources of greenhouse gases globally (Hook, 2013). Successful mitigation strategies rely on available technology and government policies to replace fossil fuel use with sustainable alternatives across sectors. Coordinating such efforts is challenging in terms of clearly communicating short and long-term risks to the public, making the business case for establishing alternatives, and disrupting current markets linked to fossil fuel extraction and consumption (Hook, 2013).

These challenges justify the magnitude of resources required to mitigate these detrimental impacts of climate change with the goal of moving towards a sustainable future (Wheeler, 2013; Adger, 2003; Patwardhan, 2003). The research field of climate change mitigation has been present for several decades and has evolved in recent years alongside innovative energy technologies, improved computational and analytical power, and public concern for future generations and long-term sustainability (Magerum, 1999; Adams, 1998; Leiserowitz, 2006). The integrated nature of climate change, adaptation and mitigation, incorporates environmental management approaches based in natural resource and energy economics, policy development, and social sciences (Heller, 2009; Walther, 2002; Runting, 2017). Themes of current research call for place-based social and economic models that not only identify where climate change mitigation strategies can be deployed, but also how these can be optimized for maximum long-term success (Magerum, 1999; Reed, 2008; Lopez, 2012; Kassner, 2008; Carley, 2009; Roe, 2007; IPCC, 2014; IPCC, 2015; Stern, 2006; Adger, 2003). Major areas of interest include improving energy efficiency, increasing renewable energy generation capacity, and reducing emissions in the fossil fuel electricity generation sector (Patwardhan 2003; Pacyniak, 2017; Self, 2013).

Energy efficiency is a crucial component of climate change mitigation and is a robust strategy for GHG reduction (Metz, 2001; IPCC, 2007). Ground source heat pump (GSHP) systems, also known as geothermal heat pumps (GHP), utilize renewable thermal technology for heating and cooling in both residential and commercial setting (Self, 2013). GHP systems are an effective yet underutilized efficiency measure that not only reduce criteria pollutants in the electric generation sector by reducing periods of peak energy demand, but also reduce the associated greenhouse gas emissions (Self, 2013). When site specific systems are designed and deployed in appropriate settings, the results can be a significant source of emissions reductions. Furthermore, a transition from natural gas heating to electrified heating will allow for additional reductions in greenhouse gases in the future (Self, 2013). In this scenario, the implications of improving energy efficiency become more important, and favor GHP adoption. This makes electrified heating more efficient and thus economically feasible.

Advances in renewable energy generation technology, such as solar photovoltaics or wind energy, are very promising in furthering greenhouse gas mitigation (Brown, 2001; Carpejani, 2020). Solar marketability and aggressive incentive regimes has resulted in a long-standing success rate and a place in the future of renewable energy adoption globally (Lutsey, 2003). Federal and state incentives have promoted the adoption and accessibility of this clean energy resource in the United States (Hart, 2010). As a result, solar photovoltaic technology is one of the most widely utilized renewable energy technologies (Kazmerski, 2006). This technology has become increasingly popular over the past three decades as efficiency and affordability of equipment has improved (Lewis, 2007). However, the solar photovoltaic market is not without its barriers and challenges. The overall success of solar photovoltaics is highly dependent on technical design of the array, land use planning, energy demand, and quality of available grid interconnection infrastructure (Sen, 2017). Furthermore, the adoption of this technology and the economic viability of the solar industry has historically been dependent upon government financial support regimes, that were initiated to temporarily jump start the industry (Lewis, 2007; Sen, 2017). These incentive regimes are based on photovoltaic generation, such as the Solar Energy Resource Credit (SRECS) program throughout the United States (Burns, 2012). The goal of this policy approach is to facilitate adoption and deployment of this energy resource across industrial and residential scales (Cohen, 2020). When externalities within the manufacturing, operation, and disposal processes are combined with design obstacles such as limited space, and conservation of valued landscapes, finding the optimal siting characteristics becomes important for developing economically viable solar markets and long-term sustainable implementation of the technology (Sen, 2017).

Climate change mitigation efforts in the electric generation sector can be a collaborative effort among non-governmental agencies and state governments. An example is the Regional Greenhouse Gas Initiative (RGGI), which is a multi-state market-based program that established a regional cap on carbon dioxide emissions from fossil fuel power plants in the Northeast Region of the United States. Owners and operators of these power plants must purchase allowances based on the emissions of the electric generating unit (EGU). The price of each allowance certificate is driven by basic supply and demand principals, with additional stability safeguards of a cost containment reserve and floor price (Ruth, 2008; RGGI, 2020). The allowance certificates are auctioned quarterly, with proceeds reinvested in the clean energy economy determined by state level policy that funds renewable energy, energy efficiency, and clean transportation programs (RGGI, 2020). Segregated energy markets within this regional program can complicate this emissions trading system. (Huber et al, 2013; RGGI, 2009; Bifera, 2013; Burtraw et al, 2006; Holt et al, 2007; Ruth et al, 2008; Hibbard et al, 2015). The borders of energy markets and participating states often do not coincide, for example New Jersey and the PJM independent system operator (ISO). Because the electric generators are dispersed throughout the ISO, some units may be economically disadvantaged to others in neighboring states. Issues can arise when the disadvantaged units are more efficient in terms of fuel mix and emissions produced. This can lead to increased GHG emissions as a result of this cap and trade program. As the RGGI program grows, both inter-state participants and the ISO are taking steps to investigate how the risk of this negative impact can be reduced (Hamamoto, 2020).

1.2 Spatial Economics

Spatial economics is inclusive of many branches of economics but is rooted in the analysis of economic processes and developments in geographical space (Fujita, 2010). Although these concepts have been evolving over centuries (Thunen, 1826; Launhardt, 1885; Marshal, 1890; Weber, 1909), more formal interpretations were published in the 1930's and 1940's (Ohnlin, 1933; Christaller, 1933; Palender, 1935; Kaldor, 1935; Isard, 1949), which commonly describe location theory as a means to analyze economic activities in the context of price, cost, and trade patterns across a geographic distribution. These early economic geographers set the conceptualized foundation for modern spatial economics known as the New Economic Geography (Krugman, 1991), which merges the concepts of spatial analysis with economic consideration of production, transportation and trade (Krugman, 1998). Research in the field of spatial economics has a large scope of applications, ranging from macroeconomics to global and national climate change mitigation strategies (Johansson, 2004; Fujita, 2010).

The spatial economic approach can be applied effectively to evaluating clean energy because energy in inherently influenced by economics and both physical and human geography (Modica, 2015). Understanding the complex and dynamic relationships between people, the environment, and technology is required in promoting the clean energy economy and long-term sustainability (Pacyniak, 2017). Increased public awareness, acceptance of climate change risks, and stakeholder engagement has facilitated the need for more comprehensive approaches for evaluating clean energy potential to mitigate climate change (Reed, 2008). In recent years, increases in data availability, computational capacity, and novel analytical approaches, has led to growth of the knowledge base of the field (Dincer, 2015).

Economics in the energy sector are influenced by many local, national and global inputs. International trade and commodity markets can have strong impacts on the price of energy and how alternative fuels are evaluated by customers and environmental policy decision makers (Sorrell, 2004). Historically, the main influence on determining what technology is used to generate electricity has been the price and availability of fuel (Hook, 2013; Bazmi, 2011). Although fossil fuel has a long history of dominating regional and global fuel mixes, increased regulation on air quality in recent decades has influenced dynamics in fuel type consumed, and technology efficiencies of combustion systems (Hook, 2013). This is manifested in some parts of the United States by the replacement of outdated fossil technology, such as coal or oil boilers, with more efficient fuel and combustion techniques, like natural gas combined cycle turbines (Kim, 2006; Colpier, 2002; Keller, 2020). The clean energy economy of the future will be under similar supply chain and regulatory influences as they move to replace fossil generation (Wu, 2020).

Affordability of retail electricity is a major concern of the public and ratepayer advocacy groups in the United States (Knapp, 2020). The strength of the clean energy economy is a function of available technology for alternative fuel sources, and government subsidy (Sattler, 2020). The affordability of a clean energy technology is influenced by economies of scale. This is most evident in the solar energy markets, where large grid supply photovoltaic systems are more economically competitive with less government subsidy than their smaller scale residential and commercial net metering counterparts (Mohn, 2020; Branker, 2011).

As in all government sponsored incentive programs and regimes, optimizing returns on public capital is critical (Ndebele, 2020; Sen, 2017). As the motives for incentivizing clean energy become focused on effectively sourcing a reliable and long-term energy source, methods for evaluating technical and economic potential become more critical in policy development (Sen, 2017). Investigations of policy strategy are now more focused on microeconomic factors such as the levelized cost of energy, timing of peak demand periods, and energy transmission congestion restraints (Dincer, 2015; Zhang, 2013). Additionally, macroeconomic factors such as global trade and fossil fuel prices have ongoing influence on the economic sustainability of clean energy (Dutta, 2020). Furthermore, new policies must consider long term grid infrastructure planning at the transmission and distribution scale as new programs are developed with the goal of establishing a strong clean energy economy (Grue, 2020; Sen, 2017).

Spatial economics provide a holistic approach to evaluating policy and technical potential of clean energy. Spatial analysis techniques such as suitability modelling, zonal statistics, and remote sensing complement energy infrastructure improvements and consumer impact investigations to better understand the economic and socio-political considerations used in developing new policy (Sun, 2013; Modica, 2015; Renga, 2014). The integration of these cross disciplinary approaches will be required to drive new technology adoption and shape a sustainable clean energy economy of the future.

1.3 Research Objectives

The level of research needed to adequately evaluate the benefits and risks for energy efficiency, renewable energy, and carbon emission trading, has not been performed in New Jersey. Thus far, many studies have focused on estimating larger, overarching concepts of technical potential (Branker, 2011; Burns, 2012; Carley, 2009; Denholm, 2007). This is informative to some level but lacks in local detail. Others have focused on specialized topics used to investigate emission reduction across a single sector (Dalhammar, 2018; Hofierka, 2009). These studies have provided a valuable knowledge base and lays the groundwork for a more complex investigation. Furthermore, there is a need for research that supports integrated clean energy approaches to assess both the technical and social issues that have prevented wide-scale clean energy adoption across sectors (Mirakyan, 2013).

Expanding clean energy policy and technology are necessary for mitigating climate change. As clean energy technologies improve over time in terms of renewable energy generation, energy efficiency, and energy storage, there is a need for innovative analyses to quantify their value (Metz, 2001; Pindyck, 2017; Mayrhofer, 2016). Understanding where these technologies may be deployed, quantifying the anticipated benefits, and mitigating risks are required for successful policy optimization (Pindyck, 2017). Moreover, clean energy technologies will be interacting with each other, as seen in the anticipated increases in energy demand due to policies promoting electric vehicle ridership and the transition to electrified heating from natural gas (NJEMP, 2020; Sterchele, 2020). These forces will influence the temporal considerations for residential electricity peak demand periods across the interconnected grid.

Rates of growth in any energy sector is influenced by many socio-political uncertainties (Laitner, 2006; Prasad, 2014; Kazmerski, 2006). The analyses used in predicting new clean energy technology deployment and impacts of a growing emission trading program are complex (Kydes, 2007). This includes but is not limited to dynamics in the political environment over time, new technology availability, international trade, supply chains, and public evaluation of conserved and underutilized landscapes (Richter, 2012; Denholm, 2007; Chu, 2017). However, with the suite of available methods throughout the research area, we can improve upon and integrate established approaches to evaluate our study area more precisely.

As in any new government policy, stakeholder engagement is used to identify key issues and potential unintended consequences (Reed, 2008). Modern government stakeholder efforts often lack clear communication across government and public entities in the early stages of new policy development (Barletti, 2020). Particularly in climate related issues, there can be shortcomings in communication and spread of misinformation leading to mistrust (Brulle, 2020). Improving communication and increasing dissemination of useful information to stakeholders can result in increased rates of participation and effective mitigation (Avato, 2008). This can inform policy makers on new opportunities and promote public confidence in government action. We identify place-based approaches in spatial data analyses and geoprocessing, along with stakeholder surveys with a geographical component to be most effective in improving communication structure between government, academia, nongovernment agencies, and individuals. Furthermore, this approach can better identify risks to the economic and ecological systems impacted by a new policy earlier in the development process.

The overarching goal of this research is to produce novel insight into the future of clean energy in New Jersey at a time when technology advancements and policy initiatives make it possible to make tangible contributions to improve environmental quality and mitigate climate change. This research addresses the three closely related topics in greenhouse emissions reduction of end user energy efficiency, renewable energy generation, and decarbonization of the electricity generation sector.

This research tests the following hypotheses:

End Use Energy Reductions: Geothermal Heat Pumps (GHP)

- How do GHP systems occur in the segments of the building sector in New Jersey?
- How do GHP systems show dispersed, random, or clustered spatial patterns within the geography of New Jersey?
- Do the cradle-to-grave environmental and human impacts of GHP systems negate their mitigation benefits?
- Are these impacts influenced by regional energy mixes?
- How do the impacts of GHP systems compare to other heating and cooling technologies?

Increasing Renewable Energy Generation: Solar Photovoltaics

- Is solar photovoltaic hosting capacity uniform throughout the electric distribution territories of New Jersey?
- How can municipal-wide remote sensing analyses be used to provide high resolution insights specific to solar potential?
- What can suitability models tell us about solar siting potential across New Jersey?
- Are known barriers to residential solar influencing clean energy access in New Jersey?
- How do New Jersey energy consumers value community solar array attributes associated with land use, environmental quality, community proximity, and energy savings?

Decarbonization of the Electricity Generation Sector: The Regional Greenhouse Gas Initiative (RGGI) emission trading scheme (ETS)

- How are interconnected competitive energy markets impacted by the RGGI ETS?
- Are these impacts creating risks of generation shifting?
- What program specific mitigation measures can be used to mitigate generation shifting in this ETS?

In Chapter 2, we apply spatial analytics to develop new information describing the current spatial distribution of GHP systems, perform spatial statistics to evaluate spatial autocorrelation and clustering, and develop a raster-based suitability model to highlight areas with growth potential in expanding GHP technology deployment. In Chapter 3, we perform a cradle to grave endpoint and midpoint life cycle assessment for GHP systems being used in New Jersey. We also compare environmental, human health, and resource impacts across three commonly used household heating and air conditioning HVAC configuration scenarios to evaluate implications of increased GHP adoption.

In Chapter 4, we investigate solar photovoltaic markets across multiple scales using geographic information systems and remote sensing with the goal of evaluating deployment potential for this technology in New Jersey. In Chapter 5, we leverage stakeholder survey in the form of a discrete choice experiment and willingness to pay analysis to evaluate the public's preference for renewable energy technology can be siting. When combining these two approaches in this fashion we are able to leverage emerging computational approaches to investigate clean energy suitability across the environment with additional considerations for stakeholder preference. The insight provided in these chapters can be used to estimate future installed capacity for this renewable energy technology in the future. Additionally, as solar incentives transition to new policies, these results can be used for clean energy policy planning to optimize solar incentives and public acceptance across new and existing solar markets.

In chapter 6, we investigate the expanding Regional Greenhouse Gas Initiative through a qualitative policy analysis with a focus on generation shifting. This carbon emission trading program targets reductions in the fossil fuel portion of the grid supply power generation sector. We evaluate methods used throughout the sector to mitigate generation shifting which undermines strategies for decreasing emissions. The results of this chapter provide timely information as the participating states move to expand this initiative and maximize the environmental benefits, avoiding unforeseen emission implications, and minimizing the negative economic impacts to energy consumers.

1.4 Study Area: New Jersey

An integrated spatial economic investigation of clean energy has not been performed for New Jersey. New Jersey is an optimal location for this type of investigation for the following reasons: First, New Jersey faces significant human health and financial risks associated with climate change (Burger, 2017; Yang, 2019). This coastal state depends on the $2 billion per year commercial fishing industry, the $16 billion per year tourism industry, and the $50 billion per year maritime industry, in addition to the millions of residences in suburban and rural communities in coastal flood zones (NJDEP CMP, 2011). Second, at the time of this research there is strong public and political environment at the state level that favor taking climate action (Pacyniak, 2017; New York Times, 2020). With these two strong forces advocating for climate policy, there is new opportunities for real-world policy applications for this research. Third, New Jersey has the built infrastructure and energy demand that can support the build out of new clean energy technology (Hart, 2010; NJEMP, 2019). The diverse landscapes within the State present challenges and opportunities for balancing conservation of open spaces with increased energy demand in the context of clean energy development.

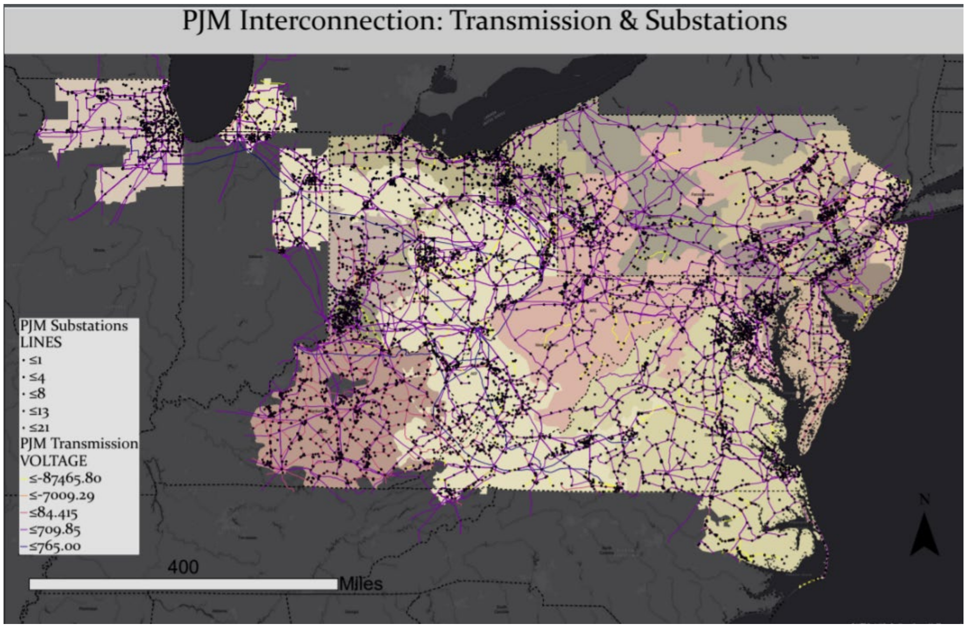
Furthermore, the socio-economic characteristics of the state span a wide range, making traditional clean energy programs not accessible to all. With over 40 % of New Jersey residences not owning their own home, and nearly 10 % living below the national poverty line (U.S. Census), it becomes apparent that many individuals are not eligible for traditional incentive programs such as residential solar net metering (Comello, 2017). As clean energy policies advance in the United States, access can be increased, as demonstrated in distributed energy programs such as community solar (Funkhouser, 2015).

Greenhouse gas profiles provide insight into sources and sinks of global warming emissions (Heath, 2010). In New Jersey, transportation is the largest contributor of greenhouse gas emissions (40.6 $MMTCO_2e$), followed by electric generation (18.1 $MMTCO_2e$), and commercial and industrial sectors (16.6 $MMTCO_2e$). This is followed by residential (15.2 $MMTCO_2e$), highly warming gases (8.0 $MMTCO_2e$), waste management (5.3 $MMTCO_2e$), and land clearing (1.0 $MMTCO_2e$). Terrestrial carbon sequestration accounts for (8.1 $MMTCO_2e$) of sink (NJDEP, 2019). As new cross government strategies attempt to optimize the abatement of these emissions, developing innovative policies that cross sectors are ideal. As demonstrated by RGGI participating states investing auction proceeds into developing clean transportation programs (Zhou 2020).

In the United States, electricity is purchased and produced under the principles of supply and demand with the goal of minimizing costs to the rate payer (Mideksa, 2010; Satchwell, 2015). Energy flows occurs in regional zones, or systems, within the United States. Independent system operators (ISO) manage the flow of energy within the region. The ISO is under the regulation of the Federal Energy Resource Commission (FERC), which sets standards for reliability and monitors energy markets (Sakti, 2018).

Within an ISO, power generators bid competitively against each other to provide energy into the system. Bid prices are a function of transmission costs and operating costs with additional operation requirements for nuclear and renewable energy (Ott, 2003). Based on these bid prices, the ISO determines which power generating facilities are dispatched. Additionally, the ISO is responsible for electricity reliability requirements and the interconnection of large renewable energy generators such as large-scale wind and solar photovoltaics. Distribution of energy and retail sales to consumers is performed by the regional Electric Distribution Company (EDC).

Figure 1: Map of PJM Interconnection



New Jersey is part of the larger energy system known as PJM Interconnection. This ISO is responsible for the flow of energy from the east coast to the mid-west spanning twelve states. As energy and environmental regulations change throughout the states within this ISO, the operating costs and associated bid pricing for the units that are subject to these regulations can influence how energy is dispatched (Sakti, 2018). This is an example of the environmental and economic energy nexus.

1.4.1 Clean Energy Policy of New Jersey

Clean energy policies in New Jersey are put into place by the state legislature and are regulated by the New Jersey Board of Public Utilities and the New Jersey Department of Environmental Protection. This is important, as the State is very influential in determining how clean energy policies, incentives, and implementation are evaluated, funded, and evolve over time. Notable energy policies in the state include the following:

- The Electric Discount and Energy Competition Act (1999): Establishes New Jersey's Renewable Portfolio Standard and the Societal Benefits Charge. The Renewable Portfolio Standard (RPS) requires each electricity distribution company or supplier that serves retail customers in the state to procure 35% of the sold electricity from renewable energy resources by 2025, which increased to 50% by 2030. The purpose of this portfolio standard was to increase renewable energy adoption and promote new clean energy technologies with the goal of improving air quality and reducing greenhouse gases (NJDEP).
- The Regional Greenhouse Gas Initiative (2005 & 2018). New Jersey was a founding member of this multi-state initiative. After a near decade long departure

from the program, New Jersey re-entered in 2018 to establish the state back into these carbon emission reduction program.

- The Global Warming Response Act (GWRA) (2007) requires a statewide reduction of greenhouse gas emissions of 80% below the 2006 levels by the year 2050. This equates to approximately 25 million metric tons of carbon dioxide equivalent ($MMTCO_2e$). This act also requires the New Jersey Department of Environmental Protection to establish a greenhouse gas inventory to track emissions in the energy and transportation sectors.
- The Offshore Wind Economic Development Act (2010) requires the New Jersey Board of Public Utilities (NJBPU) to establish a program to fund Offshore Wind Renewable Energy Certificates to create an incentive for Offshore Wind electricity generation facilities.
- The Solar Act (2012) finances the incentive of the Solar Renewable Energy Credit (SREC) and calls for 4.1% of the electricity sales in the state be generated by solar photovoltaics by the year 2028. Additionally, this act set restrictions on the land use of a proposed array location, limiting open space and agriculture and promoting the re-purposing of degraded lands such as brownfields and landfills.
- The Clean Energy Act (2018) expands upon the regulations listed above and adds additional provisions including increasing the renewable portfolio standard, sets incremental capacity goals for offshore wind, energy efficiency, and energy storage, and introduces the Community Solar Pilot Program.

New Jersey has a history of adopting clean energy technology and policies over the past two decades (Carley et al, 2009; Kydes et al, 2007; Sherwood, 2011; Richter, 2012; Wacker, 1995). Early energy policies in the state were focused on improving reliability and increasing market competitiveness, while more recent policies have targeted the increased utilization of renewable energy through portfolio standards. The clean policies of the future will likely have the goal of increasing new renewable energy across more socioeconomic settings while integrating these systems in a reliable way that can drastically reduce or eliminate the fossil fuel across the sector. This factors much studies such as this particularly useful in the environmental management context.

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2 Place-based Investigation of Geothermal Heat Pump Systems

2.1 Introduction

In this chapter we use spatial analysis to investigate geothermal heat pumps (GHP), systems in New Jersey. The goal of this research is to identify where these systems are being utilized and characterize areas with future deployment potential. In doing so we answer how GHP systems occur in the segments of the building sector in New Jersey, and how do GHP systems show dispersed, random, or clustered spatial patterns within the geography of New Jersey. We analyze the spatial distribution of installed GHP systems, perform spatial statistics to evaluate geographic autocorrelation and spatial clustering, and perform a raster suitability model to identify target areas where there is potential for new adoption. The information resulting from this chapter provides place based spatial intelligence not previously available to policy makers, which can be used to evaluate and develop new energy efficiency policies in and increase greenhouse gas mitigation in New Jersey.

Energy efficiency improvements are an important climate change mitigation strategy used to address current levels of greenhouse gas emissions and curb the impacts of future increases in energy demand (Jakob, 2009; Blum, 2011). The building sector is one of the most promising areas for economically driven reductions in energy consumption and greenhouse gas reductions (Hughes, 2008; N.J. Energy Master Plan, 2019). Geothermal heat pumps (GHP), also known as ground source heat pumps (GSHP), are proven to provide large reductions in buildings energy use associated with heating ventilation and cooling systems (HVAC) (Saner, 2010).

A heat pump system improves efficiency by transferring heat between a building and the ground. The relative temperature difference between occupant comfort and the ground is small, requiring less work to heat or cool a building. By comparison, fossil fuel and electric resistance heating systems uses higher temperatures and cycle on and off more frequently to achieve a comfortable indoor ambient temperature. GHP systems can operate in both cooling and heating modes, making them functional year-round. The ground heat exchanger in a closed loop GHP system is made up of boreholes and high-density polyethylene pipes that circulate a heat transfer fluid. Vertical closed loop systems pose less risks of distributing environmental contaminants and have lower operational and maintenance costs compared to their open loop counterparts (NJDEP GHP, 2020). GHP systems were adopted for residential and commercial buildings as early as the 1950’s with an increase of deployments in the 1970s sparked by oil shortages and anticipated increased fuel costs (Bloomquist, 1999; US EIA, 2010).

The residential, commercial, and industrial sectors make up 39% of the total greenhouse gas sources of New Jersey (NJDEP GHG Inventory, 2019). In the state, there are over 1,000 GHP systems installed with an estimate of only 0.1% of tax parcels containing a building utilizing this technology (NJDEP GHP, 2020). Although economic and geographic barriers exist, it is reasonable to infer that there is significant potential for the increase in adoption of this energy efficient technology to further harness the cost savings and emission reduction benefits. New Jersey has many opportunities for this technology across residential, industrial and commercial sectors.

2.2 Literature Review

Energy efficiency is described throughout the literature as a crucial component of climate change mitigation (IPCC, 2014). In several works, including (Stern, 2006; Betsill, 2001; Hughes, 2008; Dalhammer, 2018; Self, 2013; Patterson, 1996), the challenges associated with identifying new opportunities, overcoming obstacles of market penetration, and supporting economic drivers of energy efficiency in climate change mitigation is described as complex and requiring holistic approaches to develop solutions. Across the literature, we see a need for the acquisition and interpretation of location-based information to evaluate present conditions and predict future scenarios across the clean energy technology sector (Blum, 2010; Pelenur, 2012). Particularly in studies discussing cross-disciplinary approaches which evaluate both technical potential, engineering developments, and policy implications (Noorollahi et al, 2017; Jamshidi, 2018; Kavanaugh, 2012; Xiaobing, 2013; Mallaburn, 2014)

A wide range of published research has discussed the engineering components, life cycle analyses, and overall impact of GHP technology on greenhouse gas reduction (Blum, 2010; Yousefi et al, 2017; Noorollahi et al, 2017; Saner et al, 2010; Absesser, 2010; Blum, 2010). Economic feasibility investigations such as Yousefi et al, 2017 discuss financial details of these systems. Also, spatial analytical methodology as seen in Noorallahi et al, 2017, discusses geographical consideration in determining GHP effectiveness and performing place-based analyses to identify suitable locations (Yousefi, et al 2018; Blum, 2010). These studies, along with industry standards across the HVAC and GHP industry, identify the spatial economic factors and geophysical characteristics of a place which influence the likelihood of success to be centered around household heating fuels, geology, energy costs, and building sectors associated with high electricity consumption driven by intensive heating and cooling demands.

When GHP systems are designed effectively, the simple payback period of initial costs can be recovered in the first 5 to 10 years of the 20-year total life span of the system through efficiency savings (NJDEP, 2020, DOE, 2010, Self, 2013, Bloomquist, 1999; Deng, 2018). Economic feasibility of GHP systems are based on comparing cost factors to HVAC alternatives

(Self, 2013, Petit, 1998). In general, GHP systems consist of higher initial costs and lower operating costs as compared to traditional HVAC systems of oil, natural gas, and electric heating (Bakirci, 2010; Ellis, 2008). Cost factors associated with GHP systems include capital costs, operating costs and maintenance costs (Hughes, 2008). Although common perception is that the incremental capital costs for GHP systems is greater than that of traditional HVAC, there is significant variability associated with installation type and size of the building in which they are used (Deng et al, 2018; MacMahon, 2018; Martinopoulos et al, 2018; Moore, 1999). This variability is a function of environmental and economic conditions of a given location such as heating and cooling load, heating fuel costs, and installation costs (Hanova, 2007, Phetteplace, 2007).

Total installed cost can be estimated using the square footage of the building it is to be installed in. In the United States, this ranges from 7 - 25 USD per square foot (Liu Xiaobing et al, 2013). System costs ranges of vertical ground loop GHP systems range between $1,600 0 $4,000 per ton (Liu et al, 2013; ASHRAE 2011). A typical residence would require a system ranges from 3 to 5 tons and could see costs ranging from $8,00 to over $20,000 (IGSHPA, 2008; NJDEP, 2020; Xiaobing, 2013). The system size requirements and associated costs scale in industrial and commercial applications. The installation of these systems is the main contributor to the overall costs in both residential and commercial settings (Lund, 2001; Liu et al ,2013). Energy efficiency investment decisions are based on marginal costs (Jakob, 2006). Improving available information to policy makers and developers can improve government incentives and drive down costs of adopting the technology as seen in other clean energy sectors (Hughes, 2008).

Recent federal legislation incentivizing these systems, such as the 2007 Farm Bill, the Economic Stimulus Bill (2007), the 2007 Energy Bill, The Energy Improvement and Extension Act of 2008, and the American Recovery and Reinvestment Act of 2009, has resulted in some growth in the GHP industry in the United States (Saner, 2010). However, there is still a need for additional funding at the state level to reach a tipping point in the rates of adoption of this technology to improve labor forces and supply chains (Hughes 2008). Currently there are an estimated 1.5 million GHP systems in operation in the United States (IGSHPA, 2009), with approximately 60% residential and 40% in commercial and industrial applications (IGSHPA, 2009; US EIA, 2009). There has been growth in industry trade support organizations such as The International Ground Source Heat Pump Association, the Geothermal Heat Pump Consortium Incorporated, and the American Society of Heating, Refrigerating and Air Conditioning Engineers, and the National Groundwater Association are strong and well organized (Hughes, 2008).

Spatial analytics, also referred to more recently as spatial intelligence or geomatics, is often described as using geographical and topological concepts paired with the visual representation of cartography (Anselin, 1996; Hegarty, 2010; Patiño-Cambeiro, 2017). Spatial analysis is used throughout many fields of research and is particularly predominant in the environmental science and management investigations (Zomer, 2008; Van Riper, 2014; Rangel, 2010). Among the numerous spatial analysis methods and readily available tools, vector and raster-based suitability modeling using data indexes across inputs with varying units, are particularly useful in predicting future scenarios of clean energy deployment and climate related issues (Cutter, 2012; Charabi, 2011; Store, 2001; Ferretti, 2013). Spatial statistics and interpolation methods are robust approaches used to identify spatial relationships among place based data, summarize distribution of geographic features and estimate data gaps, and can be leveraged to gain novel insights into clean energy and climate change issues (Zomer, 2008; Bailey, 1995; Páez, 2004; Ord, 1995; Anselin, 1993; Lam, 1983; Li, 2014).

2.3 Study Rationale & Objectives

Based on the reviewed literature, we feel there is a need to evaluate the potential for expanding GHP markets in New Jersey. Further exploiting the climate change mitigation potential of this energy efficiency technology can reduce greenhouse gas emissions across the residential and industrial-commercial sectors. The State of New Jersey is an optimal location to investigate the potential of GHP energy efficiency technology. The concurrence of strong environmental and energy regulatory agencies, such as the New Jersey Department of Environmental Protection (NJDEP) and the New Jersey Board of Public Utilities (NJBPU), make for motivated energy regulators backed by a state government political administration that is driving to make New Jersey a national leader in climate change mitigation and adaptation. These agencies have provided a wealth of spatial and environmental data to the public and are developing new energy policies which call for state specific insights necessary for successful implementation and adoption of clean energy technologies. Furthermore, the geography on New Jersey is diverse, ranging between densely populated urban communities, historical sites, agricultural regions, and coastal tourism centers with high economic importance, all of which will be facing the risks and hazards associated with present and future climate change. To provide new baseline information on GHP deployment we aim to determine how these systems are used in the building sector and determine if these systems are spatially clustered which can speak to other geographic factors that may be influencing adoption.

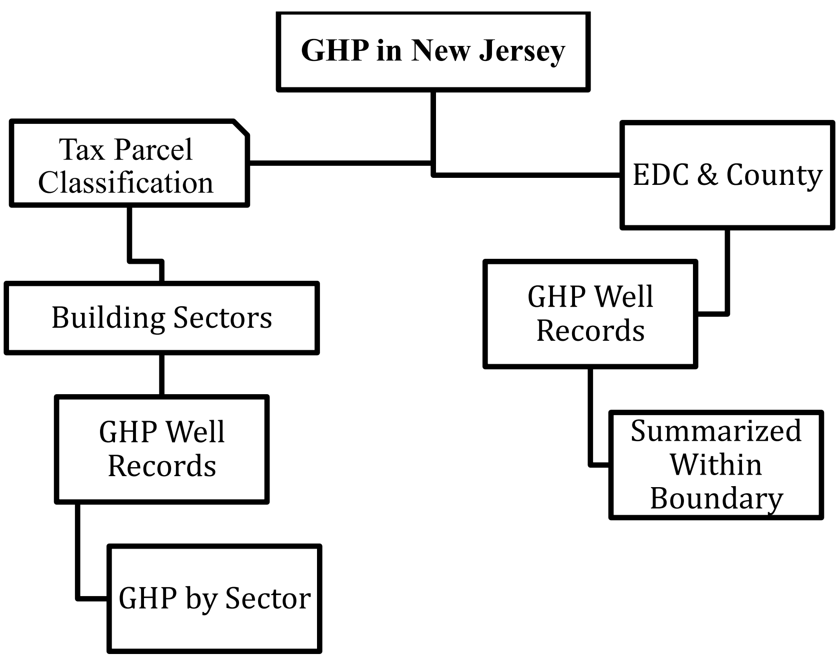
2.4 Methods

We deploy a three-stage spatial analysis approach to investigate GHP systems in New Jersey. First, we leverage state well records of GHP boreholes to illustrate the spatial distribution of systems across property classification types. This approach highlights where these systems are located and in what settings they are being used across the residential and industrial commercial building sectors of New Jersey. Second, we interpret the well record data using spatial statistics to evaluate hotspots for GHP system installations. In this approach we use Moran's I and Getis-Ord GI* statistical tests to evaluate spatial autocorrelation and spatial clustering respectively, within the study area. Finally, we develop a raster-based suitability model based on indexed geographic characteristics described in the literature to influence GHP adoption. Our suitability model provides insights at the census tract scale which can be used to prioritize more local investigations into identifying new GHP opportunities.

2.4.1 Spatial distribution of geothermal heat pump system in New Jersey

We identify a gap in information describing the current levels of GHP system operation across residential, commercial and industrial settings in New Jersey. We begin by collecting well record data on closed loop GHP systems from the New Jersey Department of Environmental Protection (DEP) Well Permitting program. This data is retrieved in a tabular format with fields describing location coordinates and depth of the completed borehole. Because the permit data alone does not provide sufficient information to make the distinction between building type, we use a geocoding and spatial overlay approach to cross reference the point locations of the GHP systems with the New Jersey tax parcel property classification dataset. We than aggregate the tax classifications into building sector categories. By doing so we are able to segment and quantify the population of systems in operation and identify how they are geographically distributed in the state. A GHP system typically comprises more than one borehole, however due to the state permitting process, a well record is created for individual boreholes. To extrapolate from individual borehole records to number of GHP systems in this high-level analysis, we assume a maximum of one system per parcel. Property classifications are described in New Jersey Administrative Code, Title 18 Department of Treasury and Taxation, Chapter 12 Local Property Tax. The seventeen property classifications codes describe the 3,449,162 parcels of the State. The resulting table was calculated by isolating the features of each classification and identifying the GHP point locations that intersect each class. To further distill the data, we perform location summary statistics describing the number of GHP boreholes and their average depths within the spatial boundaries of Electric Distribution Territories, Counties, and State Parcels.

Figure 2: Method Framework for GHP in New Jersey Building Sectors

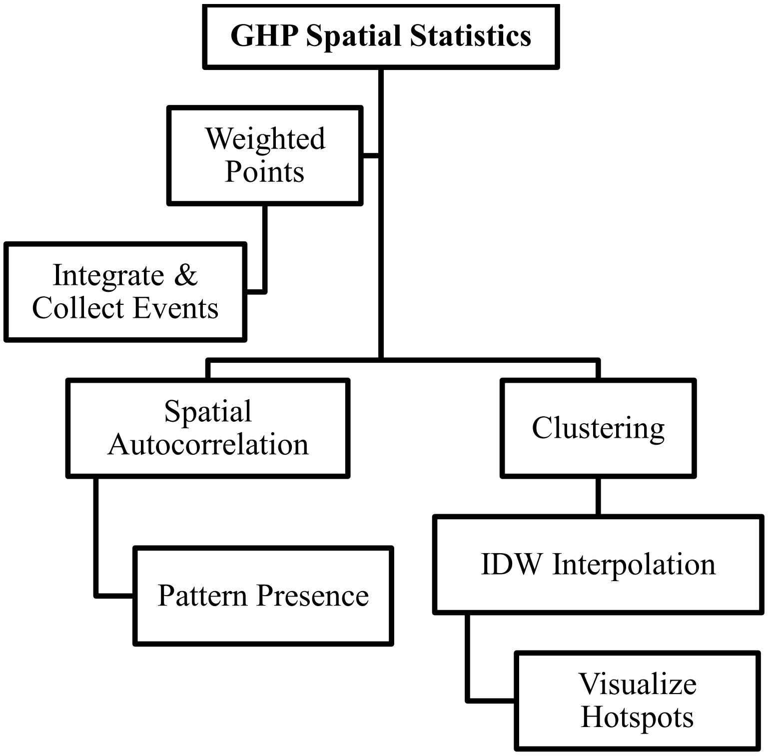


2.4.2 Spatial Statistics

Spatial statistical mapping is used to understand location and temporal occurrences of events across many fields of geography to model and interpret data (Prasannakumar, 2011; Levine, 1995, Scott, 2010, Haining, 2003). In our investigation, spatial statistical mapping related to installations are performed on the vector point GHP system data set. We conducted these analyses in ArcGIS Pro version 2.5.0 using the spatial analyst and spatial statistics extensions.

To evaluate clusters of small and large GHP installations, we utilized the *Optimized Hotspot Analysis* workflow. This procedure aggregates overlapping point features, and weights them for analysis for autocorrelation using Moran's I statistic, and clustering using Getis-Ord statistic. Moran’s I test evaluates for patterns in spatial data and classifies these patterns as random, clustered, or dispersed. The Getis-Ord statistic tells us the statistical significance of clustering. In our case, the points are weighted by the sum of overlapping co-located boreholes. Using this as a proxy for individual system size, we can determine areas of statistically significant clusters of large and small systems. For visual aid, we use inverse distance weighted deterministic interpolation, which creates a hotspot surface of the point clusters.

Figure 3: GHP Spatial Statistics Framework



First, we use the *integrate* and *collect events* tools in the software to aggregate the features, representing multiple borehole data representing a single GHP system. We do this to correct for overlapping point locations for single systems. Furthermore, since we are evaluating statistical significance, the simple overlay of parcel approach which is described in the section above would not be suitable. After this processing procedure we are left with a series of 1,298 GHP systems represented as weighted points. The weighted point represents more boreholes and thus a larger system.

After aggregating the borehole data, we perform the Global Moran's I test for spatial autocorrelation. This test uses the location of each feature and the attribute of these features, in this case the number of boreholes. Moran's I evaluates for patterns within the data expressed as random, clustered, or dispersed. This is represented in the equations:

$$\mathrm{I} = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}, z_i z_j}{\sum_{i=1}^{n} z_i^2} \qquad (1)$$

Where z_i is the deviation of an attribute for feature i from its mean (x_i - $\bar{x}$), $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the total number of features, and S_o is the aggregate of all the spatial weights:

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \qquad (2)$$

The $z_i$score for the statistic is computed as:

$$z_i = \frac{I - E[I]}{\sqrt{V[i]}} \qquad (3)$$

Where:

$$E[I] = -\frac{1}{n-1} \qquad (4)$$

$$V[I] = E[I^2] - E[I]^2 \qquad (5)$$

The null hypothesis that we are testing that there is no spatial clustering of the values. (Bailey 1995; Griffith 2003).

We define a hot spot as a location within an identifiable boundary showing concentration of GHP systems as illustrated in other topic areas (Prasannakumar, 2011). We use the weighted point feature class as the input for the hotspot analysis test using the Getis-Ord GI* statistic. This determines whether features with high values and with low values tend to cluster in the study area. If a feature's value is high, and the values within its neighborhood of features is also high, the area is identified as a hot spot. The statistical equation for calculating Gi* can be written using the equations below. The GI* statistic is the z-score used to interpret the results.

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}\, x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{[n \sum_{j=1}^{n} w^2{}_{i,j} - (\sum_{j=1}^{n} w_{i,j})^2]}{n-1}}} \tag{1}$$

Where x_j is the attribute value for feature j, $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the total number of features and:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{2}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2} \tag{3}$$

Statistically significant positive z-scores signify more intense clustering of high values, representing large GHP systems. For locations with statistically significant negative z-scores signifies clustering of low values, representing small GHP systems.

2.4.3 Raster Suitability Model

Closed loop GHP systems can be used in a wide variety of geographic settings. This is a major advantage of the technology (Hughes, 2008). Because of this flexibility drawing meaningful site-specific suitability conclusions can be challenging and inaccurate when compared to real world examples (Hughes, 2008). However, we can draw from underlying concepts within industry standards and other literature to develop coarse resolution suitability models based on large-scale input data to identify target areas for further investigations. We develop a raster-based suitability model built on indexed geographic characteristics described in the literature known to influence GHP adoption. Our suitability model considers multiple geographic input datasets that are based on the spatial economics of GHP system adoption.

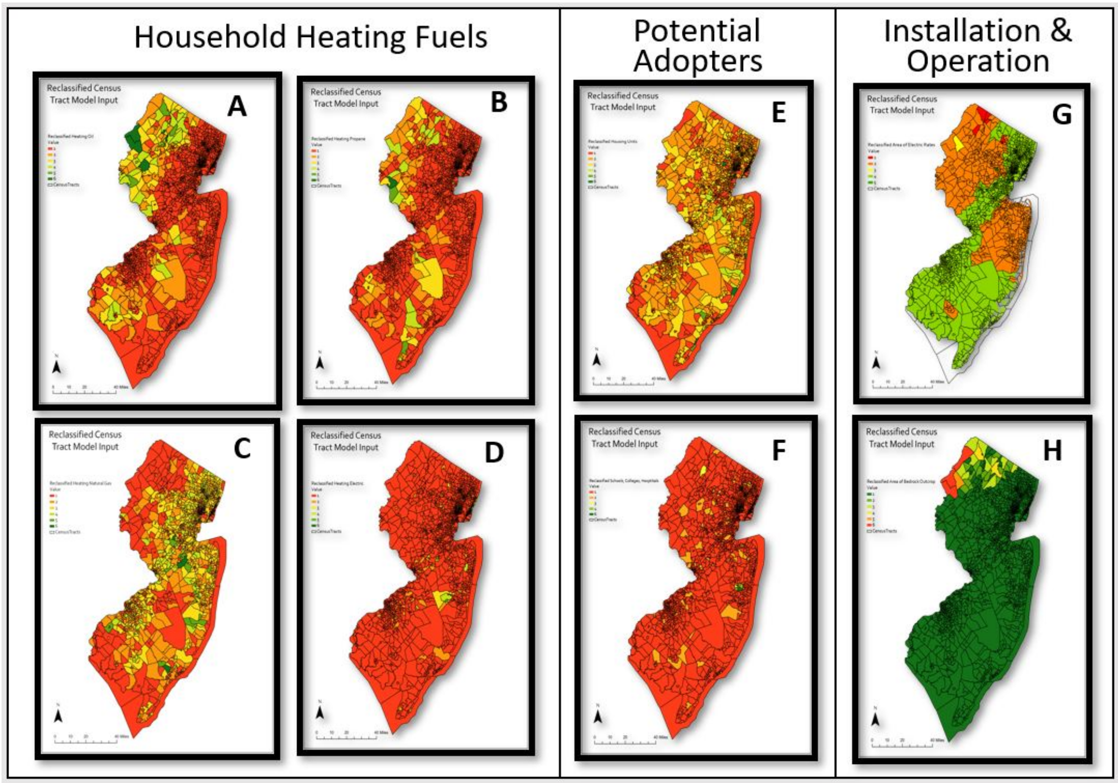
We incorporate a total of eight input datasets across three overarching suitability criteria that describe household heating fuels, potential adopters, and potential barriers associated with installation and operation. Data for our analysis is from a combination of U.S. Census, U.S. Geological Survey, U.S. Department of Energy, and NJDEP Bureau of GIS in vector format at the census tract scale. To allow for compatibility within the overlay geoprocessing tool in Esri ArcGIS software, we convert these vector inputs into raster format of thirty-meter resolution and index the values by reclassification logic from 1 to 6. Where 1 is least suitable for GHP and 6 is most suitable. In our approach we assume no single input is more influential on GHP suitability, and therefore we weight all raster inputs equally.

Our heating fuel inputs represent household heating fuel type occurrences across each census tract. We reclassify census tracts with more instances of residences using heating fuels of liquid propane, electric resistance and heating oil at a higher suitability rank because of the higher associated costs and greater GHG reduction potential. We rank tracts with more occurrences of natural gas use lower, because of the implied increased costs associated with abandoning this relatively cheap heating fuel source for a more costly, electricity intensive GHP system. Likewise, we assume tracts with higher retail electricity rates are less suitable than those with lower rates.

Our analysis of the well record data shows us that residential systems are predominant. On this basis we rank census tracts with more frequent occurrences of housing units higher. The literature highlights GHP potential at mid to large scale HVAC applications, particularly at sites with ample space to host larger borefields. To incorporate these potentially suitable sites, we summarize and reclassify point location occurrences within census tracts that contain primary schools, universities, and hospitals. To consider potentially prohibitive installation costs, incorporate bedrock outcrops into the analysis and rank census tracts with greater coverage of these features lower based on assumed additional installation costs. This input only shows spatial heterogeneity in the northwest portion of the study area. However, it is indicative of the physiographic provinces within the state.

The resulting overlay incorporates all these inputs and is illustrated in the figure below. Section A of this figure represents the distribution of heating oil occurrence in households. Section B represents the distribution of liquid propane (LP) gas for household heating. Section C represents the distribution of natural gas for household heating. Section D represents the distribution of electric heating. Section E the distribution of housing units within the state. Section F represents the distribution of schools and hospitals. Section G represents the reclassified values for electricity prices across the electric distribution territory. Section H represents the distribution of bedrock outcrops throughout the State.

Figure 4: Map Series of GHP Suitability Model Inputs

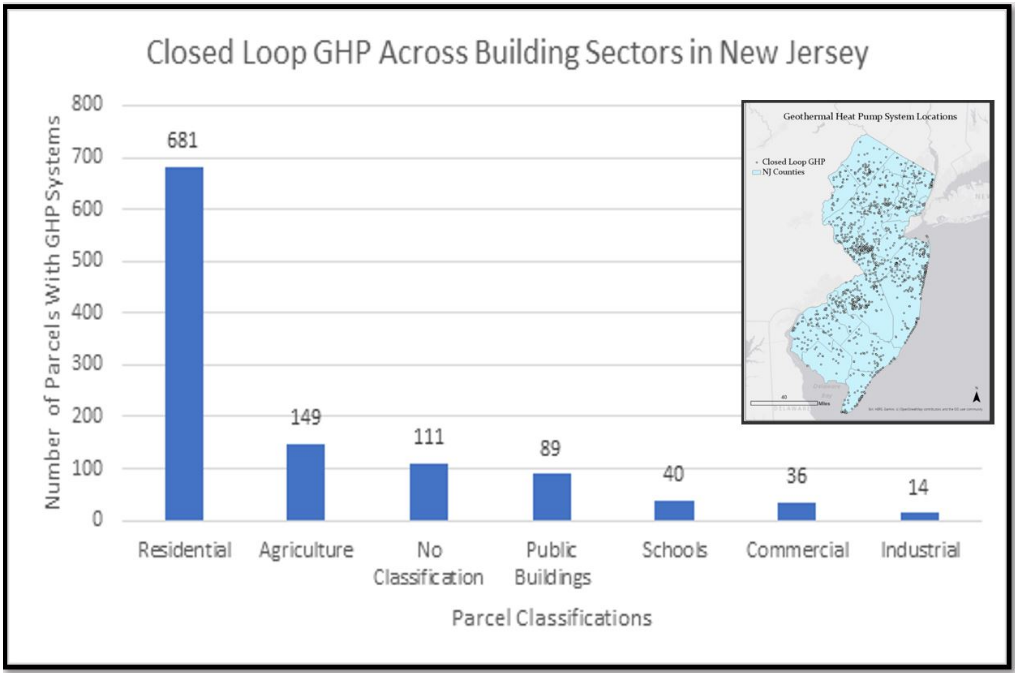


2.5 Results

2.5.1 Spatial Distribution of Installations

The resulting parcel classification information gives insight on segments of New Jersey's building sectors currently use GHP systems. We are able to see that there is a diverse application of GHP systems in the state, ranging from residential, commercial, and agricultural applications. We can also see that the most common systems are residential, followed by farmland, and public designated areas. It is important to note that there is some error in this data based on the percentage of unclassified points. This unfortunately is an unavoidable shortcoming of the tax parcel dataset.

Figure 5: Current GHP Use in New Jersey



The geographic distribution of GHP borehole record occurrence and depth by electric distribution and county boundaries are shown below. Aggregating georeferenced well data allows for cartographic visualization which shows new information summarizing GHP systems within the state. We see that the larger boundaries have more systems and systems occur more frequently in the more densely populated parts of the state. Notably, JCP & L has the most systems, most likely due to the large coverage area and geographically diverse settings in the territory. Furthermore, both the number of borehole wells and average depth as they relate to the capacity of a GHP system, are a function of local thermal conductivity of the subsurface geology. As energy efficiency efforts develop over time, the information provided here may be useful to local planners and regional distribution companies as they consider locations for targeting reductions in end energy use.

Figure 6: GHP Depths

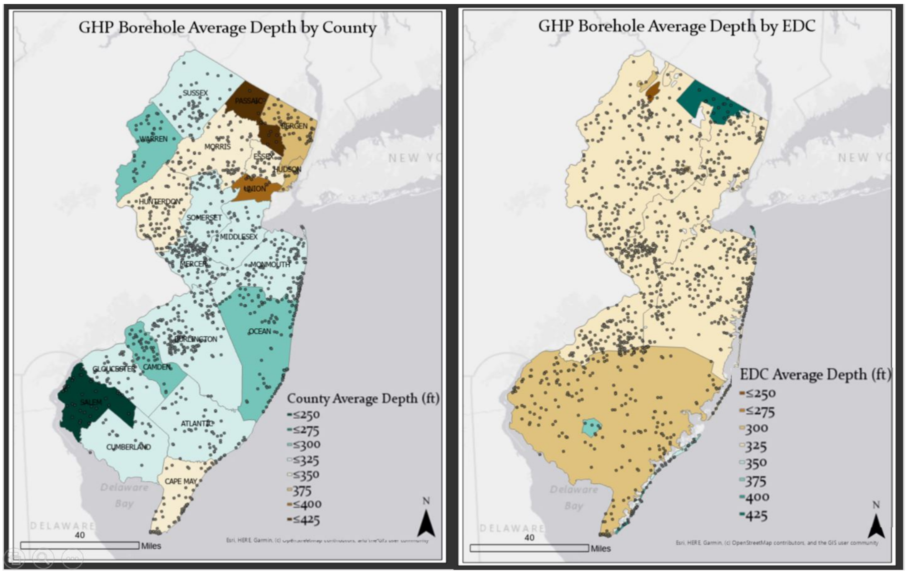
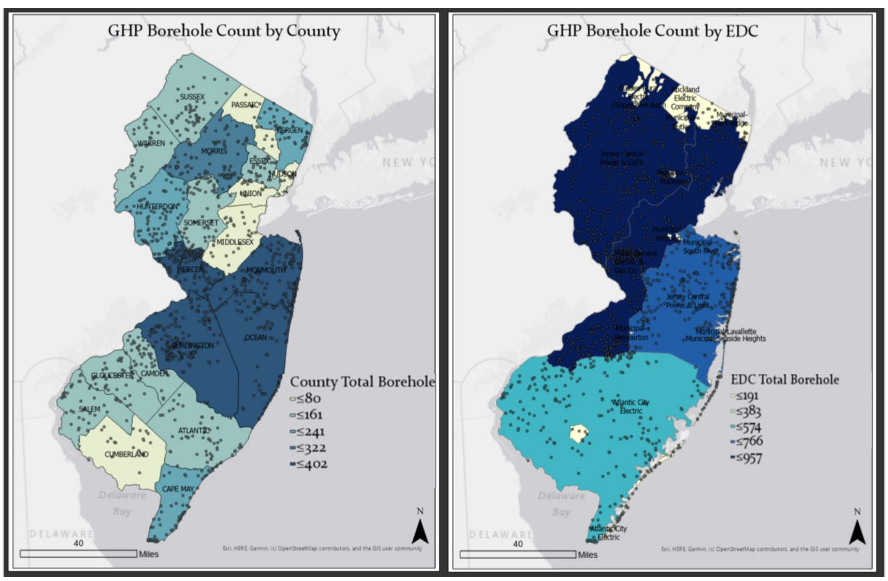


Figure 7: GHP Occurrences



2.4.2 Spatial Statistics

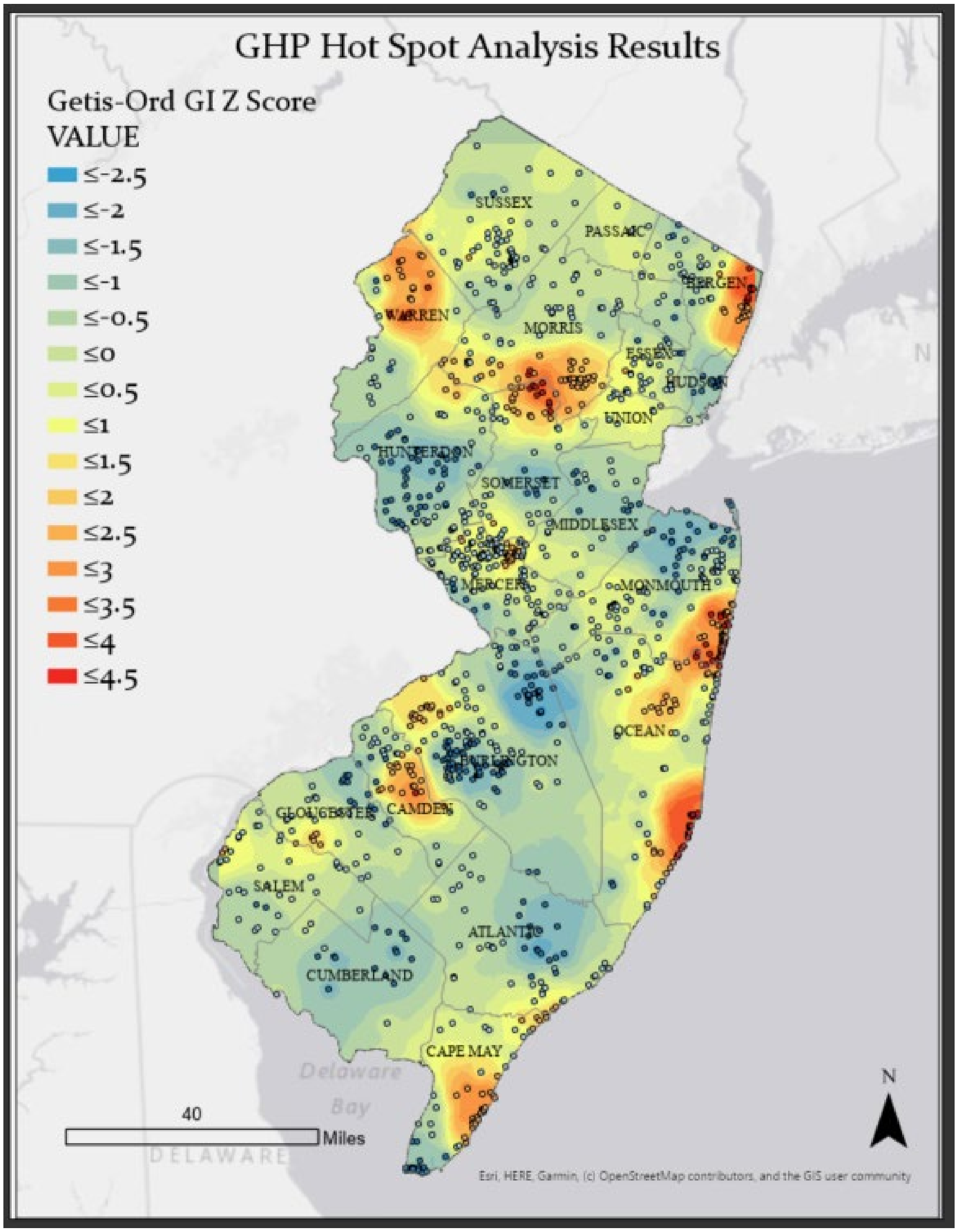
The results of the Moran's I spatial autocorrelation test of GHP systems suggests that there is strong autocorrelation and spatial clustering is occurring. The resulting z-score of 8.73, determines that there is a less than 1% likelihood that this clustered pattern could be the result of random chance. From this we can deduce that the GHP systems are likely to be influenced by geographic factors that are present within the study area. This may be explained by the presence of GHP developers, or adopters which were made aware of the benefits of these systems. Additional influences may be caused by local energy use characteristics in household heating.

Table 1: Global Moran's I Spatial Autocorrelation Results

Global Moran's I Summary				
Moran's Index	**Expected Index**	**Variance**	**Z-Score**	**p-value**
0.110542	-0.00071	0.000162	8.738551	0.00000
Dataset Information				
Input Feature Class	Input Field	Conceptualization	Distance Method	
GHP System Point	Count of Boreholes	Inverse Distance	Euclidean	

The Getis-Ord G* statistic test provides additional information on the clustering that the well record data exhibits. As highlighted in the figure below, New Jersey shows clustering of both small and large systems. These hotspots illuminate areas that have statistically significant clusters of GHP systems based on the z-score values for each weighted point. The interpolated raster surface expands on this and can help identify other forces that may be influencing adoption. The hotspots occur at various state geographies which can speak to several factors influencing GHP use.

Figure 8: New Jersey GHP System Hot Spots

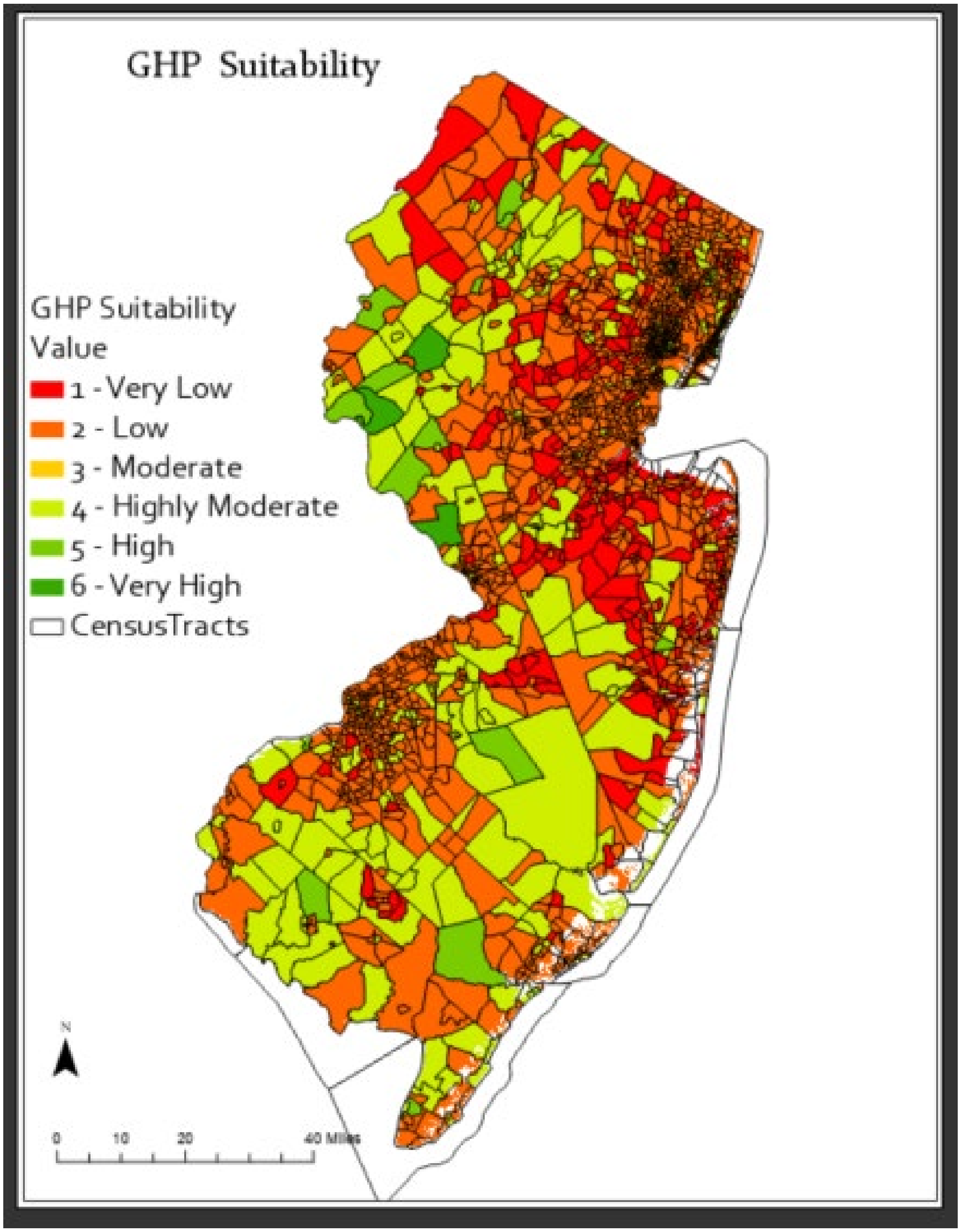


2.5.3 Results: Raster Analysis

The results of the weighted overlay suitability model represent the multicriteria approach to identifying potential for GHP technology adoption. Census tracts are the highest spatial resolution that is practical to incorporate diverse inputs while avoiding noise in the data. Additionally, because the New Jersey specific GHP known system data is not robust, fully harnessing the power of inferential statistics is challenging. As seen in the figure below, there is a heterogeneous distribution of the results of the suitability model. The majority of the State falls within the moderate and highly moderate classification scores. Because this includes a wide range of inputs, it is important to not rule out census tracts that fall within the low and even very low areas. This are simply less likely to see high rates of future GHP adoption in the near term.

The areas within the northwest region of the state are likely showing lower ranking scored because there are high occurrences of bedrock outcrops and also have less occurrences of housing units, and large buildings identified in the hospitals, school, and college and university inputs. However, areas in this region that are ranked higher are likely to exhibit concurrence of low natural gas home heating use and higher energy costs. The high occurrence of moderately ranked census tracts running diagonal from the north east to the southwest region of the state are within the urban agglomeration known as the Boston-Washington Corridor. This geographic feature of the State is known for its high levels of urban development along a major transportation corridor. This region will have higher influencing inputs for housing units and other large-scale adopters, along with low bedrock outcrops. This, region also occurs within the lowest prices for utility electricity rates within the PSEG electric distribution territory. The higher frequency of moderate scores in this area are caused by these high and lower ranking inputs cancelling out. The dispersed tracts of very low scores are most likely influenced by lower rates of housing units and other building infrastructure.

Figure 9: GHP Suitability Model Results



2.6 Discussion

Although there are some state government incentives for the procurement and installation of these systems, the dominant form of energy efficiency promoted is in the form of appliance and lighting rebates. Unfortunately, there is limited New Jersey specific qualitative and quantitative data on GHP systems and the associated economic and climate mitigation benefits. Based on the results of our analyses we are able to provide new information describing where and what type of GHP systems occur in the State. This is valuable in determining where there is new potential for maximum GHP mitigation through energy efficiencies.

In the context of future energy efficiency policy development, the results of all of these analyses will be invaluable in optimizing government spending on incentive programs. Having information such as what we present here can be used to develop clean energy mechanisms that prioritize environmental justice, renewable energy deployment, and increases in energy efficiency adoption as unison to satisfy political prioritize as well as maximize climate mitigation. In late 2019, the State of New Jersey released the 2019 Energy Master Plan. This document describes the State's short and long term goals for clean energy and climate mitigation with targeted efforts to increase the State's overall energy efficiency through a reduction in utility wide natural gas reduction, increase public awareness of the State's Clean Energy Program and associated energy efficiency programs which span residential and commercial entities (NJ EMP, 2019). Public dissemination of regulatory goals, such as those outlined in the Energy Master Plan not only consider stakeholder input from the public meetings, but also send signals to potential developers that energy efficiency incentive may be improved in the near future. This may lead to GHP developers taking more aggressive steps to market their technology to both potential customers as well as regulators. Geothermal heat pumps present an opportunity for environmental managers to capitalize on this energy efficiency technology across both residential and commercial stakeholders to optimize greenhouse gas reduction associated with HVAC systems in the building sector.

Residential buildings are the largest contributor to GHG emissions in New Jersey (NJ EMP, 2019). Considering the large proportion of current GHP is used in these settings, a targeted approach may be most effective in increasing adoption across the building sector and residential energy customers. This would be manifested as targeted funding mechanisms that vary between residential, industrial-commercial, utility customer segments of New Jersey. For residential systems compared to larger industrial scale GHP, a rebate or low-to-no interest government loan specifically favoring cost reduction at residential customers may be most effective in promoting the GHP industry and overall adoption in the state.

2.7 Conclusion

Energy efficiency is a crucial component of climate change mitigation and is a robust strategy for greenhouse gas reduction (IPCC, 2014). Ground source heat pump systems are an effective energy efficiency measure utilizing renewable thermal technology for heating, ventilation, and air conditioning (HVAC) systems that can be used across the building sector to reduce GHG. These systems not only reduce criteria pollutants in the electricity generation sector by reducing demand, but also reduce the associated greenhouse gas emissions. In addition to increasing energy efficiency, electrification of common fossil fuel-based energy consumption will aid in greenhouse gas reductions.

In this research, we are limited in the quality of our spatial data inputs. Future iterations of this method can use a case study approach of several individual GHP installations, and further investigate what specific driving forces are leading to their use within the state. This can make the reasoning behind future suitability models more robust and compensate for shortcomings in the well records and the tax parcel data. Additionally, more detailed investigation within the areas identified in the suitability model can yield more precise estimations of future GHP potential. Furthermore, engaging with potential adopters through a survey, could produce insights on what economic incentive approaches may be most effective to expand GHP use. Also, the implications of dynamics in policy and heating systems would make for an interesting scenario-based analysis across the study area.

The major findings presented here can be used in environmental management in New Jersey. We see that a majority of the total systems, and GHP capacity, are operating at residential properties. Additionally, we identify spatially significant clusters of large systems and smaller systems. Finally, we reference literature and industry standards on the spatial economics of GHP systems to identify suitable locations for GHP deployment across a large scale. The culmination of these three investigations yield new insights into the potential and current deployment of GHP technology in New Jersey. Based on the current body of knowledge and knowledge gap of GHP deployment in New Jersey, we deploy a framework for analysis aimed to fill this gap using techniques based on spatial analysis. As future end use energy efficiency policies are expanded in New Jersey, the information provided in this work can better inform policy decisions.

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3 Life cycle Assessment of Geothermal Heat Pumps

3.1 Introduction

In this investigation we utilize a Life Cycle Assessment (LCA), to explore environmental impacts of Geothermal Heat Pumps in New Jersey. Energy efficiency is a crucial component of climate change mitigation and is a robust strategy for greenhouse gas reduction (IPCC, 2014; NJ EMP, 2019). Ground source heat pump (GHP) systems, also known as geothermal heat pumps, are an effective yet underutilized energy efficiency technology (Saner, 2010; Hughes, 2008). The benefits of this technology are its ability to reduce the energy consumption and emissions associated with space heating and cooling (Saner, 2010; Hanova, 2007). These systems can also reduce energy prices and criteria pollutants in the electric generation sector by reducing periods of peak demand, and overall load (consumption) across residential and commercial sectors (Self, 2013). Furthermore, as government strategies such as those discussed in the New Jersey Energy Master Plan (2019) call for a transition from natural gas heating to electrified heating, improved energy efficiency will be needed to reduce energy costs (NJ EMP, 2019; Self, 2013). In this policy scenario, the implications of improving energy efficiency become more important, and favor GHP adoption.

GHP technology utilizes a ground heat exchanger, a heat pump, and a building heating, ventilation, and air conditioning (HVAC) system. These components are used to transfer thermal energy between a building and the surrounding environment. System size is measured in tons of heating and cooling capacity. Open loop systems use a water supply well and a reinjection well to exchange heat between a building and water in the environment. Vertical closed loop systems use high density polyethylene pipes that circulate a heat transfer fluid. Vertical closed loop systems pose less risks of distributing environmental contaminants and have lower operational and maintenance costs (Liu, 2007). GHP systems can operate in both cooling and heating modes, making them a functional year-round tool for both heating and air conditioning. When GHP systems are designed correctly, there initial costs can be recovered in the first 5 to 10 years of the 20-year total life span of the system through efficiency savings (NJDEP 2020; Kavanaugh, 2012; Self, 2013; Bloomquist, 1999; Deng, 2018).

To evaluate the broader climate change mitigation impacts of any clean energy technology, considering the generation portfolio in the electricity generation sector specific to study area is critical in accurately evaluating environmental impacts and benefits (Evans, 2009). In our LCA of GHP systems we constrain our input parameters to underscore the conditions in New Jersey with respect to residential system sizes, and the generation within the PJM Interconnection energy distribution system. In doing so we can translate established LCA methods for this technology to draw local information that can be used in future policy development for energy efficiency strategies.

3.2 Literature Review

Throughout the climate change and GHG mitigation literature we see the use of energy efficiency approaches coupled with clean energy generation technologies to optimize strategies for reducing greenhouse gases (Betsill, 2001). Additionally, numerous studies identify the need to fully evaluate the costs, benefits, and risks, across technologies (Evans, 2009). Many studies evaluate environmental impacts in terms of only emissions avoided, most commonly using carbon dioxide as a proxy (Saner 2010; Russo, 2009; Blum, 2011). Studies such as Alkell, (2009), Yasukawa (2010), provide valuable insight into the use of geothermal technology and the associated environmental impacts over long periods of time, with consideration to social, economic, and environmental impacts (Saner, 2010; Russo, 2009; Blum, 2011; Alkenna, 2009). Furthermore, these studies model GHP emissions savings over various scenarios for increased renewable generation entering the distribution system (Yasukawa, 2010).

In areas of the developing world, where heating sources are wood based, there is increased value in terms of environmental and socio-economic benefits of deploying district GHP systems as described in Blaga et at (2010). In the developed world, where heating is performed prominently by fossil fuel fired boilers or forced air systems, emissions savings are present but are highly dependent on the fuel mix of the associated distribution system (Friedleifsson, 2008, Jenkins, 2009; Hanova and Dowlatabadi, 2007). Furthermore, as more studies have taken on more sophisticated investigations into emission avoided, we see the potential in co-locating GHP systems with zero emission generation such as wind and solar (Saner, 2010; Koroneos, 2003; Rybach, 2008).

It is evident that GHP systems provide a means to reduce GHG emissions and are a practical strategy for residential and commercial energy efficiency. However, it is also discussed in the literature that environmental impacts of GHP systems have much broader and dynamic implications that can be tied to the location being studied (Saner 2010; Pehnt, 2006). The LCA approach provides a more holistic evaluation method that is used to consider additional impacts such as those to ozone depletion, environmental toxicity, and human health (Kaltscmit, 2000). Throughout the current body of knowledge, there is a limited number of studies which present comprehensive LCA approaches for GHP systems across regions. Approaches such as those presented by Saner (2010), highlight optimal LCA methodologies for evaluating GHP systems within a specific study area location. Location based information because a cornerstone of this type of study as it will determine important input parameters when developing system boundaries. The literature highlights technical guidelines for conducting the LCA based on the International Organization for Standardization (ISO) protocols (ISO, 1997; ISO, 2006). This procedure includes the goal and scope definition, the inventory analysis, the impact assessment, sensitivity analysis and evaluation of results to develop recommendations (Saner, 2010; Goedkoop, 2009).

3.3 Study Rationale & Objectives

Based on our review of relevant literature and policies, we identify the need for additional research to be performed on evaluating the long-term impacts of energy efficiency technology to mitigate climate change. There is clear consensus that energy efficiency strategies will be an important aspect in driving down the production of and the installation of GHP systems is continuously expanding on a global scale (Saner, 2010) We identify an opportunity to evaluate residential GHP systems in New Jersey as a means to draw cradle-to-grave implications of an energy efficiency technology within a specific geography, thus, allowing for targeted insights for future clean energy policy.

The objective of this research is testing the following hypotheses: 1) Do the cradle-to-grave environmental and human impacts of GHP systems negate their mitigation benefits? 2) Are these impacts influenced by regional energy mixes? 3)How do the impacts of GHP systems compare to other heating and cooling technologies? We evaluate the environmental impact of geothermal heat pump systems in New Jersey over an expected lifetime of twenty-five years. We perform an LCA and an uncertainty analyses to assess impacts across several indicators the determine the validity of our model. We also compare the relative environmental impact of geothermal heat pump systems to other HVAC configurations across both the New Jersey (PJM) and United States energy mixes. In this analysis we consider HVAC configurations of residential heating and cooling with electrical consumption associated with air conditioning, heating with oil, natural gas, and electricity to study historical, modern, and future heating methods.

3.4 Methods

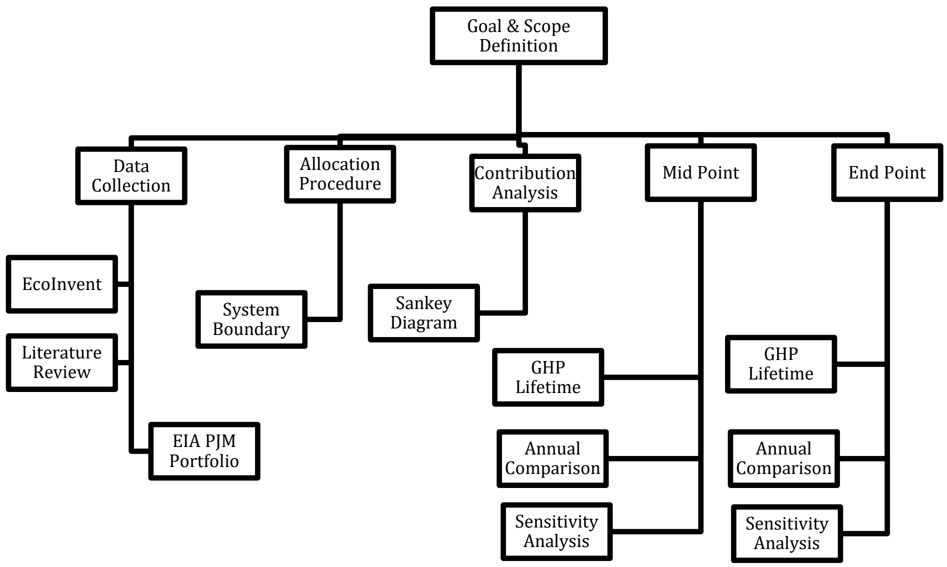
3.4.1 Life Cycle Analysis

Life Cycle Analysis (LCA) is a cradle-to-grave approach that is used to estimate the cumulative environmental impact of a system or process. LCA can be used as a decision-making tool that can be used to identify the environmental hotspots of a system and the key drivers of said hotspots to inform where changes might be made to dampen environmental impact. This comprehensive approach considers raw materials, installation/initiation, operation and maintenance, and disposal phases to better assess the ecological impact of a system throughout the entire life of a system operation.

We perform the LCA in SimaPro Version 8.5 software because it contains several impact assessment methods and an extensive inventory of databased that we could modify to best conform to the parameters of our analysis for our study area. We use the ReCiPe 2016 midpoint and endpoint methods for the analysis, using the hierarchist perspective, which is considered the consensus model most commonly used in scientific research. The midpoint method is suitable for detecting environmental impacts early in the cause-effect chain. This approach represents a large number of impact categories, including climate change, ozone depletion, photochemical ozone creation, human toxicity, ecotoxicity, eutrophication, acidification, land and water stress, and resource depletion among others. The endpoint method is better suited to evaluate the environmental impact at the end of the cause-effect chain and is based on damage, where impacts on human health, ecosystem health, and resource availability are quantified.

Using these methods, we are able to complete a number of calculations. Contribution analysis allows us to determine which processes play a significant role in the results in the form of a process tree, or Sankey diagram. Inventory analysis provides a list of substance emission to the midpoint and endpoint impact categories, and calculates the emissions associated with each of the impact categories. Comparison analysis allows us to relate the substance emissions of multiple processes. Uncertainty analysis allows us to determine the variation in the data, representativeness of the model, and incompleteness of the model. Through these multiple analyses, we can gain a more accurate depiction of the environmental impact of a system or systems, providing results which may inform management, strategy, and policy decisions. We also perform a sensitivity analysis across system sizes and future energy mixes.

Figure 10: New Jersey GHP LCA Analytical Framework



3.4.2 Goal and Scope Delineation

The goal of our geothermal heat pump LCA is to evaluate residential systems operating within New Jersey to evaluate the overarching environmental impacts. The function of our system is to operate within the heating and cooling of a HVAC system over the course of one year in kilowatt-hours (kWh). We choose this functional unit to span the heating and cooling modes of the GHP system and make comparisons possible across other heating and cooling approaches such as natural gas and electricity.

In this LCA, we explore the PJM ISO regional energy mix, of which New Jersey accesses electricity, with a heating and cooling coefficient of performance (COP) of 3.5. This coefficient indicates efficiency of the system. A COP value of 3.5 means that for each unit of energy consumed, the system will provide 3.5 units of heating or cooling. We chose this coefficient based on our data collection and literature review. GHP systems have higher COP values as compared to traditional gas furnace of less than 1.

COP is calculated using the following equations:

$$COP_{heating} = \frac{Q_H}{Q_H - Q_C} \quad (1)$$

$$COP_{cooling} = \frac{Q_C}{Q_H - Q_C} \quad (2)$$

Where Q_H is the heat transferred to the hot reservoir and Q_C is the heat collected from the cold reservoir.

In the development of our GHP LCA we consider four main components. These include the manufacturing of the heat pump, the installation of the borehole heat exchanger, the operation and maintenance of the unit, and finally the disposal to landfill of any parts that are not able to be recycled or repurposed. For our LCA, we assume annual preventative maintenance, with no need for repair, and a lifetime of 25 years with no change in heating/cooling usage. We also compare annual operation of a residential GHP in NJ, using the PJM energy generation mix, to annual operation in the general US, using estimates available in the EcoInvent database. Lastly, we explore the relative environmental impact of GHP compared to three other energy mixes used for heating and cooling in NJ, including: 100% electricity, 50% electricity and 50% oil, and 50% electricity and 50% natural gas.

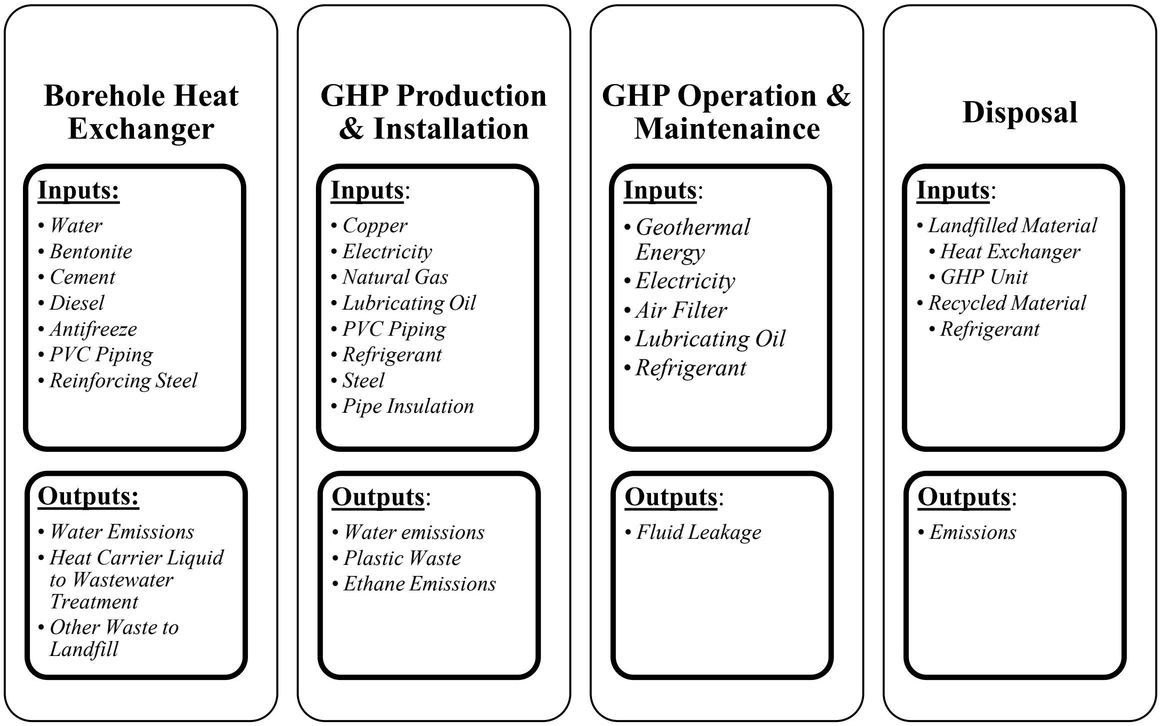
3.4.3 Data collection

The data used in this analysis was collected and adapted from the EcoInvent database, where calculations were made such that it would be representative of the installation, operation, and decommissioning of a 3-ton residential GHP unit in New Jersey. In the operational component we adjust energy generation in the Northeast region of the United States to best represent energy consideration within New Jersey and the greater PJM ISO. This allows for more accurate representation and comparisons based on where the GHP system is located. The data for the production of the 10.55kW GHP unit was adapted from a dataset developed from Arbeitsgemeinschaft (1991) with a 25-year lifetime. We adapted this data by scaling calculations to 1 p at 10.55 kW. The data for the drilling for and production of the borehole heat exchanger was adapted from a dataset developed from Luder (2003) and Arbeitsgemeinschaft (1991). We adapted this data to represent standard practices in the US which include 2 boreholes, each at a depth of 160 meters (approx. 525 feet) for a 3-ton residential unit. The data for the annual operation of the GHP system was obtained from documentation from the Energy Information Administration (EIA) for annual household energy use in NJ and the US, and maintenance data was informed from a GHP operation and maintenance manual produced by the London Southbank University's Department of Energy and Climate Change. The NJ electricity energy mix was informed from PJM's 2018 annual report, and the non-electricity energy types were collected from the EcoInvent database.

3.4.4 Allocation procedures

The system boundary includes all stages of a closed-loop GHP system life cycle, including borehole drilling, in-ground heat exchanger production and installation, heat pump unit production and installation, GHP system annual heating and cooling operation and preventative maintenance, and disposal of all non-recyclable parts. The system boundary can be viewed in the figure below.

Figure 11: GHP Life Cycle Assessment System Boundary



3.5 Results

3.5.1 Inventory Analysis Results

We used data EcoInvent to inform our data inventory and adapted the data through calculations to be representative of a GHP system in New Jersey. The borehole heat exchanger was adjusted from a dataset which used a depth of 150 meters, with a heating output of 10.25 kW and a cooling capacity of 8.25 kW. Our data used a depth of 160 meters, and a heating and cooling capacity of 10.55 kW. The geothermal heat pump production and installation was adapted, again, to be representative of a 10.55 kW capacity in NJ.

The annual operation of a 3-ton GHP system with a COP of 3.5 was calculated based on estimates from U.S. Department of Energy and the EIA. An estimated 127 million BTU energy is consumed in NJ, with 49% from heating and 3% from cooling. Based on these percentages we calculated the energy needs for both heating and cooling. Based on a COP of 3.5 we calculated the distribution between geothermal energy and electricity from the PJM energy mix. To address annual maintenance needs, we included a filter change, addition of lubricating oil calculated from a 2% loss from the original application, and addition of refrigerant calculated from a 3.77% loss from the original application. The created inventory informed the analyses as discussed in the following section. The NJ electricity energy mix was informed from documentation from PJM. We calculated the energy mix based on annual household energy consumption of 127 million BTU, or 37,220 kWh, and the given percentages of electricity generated from oil, coal, nuclear, natural gas, and solar. The energy mix comparison data compared GHP system annual operation for heating and cooling needs to other methods of doing so, including electricity, oil, and natural gas. For all electricity, we used our previously calculated New Jersey electricity energy mix as an input so that the analysis would be more representative of energy consumption in the state. This data inventory informs the analyses below.

Table 2: GHP Borehole Heat Exchanger Data Inventory

Borehole Heat Exchanger 160m output =1p		
Input	**Amount**	**Unit**
Water (drilling process)	10.87	m3
Activated Bentonite (drilling process)	8.53	kg
Cement	35.19	kg
Diesel (equipment transport and operation)	1,8054.40	MJ
Ethylene Glycol	108.79	kg
PVC (probe)	191.99	kg
Reinforcing Steel (drilling process)	35.19	kg
Output	**Amount**	**Unit**
Water (Emission to Air)	1.63	m3
Water (Emission to Water)	9.24	m3
$C_3H_8O_2$ (heat carrier liquid)	0.32	m3
Inert Waste (stone and other waste to landfill)	1,666.66	kg

Table 3: GHP Heat Pump LCA Data Inventory

Geothermal Heat Pump, Output 1p at 10.55 kWh		
Input	**Amount**	**Unit**
Copper	23.12	kg
Electricity (medium voltage)	147.17	kWh
Heat (Natural Gas)	147.17	kWh
Lubricating Oil	1.78	kg
PVC	1.05	kg
Refrigerant R134a	3.24	kg
Reinforcing steel	75	kg
Steel, low-alloyed, hot rolled	20	kg
Tube insulation	10	kg
Outputs	**Amount**	**Unit**
Ethane, 1,1,1,2-tetrafluoro-, HFC-134a (emission to air)	0.725369	kg
Water (emission to air)	0.111644	kg
Water (emission to water)	0.632648	kg

Table 4: GHP Annual Operation

Annual Heating Operation COP 3.5 18237.81 kWh		
Input	**Amount**	**Unit**
Energy (geothermal)	13,027.01	kWh
Electricity (medium voltage)	5,210.80	kWh
Annual Cooling Operation COP 3.5 4918.35 kWh		
Input	**Amount**	**Unit**
Energy (geothermal)	3,688.76	kWh
Electricity (medium voltage)	1,229.59	kWh
Air Filter	1	P
Lubricating Oil	0.03	kg
Refrigerant R134a	0.12	kg

Table 5: New Jersey Generation Energy Mix Data Inventory

Process	**Amount**	**Unit**
Oil Generation (0.20%)	744.40	kWh
Coal Generation (28.70%)	10,682.14	kWh
Nuclear Generation (34.5%)	12,840.90	kWh
Natural Gas Generation (31.20%)	1,1612.64	kWh
Photovoltaic Generation (5.40%)	2,009.88	kWh

Table 6: Energy Mix Base Case Scenario Data Inventory

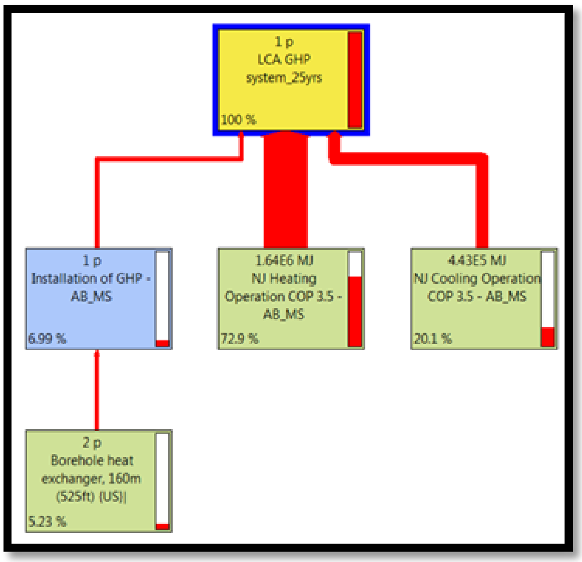
Energy comparison, base case scenario, annual operation		
100% Electricity		
Process	Amount	Unit
NJ Electricity energy mix	19,357.41	kWh
50% Fuel Oil, 50% Electricity		
Process	Amount	Unit
NJ Electricity energy mix	9,677.20	kWh
Heat, fuel oil	9,677.20	kWh
50% Natural Gas, 50% Electricity		
Process	Amount	Unit
NJ Electricity energy mix	9,677.20	kWh
Heat, natural gas	9,677.20	kWh
Geothermal Heat Pump System		
Process	Amount	Unit
Cooling operation	1,116.60	kWh
Heating operation	1,8237.80	kWh

3.5.2 Impact Assessment Results

To calculate the life cycle assessment of a GHP system operating for 25 years, we included the drilling, production, and installation of two borehole heat exchangers, the operation and maintenance of the GHP system over 25 years, and waste treatment. The operation included annual heating needs of 18,237 kWh and cooling needs of 4918 kWh, and maintenance considered an annual filter change and addition lubricating oil and refrigerant fluid to maintain the equipment. A COP of 3.5 allowed us to calculate the amount of energy from the PJM electricity mix and the amount of geothermal energy. A contribution analysis shows that heating was the primary contributor to the system's environmental impact at 72.9%, followed by cooling

(20.1%), installation of the GHP (6.99%), and installation of the borehole heat exchanger (5.23%).

Figure 12: Contribution Analysis GHP System Sankey Diagram



The impact assessment of this system calculates the total environmental impact, and the environmental impact of each component (i.e. heating, cooling) based on each of the midpoint impact categories, where the impact is calculated based on the relevant associated emission. The damage assessment of this system calculated the overall impact on human health, ecosystem health, and resource availability. Human health is measured in Disability Adjusted Life Year (DALY) which is a measure of overall disease burden, expressed as the cumulative number of years lost due to ill-health, disability, or early death. Ecosystem health is measured in number of species lost per year. Resource availability is measured as the surplus costs of future resource production over an infinitive timeframe, expressed as the unit USD 2013.

Figure 13: Midpoint Impact Assessment of a GHP System

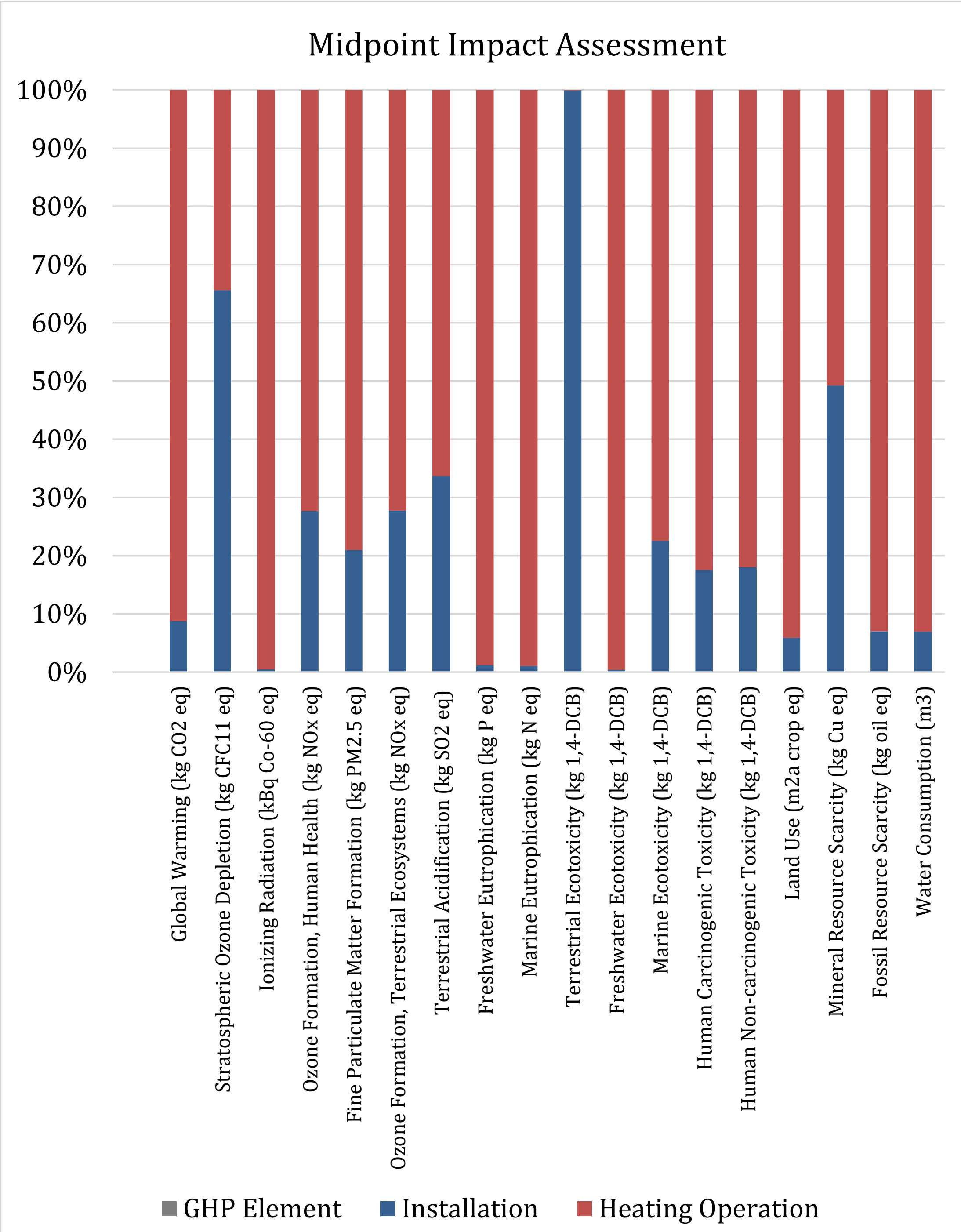


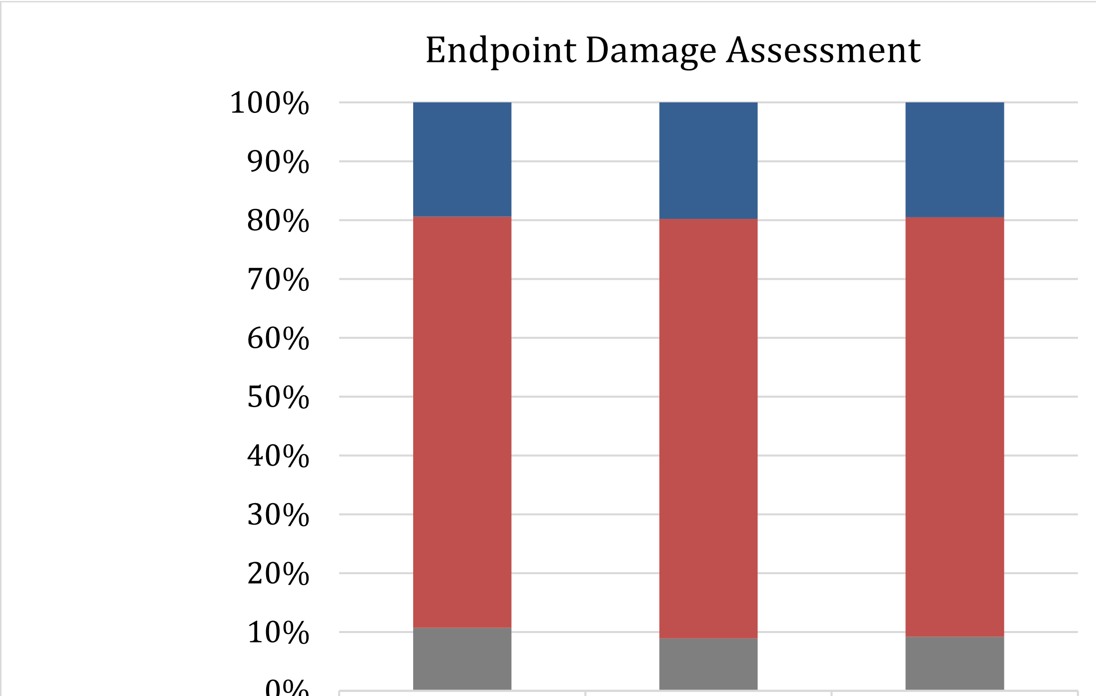
Table 7: Midpoint Impact Assessment of a GHP System

Impact Category	Installation	Heating	Cooling	Total
Global Warming (kg CO_2 eq)	6.61E+03	6.89E+04	1.90E+04	9.45E+04
Stratospheric Ozone Depletion (kg CFC11 eq)	4.98E-03	2.61E-03	1.77E-02	4.80E-03
Ionizing Radiation (kBq Co-60 eq)	1.78E+02	3.60E+04	9.74E+03	4.60E+04
Ozone Formation, Human Health (kg NOx eq)	4.33E+01	1.13E+02	3.13E+01	1.88E+02
Fine Particulate Matter Formation (kg PM2.5 eq)	1.27E+01	4.79E+01	1.35E+01	7.42E+01
Ozone Formation, Terrestrial Ecosystems (kg NOx eq)	4.41E+01	1.15E+02	3.19E+01	1.91E+02
Terrestrial Acidification (kg SO2 eq)	2.43E+01	4.79E+01	3.92E+01	2.04E+02
Freshwater Eutrophication (kg P eq)	1.39E+00	1.15E+02	6.61E+00	3.21E+01
Marine Eutrophication (kg N eq)	1.50E+00	1.40E+02	6.13E-01	4.35E+00
Terrestrial Ecotoxicity (kg 1,4-DCB)	1.79E+04	2.41E+01	1.44E+04	8.29E+04
Freshwater Ecotoxicity (kg 1,4-DCB)	1.90E+02	5.06E+04	2.59E+02	1.38E+03
Marine Ecotoxicity (kg 1,4-DCB)	2.70E+02	9.30E+02	3.63E+02	1.94E+03
Human Carcinogenic Toxicity (kg 1,4-DCB)	2.77E+02	1.30E+03	5.39E+02	2.77E+03
Human Non-carcinogenic Toxicity (kg 1,4-DCB)	5.81E+03	2.64E+04	7.38E+03	3.96E+04
Land Use (m2a crop eq)	3.65E+01	5.83E+02	1.87E+02	8.06E+02
Mineral Resource Scarcity (kg Cu eq)	5.94E+01	6.12E+01	1.71E+01	1.38E+02
Fossil Resource Scarcity (kg oil eq)	1.59E+03	2.11E+04	5.80E+03	2.85E+04
Water Consumption (m3)	2.48E+01	3.32E+02	9.40E+01	4.51E+02

Figure

14:

Endpoint Damage Assessment of a GHP System



	Human Health (DALY)	Ecosystems (Species/Year)	Resources (USD)
Cooling Operation	3.00E-02	7.35E-05	1.38E+03
Heating Operation	1.08E-01	2.65E-04	5.03E+03
Installation	1.65E-02	3.31E-05	6.48E+02

To determine if GHP systems are an appropriate fit for the state of New Jersey, we compared annual operation of a GHP system in NJ using the PJM energy mix to a GHP system in the US using the energy mix calculated in EcoInvent. A report from the Energy Information Association (EIA) informs that NJ residential units consume, on average, more energy (127 million BTU) than the US average household (90 million BTU). NJ uses an estimated 49% of that energy for heating, and 3% for cooling; while the US uses an estimated 41% for heating and 6% for cooling. Through this, we calculated 18237 kWh heating and 1055 kWh cooling in NJ using the PJM energy mix. We kept the energy use the same but recalculated the distribution of heating/cooling to be representative of the US as a whole for the comparison. Overall, the GHP system used in New Jersey has a lower environmental impact in most impact categories than that in the US general. Those impact categories associated with resource scarcity, however, were higher in New Jersey.

Figure 15: Midpoint Comparison of New Jersey and U.S. GHP Annual Operation

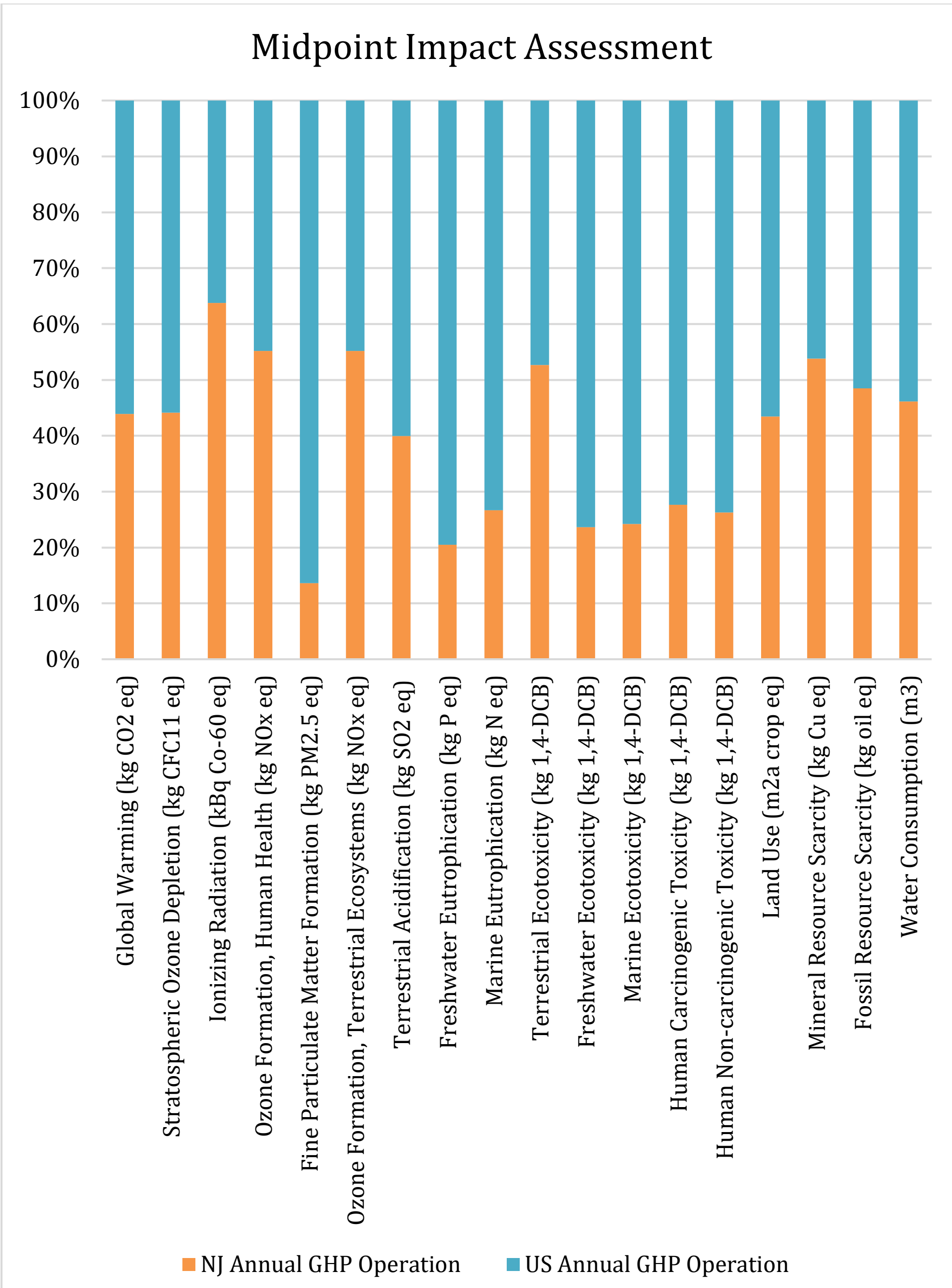
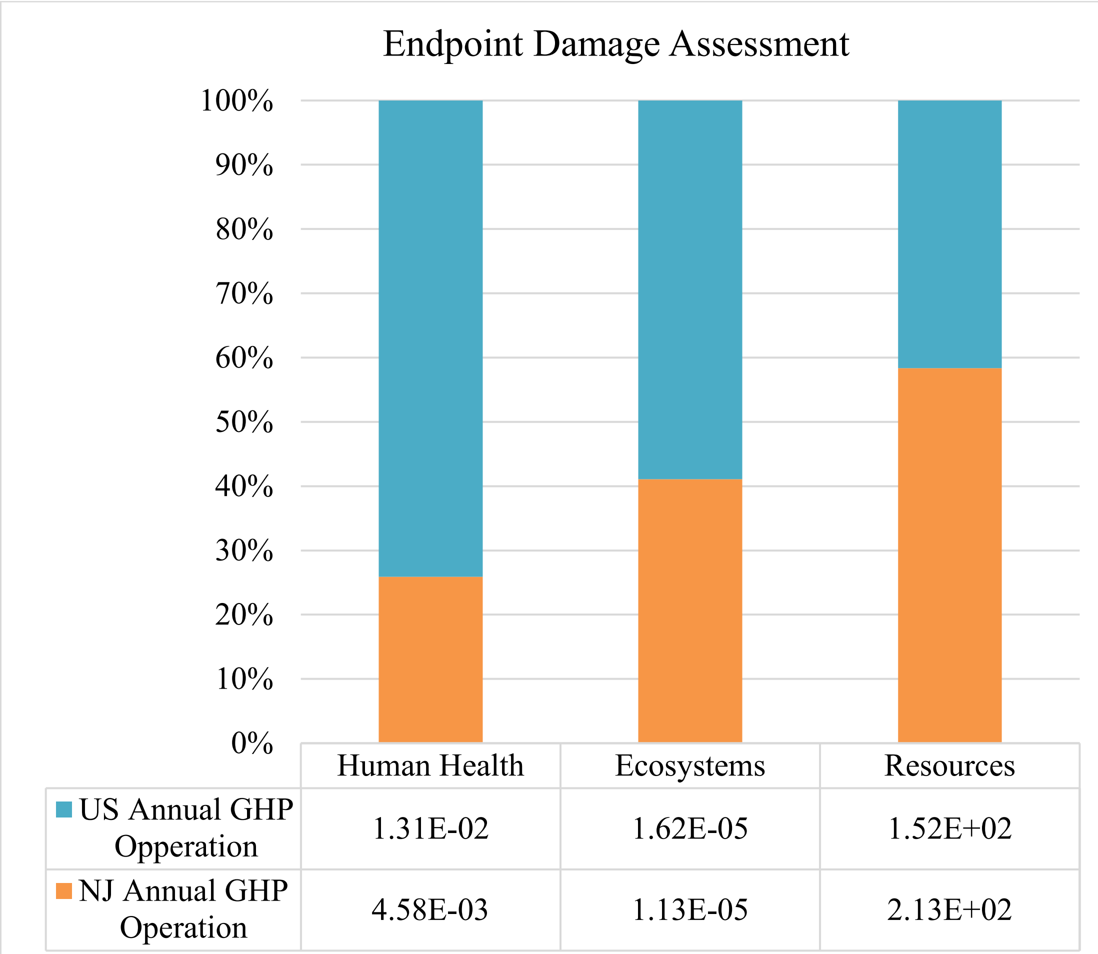


Table 8: Midpoint Comparison of New Jersey and U.S. GHP Annual Operation

Impact Category	NJ Annual GHP Operation	US Annual GHP Operation
Global Warming ($kg\ CO_2\ eq$)	2.93E+03	3.74E+03
Stratospheric Ozone Depletion (kg CFC11 eq)	1.21E-03	1.53E-03
Ionizing Radiation (kBq Co-60 eq)	1.53E+03	8.69E+02
Ozone Formation, Human Health (kg NOx eq)	4.82E+00	3.92E+00
Fine Particulate Matter Formation (kg PM2.5 eq)	2.04E+00	1.30E+01
Ozone Formation, Terrestrial Ecosystems (kg NOx eq)	4.90E+00	3.97E+00
Terrestrial Acidification (kg SO2 eq)	5.97E+00	8.97E+00
Freshwater Eutrophication (kg P eq)	1.02E+00	3.97E+00
Marine Eutrophication (kg N eq)	9.51E-02	2.62E-01
Terrestrial Ecotoxicity (kg 1,4-DCB)	2.15E+03	1.94E+03
Freshwater Ecotoxicity (kg 1,4-DCB)	3.95E+01	1.28E+02
Marine Ecotoxicity (kg 1,4-DCB)	5.54E+01	1.73E+02
Human Carcinogenic Toxicity (kg 1,4-DCB)	8.31E+01	2.18E+02
Human Non-carcinogenic Toxicity (kg 1,4-DCB)	1.12E+03	3.16E+03
Land Use (m2a crop eq)	2.50E+01	3.25E+01
Mineral Resource Scarcity (kg Cu eq)	2.60E+00	2.23E+00
Fossil Resource Scarcity (kg oil eq)	8.98E+02	9.54E+02
Water Consumption (m3)	1.41E+01	1.65E+01

Figure 16: Endpoint Comparison of New Jersey and U.S. GHP Annual Operation



The damage assessment calculated that the human health impact was 0.00458 DALY for NJ, and 0.0131 DALY for the US; ecosystem health was 1.13x10-5 species per year for NJ, and 1.62x10-5 species per year for the US; resource scarcity was 214 USD for NJ and 152 USD for the US. The midpoint categories associated with resource scarcity include mineral and fossil resource scarcity, and the primary effect is seen to be fossil resource scarcity where the cost for NJ is 213 USD and 152 USD for US.

While these findings show that New Jersey is a good location for GHP system installation and use based on higher energy consumption and a diverse energy mix, we analyzed other forms of energy to compare which energy type is ideal in terms of environmental consequence. To do this, we compared annual energy needs delivered through a GHP system, 100% electricity, 50% electricity and 50% oil, and 50% electricity and 50% natural gas. Electricity in each scenario was analyzed using the New Jersey PJM energy mix. The midpoint analysis shows that across all impact categories, GHP systems are substantially preferable to the other energy methods. Overall, 100% electricity was found to have the highest environmental impact, followed by oil mix and natural gas mix. In the figure below, we can see the measured emissions associated with each impact category.

Figure 17: Midpoint Comparison of HVAC

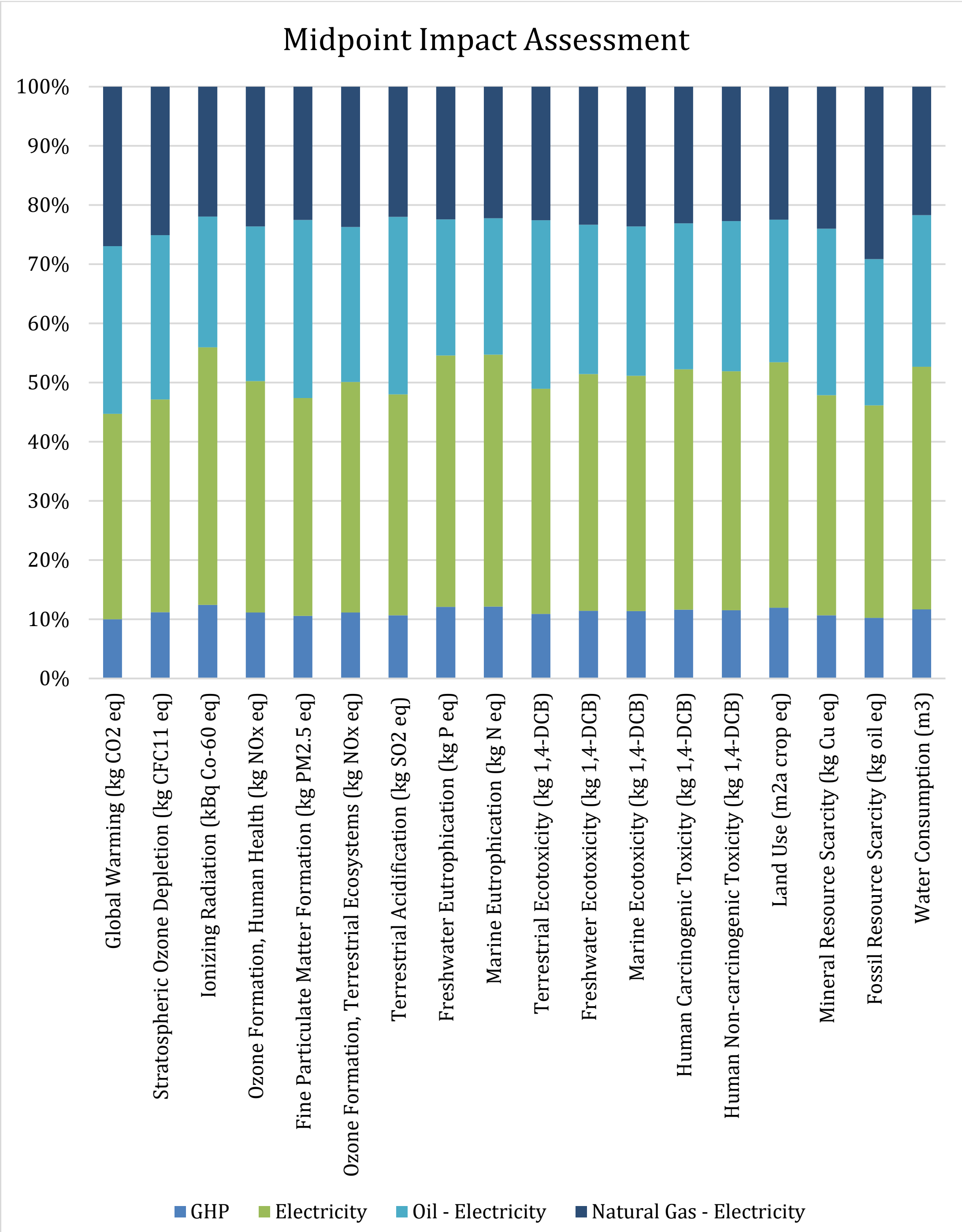
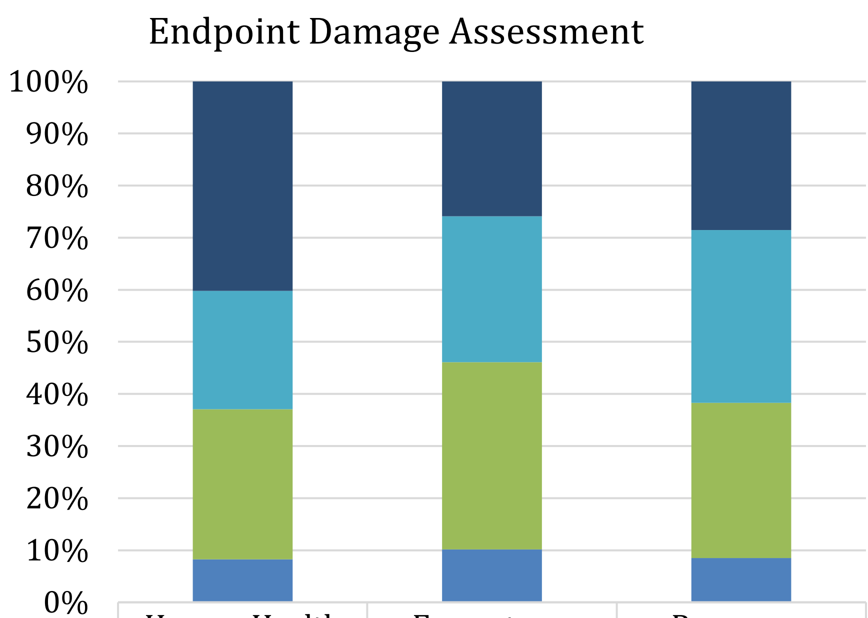


Table 9: Midpoint Comparison of HVAC

Impact Category	GHP	Electricity	Oil - Electricity	Natural Gas - Electricity
Global Warming (kg CO2 eq)	2.93E+03	1.02E+04	8.31E+03	7.91E+03
Stratospheric Ozone Depletion (kg CFC11 eq)	1.21E-03	3.88E-03	3.00E-03	2.71E-03
Ionizing Radiation (kBq Co-60 eq)	1.53E+03	5.35E+03	2.72E+03	2.70E+03
Ozone Formation, Human Health (kg NOx eq)	4.82E+00	1.69E+01	1.13E+01	1.02E+01
Fine Particulate Matter Formation (kg PM2.5 eq)	2.04E+00	7.12E+00	5.82E+00	4.35E+00
Ozone Formation, Terrestrial Ecosystems (kg NOx eq)	4.90E+00	1.71E+01	1.15E+01	1.04E+01
Terrestrial Acidification (kg SO2 eq)	5.97E+00	2.09E+01	1.68E+01	1.23E+01
Freshwater Eutrophication (kg P eq)	1.02E+00	3.58E+00	1.94E+00	1.89E+00
Marine Eutrophication (kg N eq)	9.51E-02	3.33E-01	1.80E-01	1.74E-01
Terrestrial Ecotoxicity (kg 1,4-DCB)	2.15E+03	7.52E+03	5.62E+03	4.46E+03
Freshwater Ecotoxicity (kg 1,4-DCB)	3.95E+01	1.38E+02	8.72E+01	8.05E+01
Marine Ecotoxicity (kg 1,4-DCB)	5.54E+01	1.94E+02	1.23E+02	1.15E+02
Human Carcinogenic Toxicity (kg 1,4-DCB)	8.31E+01	2.90E+02	1.76E+02	1.65E+02
Human Non-carcinogenic Toxicity (kg 1,4-DCB)	1.12E+03	3.93E+03	2.47E+03	2.21E+03
Land Use (m2a crop eq)	2.50E+01	8.66E+01	5.03E+01	4.69E+01
Mineral Resource Scarcity (kg Cu eq)	2.60E+00	9.06E+00	6.85E+00	5.84E+00
Fossil Resource Scarcity (kg oil eq)	8.98E+02	3.14E+03	2.16E+03	2.55E+03
Water Consumption (m3)	1.41E+01	4.94E+01	3.09E+01	2.62E+01

Figure 18: Endpoint Comparison of HVAC



	Human Health (DALY)	Ecosystems (Species/Year)	Resources (USD)
Natural Gas - Electricity	2.23E-02	2.83E-05	7.16E+02
Oil - Electricity	1.26E-02	3.06E-05	8.32E+02
Electricity	1.60E-02	3.93E-05	7.47E+02
GHP	4.58E-03	1.11E-05	2.14E+02

The damage assessment per impact category can be seen in F where we can see that annual operation of a GHP unit for heating and cooling holds a significantly lower impact for each sustainability metric. Overall, our results show that GHP systems which use a combination of electricity and geothermal energy have a substantially lower environmental impact than other non-renewable energy mixes. We have also shown that NJ as a state is well suited for GHP systems based on the energy mix available through PJM. The LCA of a GHP system that lasts 25 years shows that improvements on technology and energy use should be made to address certain impact categories. As we know the majority of energy consumption is due to heating, heating efficiency and energy storage should be considered highest priority when informing decisions to lessen environmental consequence.

Uncertainty analysis shows the variation, or distribution, in data expressed as a range or standard deviation. SimaPro software uses the Monte Carlo technique to calculate the data uncertainty at a 95% confidence interval in the LCA results. We can see that there is a large level of uncertainty in the water consumption, human carcinogenic toxicity, and ionizing radiation impact categories. The midpoint uncertainty analysis shows a large level of variation across many impact categories with only 7 of the 18 impact categories showing a coefficient of variance (CV) under an acceptable level of 30%. However, the damage assessment uncertainty analysis shows a CV of 9.98% for resource availability, 11.9% for human health, and 12.3% for ecosystem health which suggest that this model is acceptable. This result shows that the endpoint method is a better fit for the data available, and more data is required for the midpoint method given the larger level of variation.

Table 10: Midpoint Uncertainty Analysis

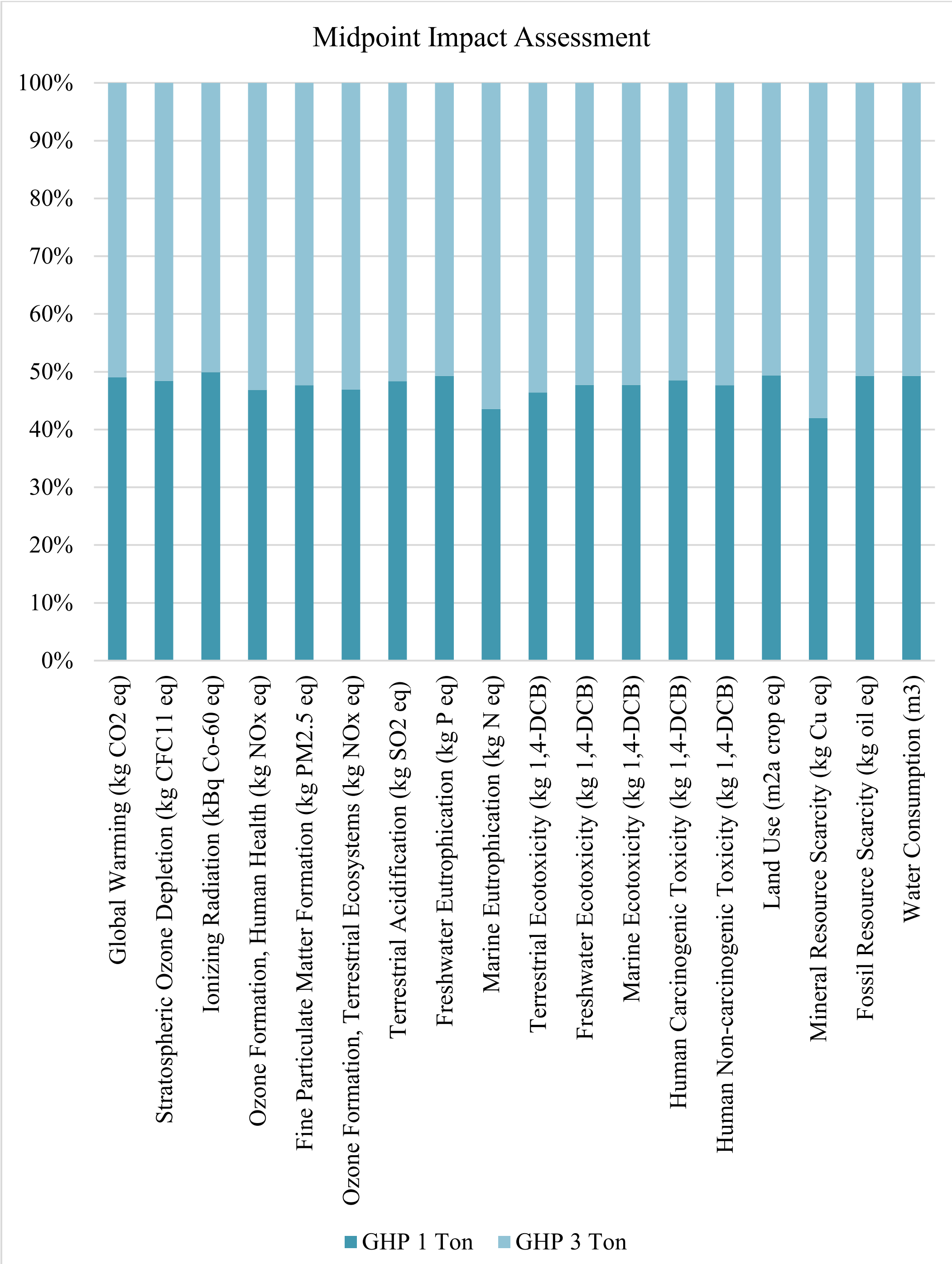
Impact Category	Mean	Median	SD	CV	2.50%	97.50%	SEM
Global Warming (kg CO2 eq)	1.79E+01	1.95E+01	8.55E+01	478.00%	-1.69E+02	1.81E+02	2.71E+00
Stratospheric Ozone Depletion (kg CFC11 eq)	2.17E+03	1.96E+03	1.10E+03	50.80%	1.22E+03	4.46E+03	3.48E+01
Ionizing Radiation (kBq Co-60 eq)	5.95E+00	5.90E+00	4.80E-01	8.07%	5.19E+00	7.16E+00	1.52E-02
Ozone Formation, Human Health (kg NOx eq)	1.21E-03	1.18E-03	2.21E-05	18.20%	8.68E-04	1.72E-03	6.98E-06
Fine Particulate Matter Formation (kg PM2.5 eq)	4.88E+00	4.85E+00	4.19E-01	8.58%	4.12E+00	5.78E+00	1.30E-03
Ozone Formation, Terrestrial Ecosystems (kg NOx eq)	4.81E+00	4.77E+00	4.17E-01	8.67%	4.04E+00	5.69E+00	1.32E-02
Terrestrial Acidification (kg SO2 eq)	2.59E+00	2.54E+00	4.39E-01	17.00%	1.84E+00	3.59E+00	1.39E-02
Freshwater Eutrophication (kg P eq)	9.49E-02	9.41E-02	9.76E-03	10.30%	7.87E-02	1.16E-01	3.08E-04
Marine Eutrophication (kg N eq)	5.40E+01	4.30E+01	4.08E+01	75.50%	2.13E+01	1.15E+02	1.29E+00
Terrestrial Ecotoxicity (kg 1,4-DCB)	2.52E+01	2.31E+01	9.05E+00	35.80%	1.42E+01	5.00E+01	2.86E-01
Freshwater Ecotoxicity (kg 1,4-DCB)	1.51E+03	8.76E+02	2.23E+03	148.00%	2.57E+02	7.34E+03	7.04E+01
Marine Ecotoxicity (kg 1,4-DCB)	1.08E+03	7.64E+02	1.07E+03	99.90%	2.66E+02	3.67E+03	3.40E+01
Human Carcinogenic Toxicity (kg 1,4-DCB)	7.83E+01	4.34E+01	1.44E+02	184.00%	1.90E+01	3.39E+02	4.56E+00
Human Non-carcinogenic Toxicity (kg 1,4-DCB)	2.92E+03	2.92E+03	1.01E+02	3.46%	2.74E+03	3.12E+03	3.20E+00
Land Use (m2a crop eq)	1.03E+00	8.47E-01	7.06E-01	68.70%	2.97E-01	2.82E+00	2.23E-02
Mineral Resource Scarcity (kg Cu eq)	3.86E+01	3.09E+01	2.90E+01	75.10%	1.54E+01	1.10E+02	1.96E-01
Fossil Resource Scarcity (kg oil eq)	9.00E+02	8.98E+02	7.56E+01	8.41%	7.63E+02	1.05E+03	2.39E+00
Water Consumption (m3)	2.03E+00	2.02E+00	1.45E-01	7.13%	1.80E+00	2.38E+00	4.58E-03

For completeness and to further evaluate the LCA we performed a sensitivity analysis which considers a smaller GHP system, and future renewable generation within the PJM ISO. We compared the 3-ton residential system with a 1-ton residential system (size of unit was at 33.3%, using 2 boreholes each at a depth of 80m). Both systems used the same amount of annual energy over the course of 25 years. The smaller unit allows for a lower environmental impact across all impact categories, though the highest contribution for both units was still the annual heating (followed by cooling) energy requirements. Based on this, the focus of technology development should move towards energy efficiency based on the capability of air conditioning retention for the building as well as efficiency of the HVAC unit to allow for lower energy requirements.

Table 11: Midpoint Sensitivity Analysis of GHP Unit Size

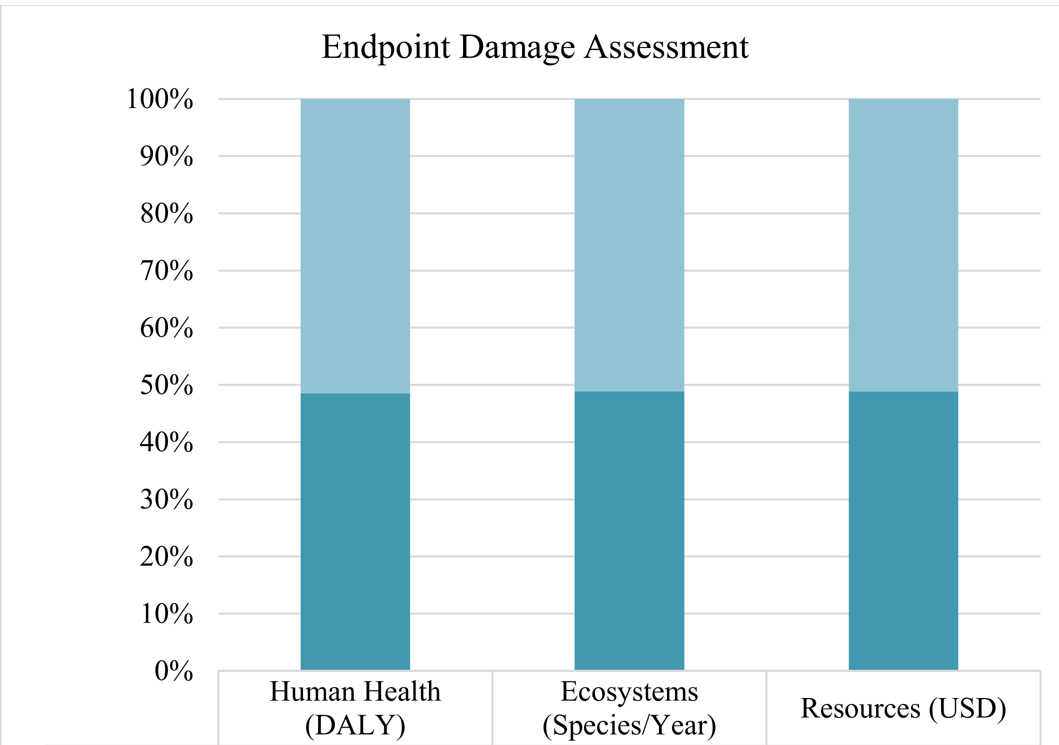
Impact Category	GHP 1 Ton	GHP 3 Ton
Global Warming (kg CO2 eq)	9.09E+04	9.45E+04
Stratospheric Ozone Depletion (kg CFC11 eq)	4.58E-02	4.88E-02
Ionizing Radiation (kBq Co-60 eq)	4.59E+04	4.60E+04
Ozone Formation, Human Health (kg NOx eq)	1.66E+02	1.88E+02
Fine Particulate Matter Formation (kg PM2.5 eq)	6.76E+01	7.42E+01
Ozone Formation, Terrestrial Ecosystems (kg NOx eq)	1.69E+02	1.91E+02
Terrestrial Acidification (kg SO2 eq)	1.91E+02	2.04E+02
Freshwater Eutrophication (kg P eq)	3.12E+01	3.21E+01
Marine Eutrophication (kg N eq)	3.36E+00	4.35E+00
Terrestrial Ecotoxicity (kg 1,4-DCB)	7.18E+04	8.29E+04
Freshwater Ecotoxicity (kg 1,4-DCB)	1.26E+03	1.38E+03
Marine Ecotoxicity (kg 1,4-DCB)	1.77E+03	1.94E+03
Human Carcinogenic Toxicity (kg 1,4-DCB)	2.61E+03	2.77E+03
Human Non-carcinogenic Toxicity (kg 1,4-DCB)	3.61E+04	3.96E+04
Land Use (m2a crop eq)	7.86E+02	8.06E+02
Mineral Resource Scarcity (kg Cu eq)	1.00E+02	1.38E+02
Fossil Resource Scarcity (kg oil eq)	2.77E+04	2.85E+04
Water Consumption (m3)	4.38E+02	4.51E+02

Figure 19: Midpoint Sensitivity Analysis of GHP Unit Size



The endpoint analysis shows similar results, with marginally lower impact for the 1-ton unit, the largest difference being human health where there is an impact of 0.0145 DALY compared to 0.0154 DALY. Important to note that despite the size the difference in endpoint impact categories is still within 5-6% of each other. Size of the unit is substantially less significant than the energy requirements of a household.

Figure 20: Endpoint Sensitivity Analysis of GHP Unit Size



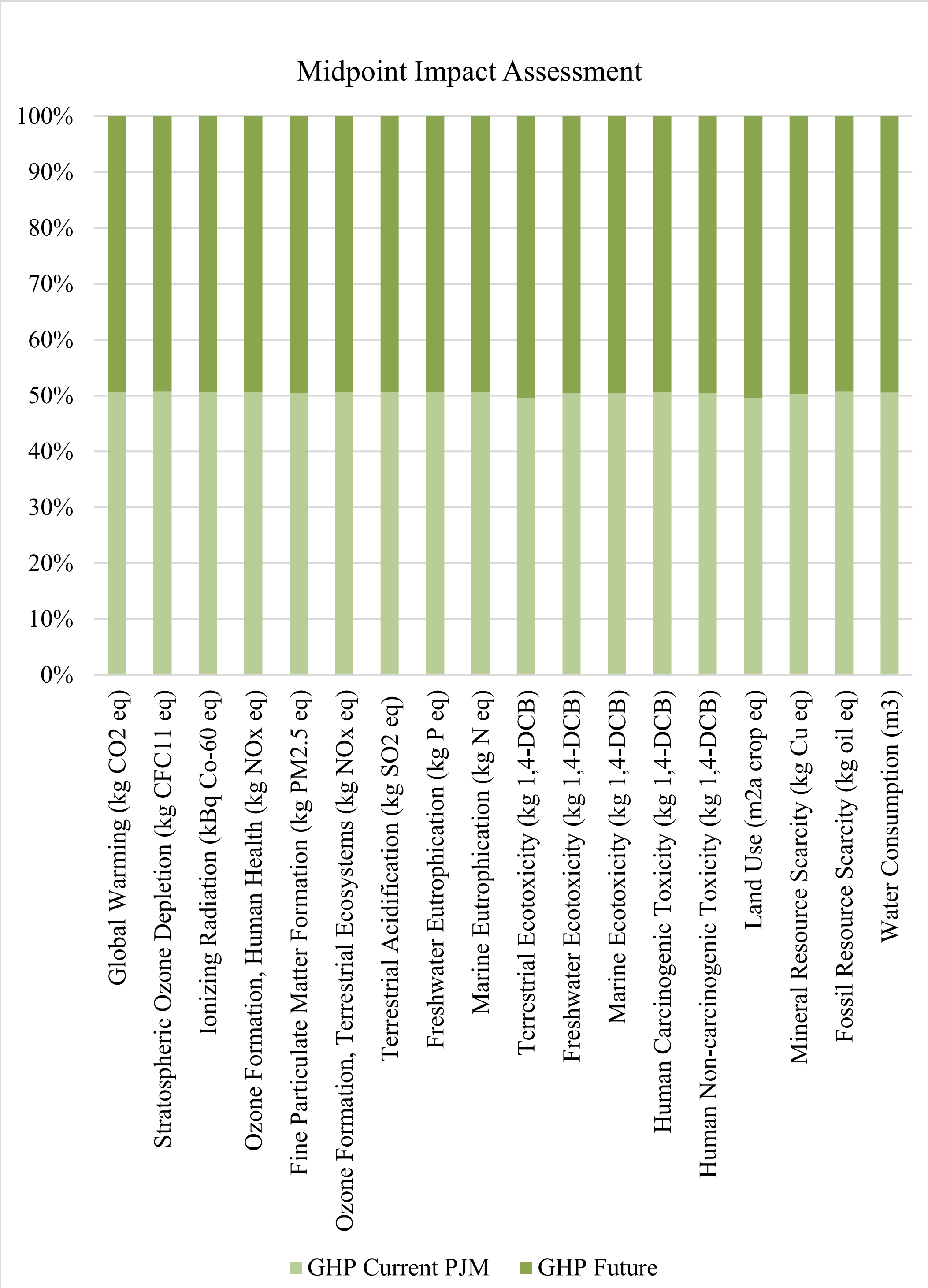
	Human Health (DALY)	Ecosystems (Species/Year)	Resources (USD)
GHP 3 Ton	1.54E-01	3.69E-03	7.06E+03
GHP 1 Ton	1.45E-01	3.53E-03	6.73E+03

We also completed a sensitivity analysis to explore the annual operation of a 3 ton unit in New Jersey using the current PJM energy generation mix and a 'future' mix which included a 20% increase of renewable energy generation while the remaining energy generation remained the same, albeit with new percentages (oil 0.2%, coal 28.39%, nuclear 34.13%, ng 30.87%, renewable 6.41%). This new energy mix shows a lower environmental impact across most midpoint impact categories. Terrestrial ecotoxicity and land use impact categories were shown in the future PJM energy generation mix, which could be attributed to increased generation from grid supply solar photovoltaics and associated land use changes. However, across all impact categories there was a difference within 3%, which is marginal. While an increase in renewable energy provides some mid-term environmental benefit the focus of future energy generation should not only focus on increased renewables but decreased reliance on fossil fuels to see a greater impact.

Table 12: Midpoint Sensitivity Analysis of PJM Energy Generation Mix

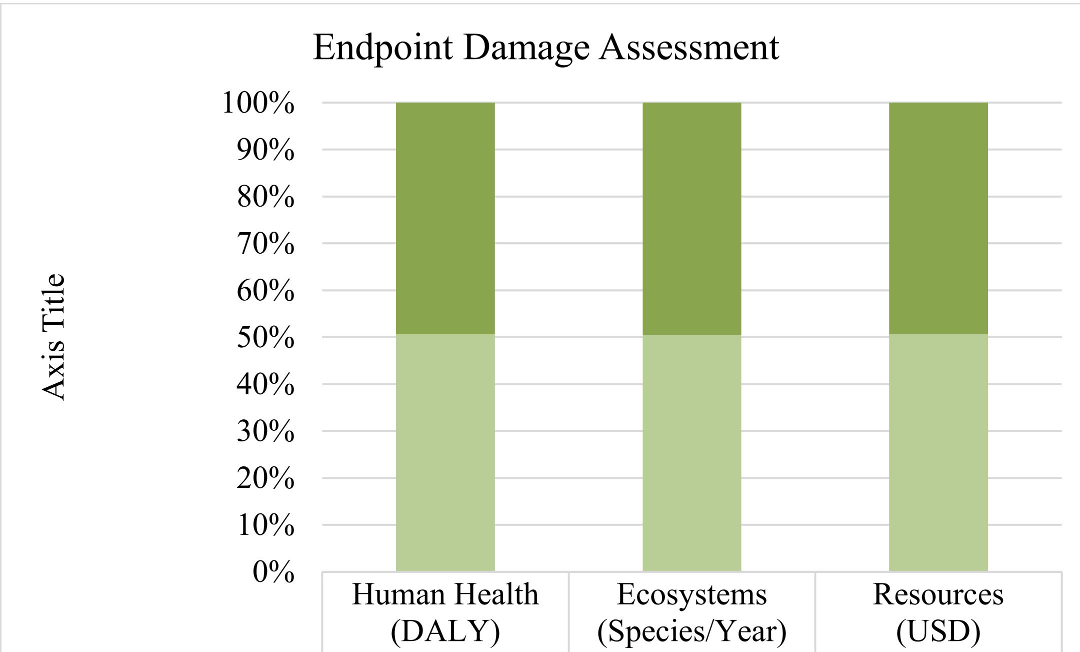
Impact Category	GHP Current PJM	GHP Future PJM
Global Warming (kg CO2 eq)	2.73E+03	2.66E+03
Stratospheric Ozone Depletion (kg CFC11 eq)	1.07E-03	1.04E-03
Ionizing Radiation (kBq Co-60 eq)	1.53E+03	1.49E+03
Ozone Formation, Human Health (kg NOx eq)	4.18E+00	4.07E+00
Fine Particulate Matter Formation (kg PM2.5 eq)	1.62E+00	1.59E+00
Ozone Formation, Terrestrial Ecosystems (kg NOx eq)	4.25E+00	4.14E+00
Terrestrial Acidification (kg SO2 eq)	4.66E+00	4.55E+00
Freshwater Eutrophication (kg P eq)	1.02E+00	9.93E-01
Marine Eutrophication (kg N eq)	9.48E-02	9.24E-02
Terrestrial Ecotoxicity (kg 1,4-DCB)	1.47E+03	1.50E+03
Freshwater Ecotoxicity (kg 1,4-DCB)	3.92E+01	3.84E+01
Marine Ecotoxicity (kg 1,4-DCB)	5.44E+01	5.34E+01
Human Carcinogenic Toxicity (kg 1,4-DCB)	8.20E+01	8.01E+01
Human Non-carcinogenic Toxicity (kg 1,4-DCB)	1.11E+03	1.09E+03
Land Use (m2a crop eq)	2.47E+01	2.51E+01
Mineral Resource Scarcity (kg Cu eq)	2.55E+00	2.52E+00
Fossil Resource Scarcity (kg oil eq)	8.37E+02	8.14E+02
Water Consumption (m3)	1.36E+01	1.33E+01

Figure 21: Midpoint Sensitivity Analysis of PJM Energy Generation Mix



The endpoint analysis shows similar results, with the largest difference in resource availability where the current PJM energy mix has an impact of 186 USD and the future PJM energy mix has an impact of 181 USD, showing that increasing reliance on renewable energy generation will not only decrease the environmental impact but has a lower cost as well. While these findings show positive change, all findings are still within a 3% difference, strengthening the argument that increasing renewables in addition to decreasing fossil fuel-based energy generation should be a focus of environmental planning

Figure 22: Endpoint Sensitivity Analysis of PJM Energy Generation Mix



	Human Health (DALY)	Ecosystems (Species/Year)	Resources (USD)
GHP Future	4.03E-03	1.01E-05	1.81E+02
GHP Current PJM	4.13E-03	1.03E-05	1.86E+02

3.6 Discussion

The life cycle analysis of a 3 ton GHP system showed that the 25 year operation of the system unit (primarily space heating) was the largest contributor to negative environmental impacts. As we see the physical components and installation of the GHP system relatively low impact within the greater perspective, these findings support how the focus of energy efficiency systems for residential space heating and cooling should focus on the relative efficiency of HVAC systems and building heat retention. By focusing on the units that work in conjunction with a GHP system, household can expect to use less energy to reach their space heating and cooling needs which would lead to an even lower environmental impact.

The comparative analysis of a 3 ton GHP system operating in New Jersey, and accessing energy generated in PJM, compared to operating in the United States generation energy mix from Ecoinvent, showed that operation in New Jersey is relatively more expensive at 213 USD compared to 152 USD in the U.S. These findings could be due to transportation costs associated with the various fossil fuel types used in other areas of the country where there is fossil fuel resources and generator demand for those fuels.

The comparative analysis of a 3 ton GHP system operating to other means of household heating and cooling, showed that the GHP system had the lowest environmental impact across all midpoint impact categories, followed by natural gas, oil, and electricity. The endpoint analysis showed similar results, where the GHP system showed a minimum of 10% less overall impact on environment, human health, and resource availability compared to the other means of space heating and cooling. These findings show how GHP systems are substantially more energy efficient, even without considering the relative efficiency of building heat retention or HVAC system efficiency.

The sensitivity analysis of the GHP system size shows that a smaller unit has relatively lower environmental impact. However, it is still the energy requirements for heating and cooling that holds the highest impact. This finding supports that GHP systems allow for a great deal of energy efficiency compared to other means. We further explored the operation of GHP systems within a 'future' PJM energy generation mix, assuming a 20% increase in renewable energy generation. We found that this increase in renewables allows the GHP system to have an even lower environmental impact, albeit marginal. This finding shows that the focus of energy generation should not only be to increase renewable energy generation, but also to decrease reliance on fossil fuels.

With all clean energy technologies, there are barriers to adoption for GHP systems which include high upfront costs, lack of consumer knowledge and limited developed supply chains. Furthermore, government incentives for this technology can vary greatly from state to state in the U.S. Actions described in the literature that would address the barriers and facilitate rapid growth of GHP industry include collecting more data on the costs and benefits of GHP systems, assessing the national benefits of GHP deployment, the streamlining and establishment of a nationwide incentive program to fund GHP infrastructure, the development of analyses and tools to enable the lowest life-cycle-cost (Hughes 2008, Liu et al 2013, Ozgener 2007, Bakirci 2010). When new insights can be provided such as in the results of our LCA, the business case for policy buy in becomes possible.

3.7 Conclusion

In this study we perform an LCA to evaluate benefits and impacts of GHP energy efficiency for residential systems in New Jersey. The system boundaries in our analysis include the drilling and installation of the borehole heat exchanger, the manufacturing and installation of the heat pump, the operation and maintenance of the system, and the disposal of the system components. The results of the ReCiPe hierarchical midpoint and endpoint analyses highlight environmental impacts across the categories of climate change, ozone depletion, photochemical ozone creation, human toxicity, ecotoxicity, eutrophication, acidification, land and water stress, and resource depletion. To compare the overall cradle-to-grave implications of GHP in New Jersey, we conduct the endpoint analysis to evaluate impacts across heating and electric air conditioning scenarios of fuel oil, natural gas, and electricity which highlights the cost savings as well as human health, and ecosystem. We show that annual operation of a GHP unit for heating and cooling holds a significantly lower impact for each sustainability metric. The results provided in this research can provide supporting information in future policy development in New Jersey. Our procedure can be modified in future analyses to conduct the GHP LCA under various generation portfolio fuel mixes scenarios based on anticipated additional deployment of clean energy as described in the New Jersey 2019 Energy Master Plan.

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4 Evaluating Solar Photovoltaic Potential with Hosting Capacity Interpolation, Suitability Models, and Remote Sensing

4.1 Introduction

In this chapter we utilize spatial economics to investigate solar photovoltaic energy potential in New Jersey. The methods used include a suitability siting model for solar photovoltaic systems across multiple markets, hosting capacity analysis, remote sensing analysis of rooftop infrastructure and solar radiation estimates. The goal of this research is to test the following hypotheses: 1) Is solar photovoltaic hosting capacity uniform throughout the electric distribution territories of New Jersey? 2) How can municipal-wide remote sensing analyses be used to provide high resolution insights specific to solar potential? 3) What can suitability models tell us about solar siting potential across New Jersey?

Solar photovoltaic energy will play an important role in the future of clean energy on global, national, and local scales (Engel-Cox, 2020). Benefits of solar photovoltaic energy are centered around avoiding emissions associated with the fossil fuel electricity generation sector, which is the largest contributor to carbon dioxide emissions in the United States (Singh, 2013). Although theoretical concepts of the photovoltaic effect have been studied since the nineteenth century, practical applications for electric generation were not developed until the 1950s (Singh, 2013; Mishra, 2020). Solar energy has become increasingly utilized over the past three decades as supply chains, efficiency, and affordability of the technology improved (Feldman, 2020; Singh, 2008).

Modern solar photovoltaic systems are composed of photovoltaic modules, electrical inverters, and installation equipment. Electrical generation occurs as solar radiation excites electrons within the silicon-based semiconductor material of a solar cell. Solar modules are made up of several of these cells enclosed in a glass and metal panel. Solar arrays (systems) are the integration of several solar modules, orientated to maximize exposure to solar radiation. Electricity is generated in the form of direct current (DC) and is converted to alternating current (AC) using an inverter. Although there are energy losses as a result of this conversion, it is required for integration into the larger energy system (Hadi, 2020).

Installation equipment refers to the mechanical infrastructure used to secure the solar array on the landscape. The main installation types used in the United States are roof mounted, ground mounted, and canopy (Abu-Rayash, 2020; Pokhrel, 2020). Roof mounted systems are commonly used for residential photovoltaics (Abu-Rayash, 2020). Ground mounted systems are frequently larger and are ideally located on degraded lands such as landfills or brownfields to maximize environmental benefits (Heeter, 2020). Solar canopies are commonly installed on impervious surfaces such as parking lots (Pokhrel, 2013). The limitations of installation equipment is an important consideration when designing a solar array and identifying feasible siting locations (Abu-Rayash, 2020). Modern photovoltaic technology is scalable and can be integrated with other energy technologies such as battery storage and microgrids, making it a strong contributor to future generation portfolios (Zobaa et al, 2011; Lewis et al, 2007; Wang et al, 2014; Maity et al, 2010).

Solar photovoltaics can function both connected and disconnected to energy distribution systems. Disconnected systems are commonly used to provide energy access in remote areas and parts of the developing world, where energy security and reliability is limited (Miller, 2000). Interconnected solar photovoltaics dominate global deployment, and pose much more complex issues of environmental impact, economic feasibility, and public policy (Branker, 2011; Singh, 2013; Coddington, 2012; Feldman, 2020). The three established markets of solar photovoltaics in the Unites States include residential, commercial-industrial, and utility-scale (Feldman, 2020). Residential, commercial and industrial applications operate under the net metering (behind the meter) billing mechanism. In this approach, energy consumption is offset by a local photovoltaic system, with additional generation being injected into the distribution system. Utility-scale photovoltaic systems operate as solar powerplants, with all generation entering the distribution system. A hybrid approach, known as distributed generation (virtual net metering), is an emerging clean energy strategy (Feldman, 2020; Heeter, 2020). In distributed generation, a photovoltaic system serves multiple consumers located in the general proximity of the array and distributes energy using the pre-existing distribution infrastructure (Heeter, 2020).

Residential net metering systems are designed to offset the electricity consumption of a homeowner (Comello, 2017). In this scenario, a solar developer and residential homeowner will contractually agree to a sale of equipment, lease, or power purchase agreement (PPA) (Comello, 2017). Residential net metering systems are much smaller than their commercial-industrial counterparts and require stringent financial qualifications for the homeowner (Londo, 2020). These systems require viable roof space with sufficient solar radiation exposure to meet the capacity requirements to make a system economically viable to both the developer and consumer (Londo, 2020).

Commercial and industrial applications of net metering can benefit from economies of scale related to high energy demand associated with manufacturing, refrigeration, and other energy intensive industries (Heeter, 2014). Furthermore, industrial buildings often have sufficient roof space with optimal solar radiation exposure (Heeter, 2014). In industrial areas net metering can provide additional benefits of reducing the need for nearby fossil generation and alleviate grid congestion constraints (Heeter, 2014).

Distributed power generation is growing in popularity in the United States (Blaabjerg, 2006). This approach increases clean energy access to consumers by removing roadblocks of traditional net metering, such as home ownership, roof quality requirements, and long-term commitments to lease programs or equipment ownership (Heeter, 2020). Community solar programs are distributed power generation policies which targets renters and low to moderate income (LMI) participants (Chan, 2017). In community solar, electricity customers subscribe to a solar company as they would other utilities like cable or telecommunications, and purchase electricity from a solar array in a location other than their property (Heeter, 2020). This creates an opportunity for more individuals to access clean energy and creates added economic benefits for solar developers such as improved pricing schedules and the economies of scale associated with larger systems (Heeter, 2020; Chan, 2017).

Across all photovoltaic systems, array design requires many site-specific details describing the proposed location of the system (Perez, 1997). For ground mounted arrays, environmental factors such as land use, slope, and flood hazards are critical in determining site suitability (Wolfe, 2012). In rooftop mounted systems, developers must evaluate building geometry, roof quality, and estimate shading from vegetation and other obstructions (Wolfe, 2012; Perez, 1997). Traditional evaluation techniques include many in situ measurements that are time and labor intensive. Furthermore, occupational hazards such as roof inspection can put individuals at risk (Bakhiyi, 2014). The time and labor costs associated with evaluating these design considerations is a major factor in determining the levelized cost of energy (LCOE) and overall economic feasibility of a project (Branker, 2011). Driving down the LCOE of solar photovoltaics is required to decrease costs and increase solar generation across the United States and internationally (Said, 2015). Siting considerations are also considered when determining likely build out scenarios across solar markets (Burns, 2012).

As solar photovoltaic systems commence operation, utilities are required to ensure that the additional generation entering the distribution system does not negatively impact electric power quality or reliability (Horowitz, 2018). Hosting capacity of a distribution system is a means of estimating additional solar capacity that can be interconnected to a distribution system without requiring infrastructure upgrades (Horowitz, 2018). Hosting capacity is represented at various spatial scales including substations, feeder, and local nodal levels (Horowitz, 2018). Upgrading solar hosting capacity of distribution systems can be prohibitively expensive, especially for smaller solar systems (Horowitz, 2018). Long term planning of solar generation will need to consider the costs associated with upgrades and improvements required in the transmission and distribution infrastructure, and the cost burden that will ultimately impact ratepayers (Coddington, 2012).

4.2 Literature Review

Solar energy is discussed extensively in environmental, socio-economic, and engineering literature (Branker, 2011; Burns, 2012; Stoppato, 2008; Fthenakis, 1984; Buckman, 2011). Studies on this topic are commonly divided into the sub-categories of emerging photovoltaic technology (Fthenakis, 1984; Woyte, 2003), economic theory across the energy sector and global trade (Branker, 2011; Said, 2015), place based technical assessments (Woyte, 2003), energy equity in social systems (Mulvaney, 2013); and policy dynamics in the context of a growing clean energy economy (Sing, 2013; Burns, 2012). Literature describing solar policies and financial support regimes across the United States are the basis of the spatial economic approaches we use in our investigation. Solar policies are fluid from state to state, and heavily dependent on energy markets (Burns, 2012, Buckman, 2011; Yin, 2010). Supporting policies in the United States include federal tax credits, cash rebates, net metering mechanisms, renewable portfolio standards, and solar renewable energy credits (SCRECs) (Burns, 2012; Wiser, 2010; Coulon, 2015). Solar policy instruments and support regimes have been dynamic over time in attempts to expand the solar industry and optimize the environmental benefits (Burns, 2012).

Literature covering the geographic based approaches for solar technology investigates demographic influence on clean energy accessibility, land use conservation, evaluating risks of natural hazards, and remote sensing (Renga et al, 2014; Talavera et al, 2015; Sun et al, 2013; Hofierka et al, 2009; Denhol et al, 2007; Carneiro et al, 2009; Jochem et al, 2009; Lukac et al, 2013; Suomalainen et al, 2017, and Burns et al, 2012). Visual references and cartographic techniques are also discussed as preliminary research approach. However, it can be insufficient in fully quantifying and understanding geographically based issues (Hegarty, 2010; Anselin, 1995). Spatial analysis methods are more sophisticated than cartographic methods and can give insight into driving forces of clean energy success and make it possible to model future policy scenarios under projected conditions of climate change, political will, and stakeholder action (Anselin, 1995; Zomer, 2008). Spatial analysis approaches are critical to further analyze the spatial effects of model inputs and provide accurate interpretations of causational relationships within results (Anselin, 1996; Bailey, 1995). Among the myriad of spatial analysis methods, vector and raster-based suitability modeling are particularly useful in predicting future scenarios of clean energy deployment and other climate related issues (Zomer, 2008). Indexing and reclassifying suitability model inputs is common practice in these types of investigations as a means to scale qualitative data as it relates to the subject matter and integrate multiple input criteria in a weighted additive format (Store 2001; Charabi, 2011; Cutter, 2012; Singh & Vedwan, 2015). The field of spatial analysis is used across many disciplines to conduct descriptive and inferential statistical analyses (Store, 2001; Rangel, 2010; Páez, 2004). Additionally, zonal statistics is an approach that is used to collect and summarize spatial information within a defined study area or boundary (Anselin, 1993; Sharma, 2011).

Spatial interpolation methods, based on spatial autocorrelation, are useful in estimating gaps in spatial data (Lam, 1983). Spatial autocorrelation theory postulates that all geographic features are related, and features within close proximity are more related than those further apart (Tobler, 1970). The results from analyzing spatial autocorrelation is a measure of spatial heterogeneity of geographic features (Ord, 1995). Interpolation leverages autocorrelation to predict geographic data values across an area (Lam, 1983). Spatial autocorrelation and interpolation methods are useful in clean energy spatial analysis to analyze model inputs, and predict future outcomes, particularly when there are data gaps (Li, 2014; Lam, 1983; Anselin, 1993; Ord, 1995).

The aspects of society and the environment that are analyzed in the context of the clean energy economy and climate change hazards occur at numerous spatial and temporal scales (Cutter, 1996; Fekete et al, 2010). To adequately investigate these systems, it is required to examine the variation among scales, and investigate these systems across multiple scales (Canton, 2011, Lindstrom, 2013). Scale of geographic data is a way to describe the spatial extent, shape, size, and orientation of a geographic feature being measured (Atkinson and Tate, 2000). In climate adaptation and mitigation literature, spatial analysis methods often focus on a single scale, or integrate a multi-scale approach, as seen in (Cutter, 1996; Cutter et al, 2000; Cutter et al, 2003; o'Brien et al, 2004; Cutter et al., 2008; Burton, 2010; Fekete et al., 2010; Petrosillo et al., 2010; Paquin et al., 2016). When study areas span large areas, it is common for input data to be of coarse resolution (Cutter et al., 2003). Conversely, as investigations target smaller study areas, a higher resolution quality of input data is used, or a combination of coarse and high resolution depending on the nature of the specific input data (Cutter, 1996; Comfort et al., 1999; Cutter et al., 2000; Williams and Kapustka, 2000; McLaughlin et al., 2002; Cutter et al., 2003; Klemas, 2009; Fekete et al., 2010; Klemas, 2010, 2014; Nelson et al., 2015). Utilizing large spatial scales are a practical way to avoid noise in the input data. However, only resolution of this quality can be limiting in producing functional results for the application in a local setting where applied management efforts often occur (McLaughlin et al., 2002; Vatsa, 2004; Birkmann, 2007; Fekete et al, 2010, McLaughlin and Cooper, 2010). Uncertainty and error in geographic information is a function of spatial scale. Comprehensive and precise results demand data spanning multiple scales in to optimize analyses (Cutter et al., 2003; Adger et al., 2005; Birkmann, 2007; Fekete et al., 2010).

Remote sensing and aerial imagery interpretation are a means to collect vast amounts of data over large spatial extents (Klemas, 2009). This method is often more cost effect from a data quality approach when conducted on large scales. Remote sensing is a proven methodology for investigating the applicability renewable energy technology (Jochem et al, 2009; Kassner et a,l 2008; Carneiro et al, 2009; Lukac et al, 2013; Suomalainen 2017). When remotely sensed data such as Light Detection and Ranging (LiDAR) and high-resolution imagery are available, powerful analyses can be performed at minimal costs (Jochem et al, 2009). Large-scale three-dimensional modeling is computationally expensive, thus making this application limited to medium and small study areas (Carneiro et al, 2009).

4.3 Study Area

New Jersey is an ideal location for spatial-economic investigation of solar energy due to its history of installed photovoltaics, established solar industry and supply chains, and aggressive state policies that promote adoption. The solar industry in New Jersey is supported and regulated by the New Jersey Solar Act of 2012. This state law established the modern financial and regulatory mechanisms which determine how photovoltaics are installed across the State. The State's renewable portfolio standard (RPS), and Solar Renewable Energy Credit (SREC) programs are the driving economic forces for new solar generation. The RPS rules determine goals for clean energy electric generation. The SREC program is a generation-based incentive program that determines funding across project types. These laws and policies are dynamic and evolve overtime as goals are reach and solar markets fluctuate. Current political environments in the State are favorable to new solar programs that focus on increasing photovoltaics across sectors. As the regulatory agencies enter early stages of new policy development, such as the transition renewable energy credit (TREC) and community solar pilot programs, policy makers will benefit from investigations that highlight new opportunities and potential obstacle.

As of August 2019, there are 168 grid supply projects in New Jersey, with an aggregate capacity of 614 Megawatts. This is roughly 20% of the States total solar installed capacity. With over 115,000 systems, Net Metering (Behind the Meter) projects account for 2,341 Megawatts of capacity, accounting for 79% of the States solar capacity. The New Jersey net metering solar market is dominated by commercial and residential systems. Net metering projects are relatively flexible in their application. In New Jersey, there is a wide variety of customer types in which there is economic benefit to offset grid supplied energy with a collocated solar array. Although the commercial sector represents more capacity, residential systems are much more frequent.

This is important when considering the increased number of stakeholders and indirect economic benefits associated with a robust solar industry workforce. Residential photovoltaic systems provide economic benefits such as employment in the solar industry through sales, design, and installation. Although residential net metering is widespread throughout the State, there are significant barriers to entry for some, which can prevent adoption of this clean energy technology. Barriers include not having sufficient suitable space for the equipment, not owning your own home, financial restrictions.

Table 13: New Jersey Solar Installations

New Jersey Solar Photovoltaic System Installation by Interconnection Type			
Interconnection Type	**Number of Projects**	**Installed Capacity (kW)**	**Percent of Total Capacity**
Net Metering	115,303	2,341,014	79.2%
Grid Supply	168	614,214	20.8%
Total	115,471	2,955,228	100%
This data represents installed solar systems in New Jersey as of August 2019 and was collected from the New Jersey Board of Public Utilities Clean Energy Program			

Table 14: New Jersey Grid Supply Solar Installations

New Jersey Grid Supply System Installation by Solar Act Subsection			
Description	**Number of Projects**	**Installed Capacity (kW)**	**Percent of Total Capacity**
EDC	80	80,860	13.16%
Subjection q	31	194,412	31.65%
Subjection s	10	74,488	12.13%
Subjection t	14	141,929	23.11%
Pre-Solar Act	33	122,526	19.95%
Total	168	614,214	100%
This data represents installed grid supply solar systems in New Jersey across the Solar Act (2012) Subsections as of August 2019 and was collected from the New Jersey Board of Public Utilities Clean Energy Program. For a project to receive incentives it must qualify for one of the subsections listed below.			

Table 15: New Jersey Solar Act Subsections

New Jersey Solar Act (2012) Subsection Types for Grid Supply Photovoltaics	
Type	**Description**
Subjection q	Systems less than 10 MW in capacity injecting into grid
Subjection s	Systems installed on farmland
Subjection t	Systems installed on brownfields, historic fill, or properly closed landfills
The descriptions above are used to qualify potential solar photovoltaic systems for generation incentives within the New Jersey Solar Act (2012)	

Table 16: New Jersey Net Metering Solar Photovoltaic System Installations

New Jersey Net Metering System Installations by Customer Classification			
Classification Type	**Number of Projects**	**Installed Capacity (kW)**	**Percent of Total Capacity**
Commercial	4,546	1,077,038	46.0%
Farm	151	5,339	0.2%
Government	99	29,181	1.2%
Municipality	258	49,968	2.1%
Non-Profit	617	44,068	1.9%
Private University	12	1,224	0.1%
Public University	48	23,324	1.0%%
Residential	108,792	908,849	38.8%
School (Charter)	1	209	0.1%
School (Other)	110	35,345	1.5%
School (PublicK12)	610	164,946	7.0%
Other	59	1,523	0.1%
Total	115,303	2,341,014	100%
This data represents installed net metering solar systems in New Jersey by customer classification as of August 2019 and was collected from the New Jersey Board of Public Utilities Clean Energy Program.			

Recent community solar policy efforts in New Jersey, pose exciting opportunities to apply information from this study to new programs that expand access to clean energy. The State’s community solar pilot program was introduced in late 2019 with the goal of evaluating opportunities and challenges associated with a statewide virtual net metering policy. The program calls for a site host, a project developer, and an energy subscriber. The site host owns or leased land where the solar system will be installed. The developer designs, builds, and maintains the array. Developers or their partners are also responsible for acquiring subscribers. Subscribers are individuals or businesses that pays monthly based on their energy usage, or up front as a partial owner of the array. In the monthly subscription scheme, subscribers see deductions on their utility electrical bill based on the generation and sharing configuration of the community solar array administered by the developer.

The pilot program solicited 75 MW of solar capacity across 45 new solar projects that were evaluated and selected based on geographic, demographic, and economic factors. The pilot program is structured to promote siting projects on impervious surfaces and degraded lands such as brownfields and landfills. Additionally, projects are required to serve low-to-moderate-income (LMI) communities within the same electric distribution company (EDC) territory (N.J. Community Solar Pilot Program Application). Providing location-based insights into potential project locations with considerations of interconnection, conservation, and public preference will be critical in the development of future iterations of community solar in New Jersey.

4.4 Theoretical Framework

4.4.1 Study Rationale and Objectives

We identify a disconnect between the cross disciplinary evaluation techniques used throughout the modern literature and those currently applied to predict solar photovoltaic potential in New Jersey. Evaluating solar photovoltaic potential is needed for future clean energy policy (Engel-Cox, 2020). Physical and socioeconomic barriers exist in solar energy access, which must be addressed through comprehensive policy programs (Heeter, 2020). Spatial analysis and remote sensing are useful approaches in gathering and interpreting large amounts of information that is useful in estimating photovoltaics generation (Jochem, 2009). Our approach investigates multiple solar photovoltaic markets using geographic information systems and remote sensing. In combining these two approaches we are able to leverage emerging computational approaches to investigate clean energy suitability across spatial scales. The objectives of this chapter are to identify and evaluate the energy distribution infrastructure for predicting future deployment of photovoltaics for New Jersey, develop a multimarket suitability model for identifying areas for more targeted investigations, and deploy remote sensing techniques to evaluate flooding hazards, roof plane geometry, and solar radiation across three municipalities of the State.

4.4.2 Analytical Framework

Our cross analytical approach will utilize spatial analysis and remote sensing to draw conclusions on the future of solar photovoltaics in New Jersey through the lens of spatial economics. We focus our investigation on evaluating interconnection hosting capacity, suitability modeling across solar markets, remote sensing of solar radiation and roof infrastructure geometry.

Interconnection into the electricity distribution system is a critical component of all solar photovoltaic system planning and design (Ardani, 2015). This process involves evaluating the capacity of existing energy infrastructure to accept new load. Upgrades to transmission lines, distribution components, and installing new substations are very expensive and can take years to complete (Ardani, 2015). Electric distribution companies (EDC) in the State are maintaining the distribution infrastructure. In New Jersey, the four largest electric distribution companies are Orange Rockland Electric Company (REC), PSE&G, JCP&L, and Atlantic City Electric (ACE). These EDC's provide hosting capacity data to solar developers and energy regulators for a given interconnection point. Having access to a spatial surface data set representing solar photovoltaic hosting capacity can be useful to visualize areas in need of electricity infrastructure upgrades in the future. To set baseline data for future potential we perform an analysis to evaluate the hosting capacity for each EDC using spatial interpolation. We then use impervious surface spatial data of building footprints, and parking areas to identify locations and quantify interconnection potential for new photovoltaic systems across New Jersey. To further identify potential across sectors, we use tax parcel classification data to cross-reference the impervious data listed above. This results in geographic features with represent residential and nonresidential settings.

Statewide analytics of siting locations across solar markets using suitable models is needed for informed policy decision making. In New Jersey, relatively simple, single criteria analyses have been published by regulatory agencies, which show areas that may be suitable for new solar installations (NJDEP Solar Siting Analysis). We improve upon this method by developing three multi-criteria weighted overlay suitability models at the census tract scale with consideration across solar markets. In New Jersey, the ability of a residential customer to participate in net metering is determined by building stock, property classification, electricity retail rates, energy expenditures, and ability to financially quality for lease or power purchase agreement programs. We consider all of these inputs in our residential suitability model. In our second raster analysis we look to identify areas that are suitable for large ground mounted net metering and grid supply photovoltaic systems. Ground mounted systems in these markets are more common and pose more complex policy interpretations than their rooftop counterparts. We identify land use classifications that would be suitable based on available space, the built environment, and conservation of valued natural landscapes such as forests and wetlands. In the reclassification of land use land cover for this analysis we excluded single unit residential areas, water bodies, roadways, and the related nonviable land use classifications. In areas where it is possible to locate arrays but occur in areas that may pose safety hazards or reduce natural carbon sequestration, we assign low reclassification values. In nonresidential urban and compromised lands such as altered or barren lands we assign a high value. We also consider risks associated with the natural hazards of coastal storms and flooding into our analysis. In our third overlay analysis we aim to identify locations where potential community solar subscribers. In this assessment we identify renter occupied housing units, energy expenditures, and utility rates. We also use the ability to pay index as an indicator of a potential customer's inability to qualify for traditional residential solar. These inputs are used as they represent a sample of the population that are less likely to have access of a traditional residential net metering program.

Remote sensing is a practical approach to collecting vast amounts of high-resolution spatial data. Harnessing this powerful form of analysis is beginning to enter the clean energy arena. As more data becomes available for analysis, remote sensing techniques for evaluating potential clean energy projects will reduce the need for in situ measurements in the field. In the design of a photovoltaic array, site specific conditions determine if a project is feasible, how productive a proposed project may be, and what environmental risks are present. We use remote sensing to investigate solar potential in the three municipalities of Camden, Newark, and Atlantic City, New Jersey. We use LiDAR to collect roof plane geometry. We also derive a digital surface model of each municipality to evaluate storm surge hazards, and annual solar radiation. We selected these municipalities based on their distributed energy potential and hosting capacity characteristics.

4.5 Methodology

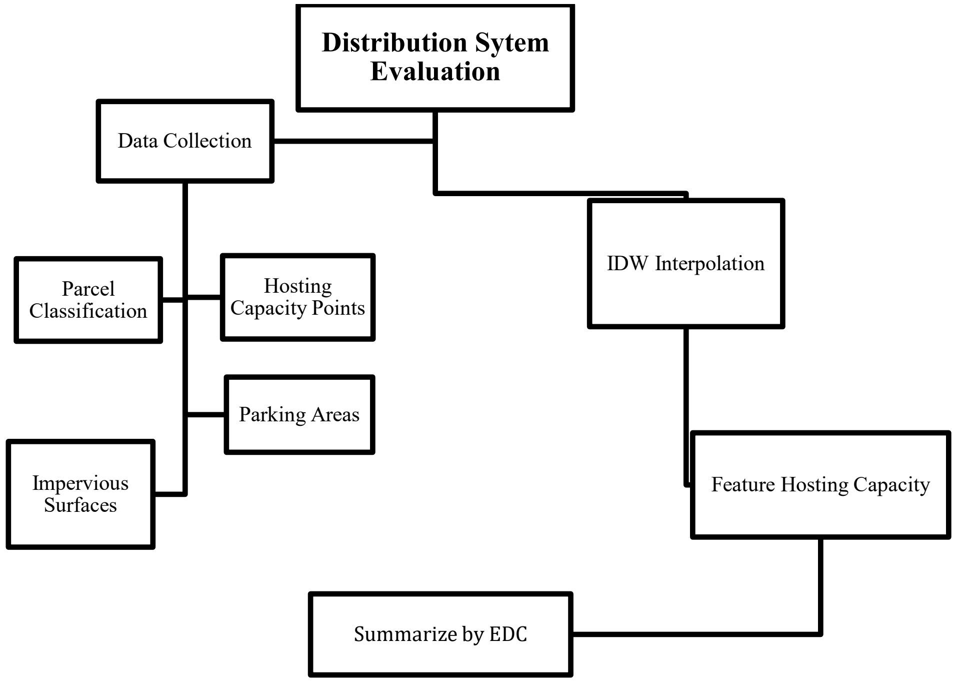
4.5.1 Solar Hosting Capacity Interpolation.

In our solar interconnection analysis, we use spatial data representing hosting capacity across electricity distribution system nodes within the electric distribution companies' territories of New Jersey. We also identify geographic features representing potential locations to site solar systems across sectors. We classify the hosting capacity of these features to imply interconnection considerations of future photovoltaic build out. The units of the hosting capacity data is in kilowatts of photovoltaic energy that can be interconnected without compromising the reliability of the local distribution system.

To perform this analysis, we need to first collect hosting capacity from the New Jersey Department of Environmental Protection. The hosting capacity data is sourced from the electric distribution companies. This data is shared in point and line vector formats. To draw information across the EDC territories we transform the hosting capacity vector data into a raster surface using inverse distance weighted interpolation (IDW). The resulting raster surface is a function of the weighted distance average of the data inputs (Watson and Philip 1985). This approach is well suited when sampling is dense in terms of location variation simulation. Limitations in terms of error is a function of number of input points and their spatial distribution (Watson and Philip, 1985). The influence of the input point data is isotropic because it is related to the distance, in any direction, from point to point (Philip and Watson, 1982). The density and values of the associated inputs were sufficiently dense to draw conclusions from this analysis, with areas of less point density, and more interpolated inaccuracies coincide with areas of low to no energy infrastructure development. Lines and point features that represent how much photovoltaic capacity is acceptable for a nodal circuit within the energy system were transformed into raster surface comprised of a matrix of cells, each cell representing our estimated hosting capacity. Upon the creation of this new dataset we then evaluated impervious surfaces known to be ideal for siting new solar systems. It is an important note that hosting capacity is not a single determinant factor in the capability of a system to be interconnected. To make this high-resolution data more functional in our analysis we normalize the data by transforming the interpolated surface into five classes. The inverse distance weighted surface is calculated on the principles of spatial autocorrelation. Using this approach, we are able to reduce noise in the data and apply the information on a functional spatial scale.

We classify the hosting capacity for these features into five categories based on the capacity of photovoltaic systems across solar markets. These include 50 kW, which is suitable to accept one or more residential arrays, 100 kW which would be able to accept a moderately sized net metering project or small community solar project, 1,000 kW (1MW) for community solar and smaller grid supply projects, 5,000 kW (5 MW) and EDC max for larger or multiple moderately sized arrays. The spatial data representing the impervious features was collected from the New Jersey Department of Environmental Protection, Bureau of Geographic Information Systems and Open Street Map (OSM). The original building footprint data was collected and analyzed using a combination of LiDAR point cloud classification, and object-oriented image classification. We determine the geographic union between the interpolated surface, and the host features using the *summarize within* tool and calculate summary statistics for the feature counts in each category using ArcGIS.

Figure 23: Hosting Capacity Methods Framework



4.5.2 Multi-Criteria Weighted Overlay Suitability Assessments

We selected the weighted overlay suitability model approach because of its applicability in incorporating several input raster datasets using a common scale of measurement and weighing each input based on its relative importance. This method requires all input raster datasets the be integer format of the same spatial unit. The cell size (resolution) was determined by the original bounds of the vector inputs and converted to a 10m by 10m resolution. This model produces functional results across the relatively large study area. Spatial data related to solar suitability was collected from a variety of sources including the New Jersey Department of Environmental Protection Bureau of Geographic Information Systems, the United States Census, and the National Renewable Energy Lab (NREL). The suitability indexing data sets including the Ability to Pay Index, Housing Unites by Vintage, Energy Burden, and Retail Electricity Rates, were collected from the NREL Solar for all web GIS portal. National data was collected as a geodatabase and processed for spatial extent and projection for optimization within the study area. All geoprocessing was performed using the New Jersey State Plane projected coordinate system.

4.5.2.1 Residential Suitability Model

In our assessment of residential net metering potential, we use a series of national data distilled down to statewide datasets at a census tract spatial resolution. Vector data sets that represent residential photovoltaic installation potential were collected and converted into a raster data set which was reclassified for the weighted overlay analysis. Identifying residential households is the first step in our analysis. The 2015 statewide land use land cover vector dataset produced by the New Jersey Department of Environmental Protection allowed for the isolation of single unit residential areas. This data is classified based on the widely used Anderson Land Use Land Cover (LULC) system. In our analysis we identified and isolated single unit residences. All other land use classifications are omitted in our overlay analysis.

Residential roof infrastructure influences the cost and feasibility of photovoltaic installation. We use the number of housing units by vintage, at the census tract level published by NREL, which is derived from 2011-2015 American Community Survey (ACS) 5-year tract estimates. As a proxy for building infrastructure we use housing unit vintage data was collected from U.S. Census Bureau (2015 ACS) to estimate building infrastructure quality. We assume newer buildings are more suitable to host solar photovoltaic installation equipment and census tracts with higher numbers of newer housing structures are more suitable to host new residential photovoltaic systems.

We use the NREL Ability to Pay Index as a proxy for a consumer's available household budget which would influence the financial qualifications of a homeowner that may wish to participate in a residential net metering program. This data set is defined as household income minus housing costs and has the spatial resolution of census tract. This data assumed housing costs are the sum of monthly bills of mortgages, rent, real estate taxes, fire hazard, flood insurance, utilities, and fuels. This data set was calculated using an Analytical Hierarchical Process (AHP) which is a weighting method used to reconcile the importance of income compared to housing costs. (Lin et al. 2018).

Retail rates of electricity will also influence the business case for a residential customer entering the net metering market. We incorporate this into our suitability model with average utility rates across the electric distribution companies of New Jersey. The average cost of electricity in price per kilowatt hours ($/kWh) was collected from the NREL solar for all web portal and is derived from the United States Energy Information Administration (U.S. EIA) form 861. Data included reported average monthly residential electric prices at the census tract level for 2016. We reclassify these prices and rank them from high to low as an input in the weighted overlay model. We also use electricity energy expenditures data which illustrates the price per month of electricity for all houses in a census tract. This data was also published by NREL and was derived from a weighted average household electricity expenditure from the Low-Income Energy Affordability program (LEAD). The map series and table above represent the spatial input data and its source that was used to develop our weighted overlay suitability model for residential photovoltaic systems. We leverage several data sources across the public domain to best incorporate opportunities and challenges for the residential market.

Figure 24: Residential Suitability Model Framework

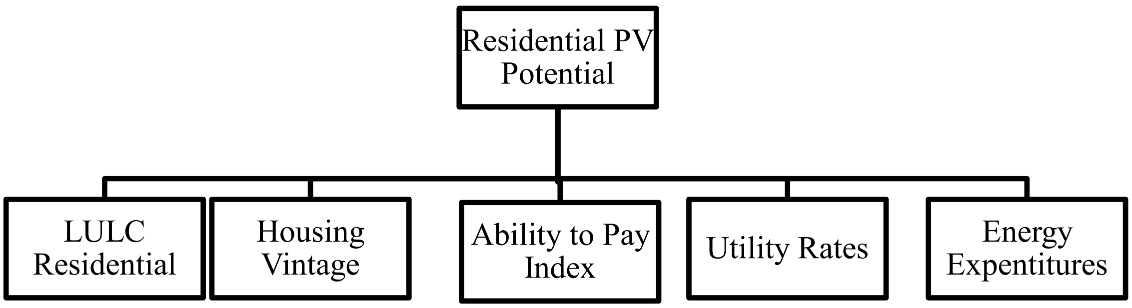
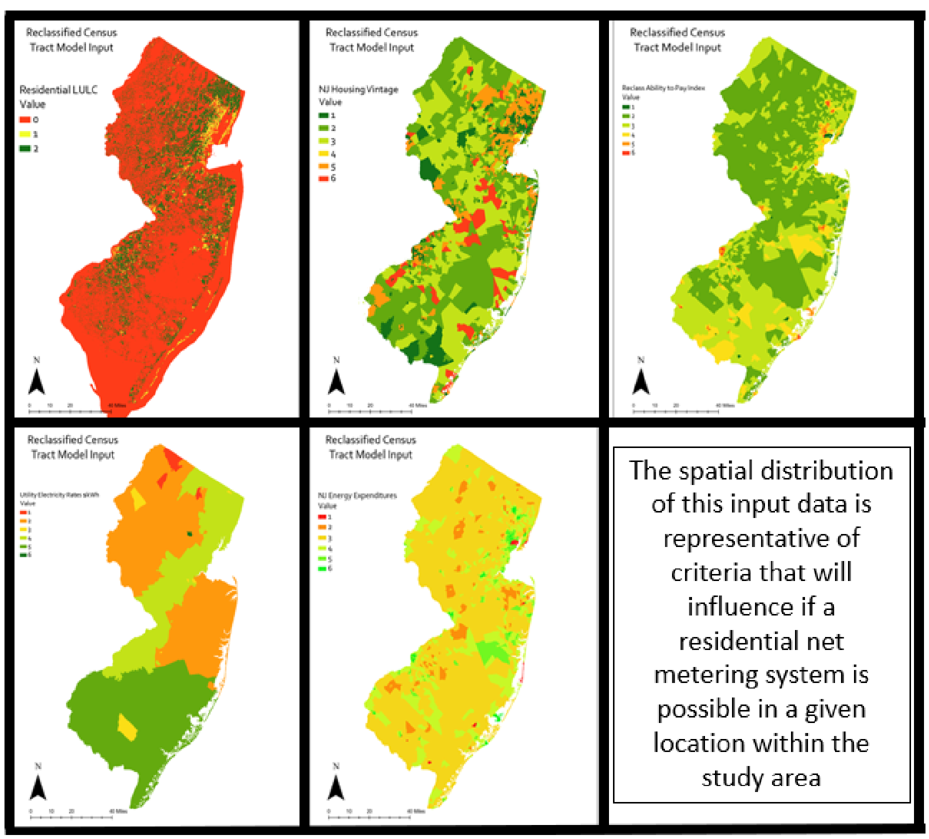


Figure 25: Residential Solar Suitability Model Inputs



4.5.2.2 Ground Mount Suitability Model

In our second suitability assessment we look to identify areas that are suitable for large ground mounted net metering and grid supply photovoltaic systems. Ground mounted installations are more common in grid supply and industrial-commercial net metering settings because of the space needed to site an array large enough to meet the capacity demands in these markets. Additionally, the LCOE is lower when system installations do not need to consider roof mounting conditions. Land use regulation in New Jersey are only restrictive to specific Anderson code classes, such as wetlands and preserved agricultural spaces. This can make evaluating new projects slightly more nuanced, particularly when utility grid supply arrays do not depend on state-regulated incentive mechanisms, but rather federal class II RECs and economies of scale associated with selling electricity into the wholesale energy market.

In this overlay analysis we interpret Anderson land use classifications that would be suitable based on available space, the built environment, and conservation of valued natural landscapes such as forests. In the reclassification of land use land cover for this analysis we excluded single unit residential areas, water bodies, roadways, and the related nonviable land use classifications. In areas where it is possible to locate arrays but occur in areas that may pose safety hazards or reduce natural carbon sequestration, we assign low reclassification values. In nonresidential urban and compromised lands such as altered or barren lands we assign a high value. We also consider risks associated with the natural hazards of coastal storms and flooding into our analysis using the Susceptibility to extreme weather events data published by NREL. This data is derived from event-specific indices, regional modeling, and the National Oceanic and Atmospheric Administration (NOAA) Sea, Lake, and Overland Surges From Hurricanes (SLOSH) model.

Figure 26: Ground Mount Suitability Model Framework

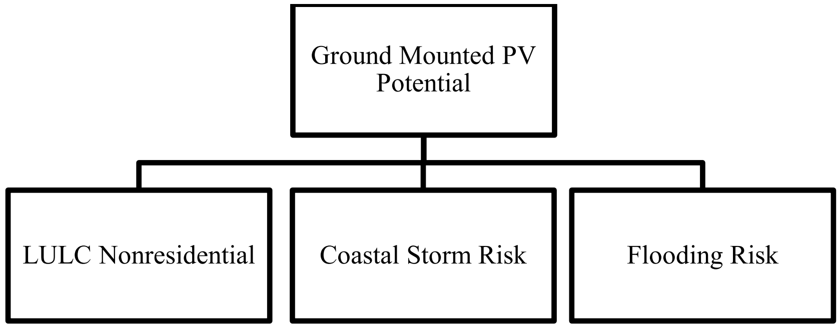
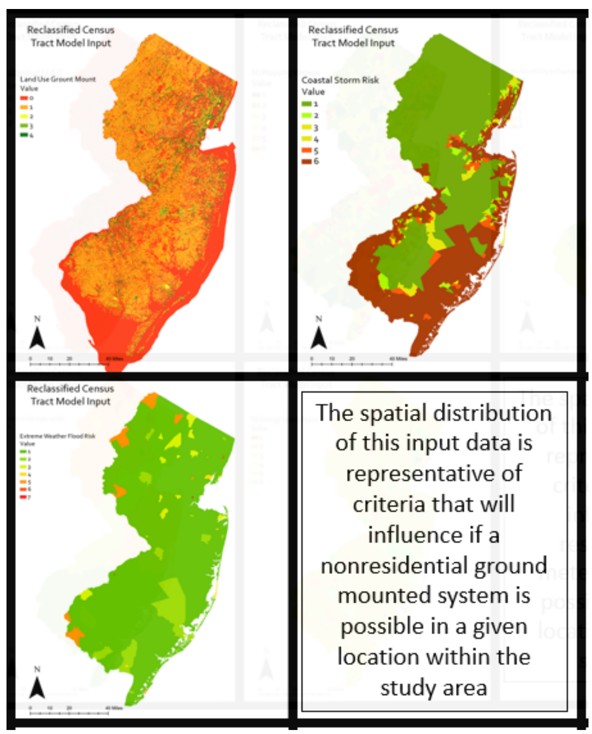


Figure 27: Ground Mounted Suitability Model Inputs



The map series in the figure above represents the spatial input data that is used to develop our weighted overlay suitability model for nonresidential ground mounted systems. This data includes reclassified land use land cover, coastal storm risks, and extreme weather flooding hazards. Values are reclassified and converted to raster format. In the parameters of our weighted overlay, we weigh the land use and land cover at fifty percent influence and the two natural hazard inputs at twenty five percent each based on site specific design measured that can be used to mitigate those hazards.

4.5.2.3 Community Solar Suitability Model

In our third and final weighted overlay suitability assessment we aim to identify locations where potential community solar customers are located based on the New Jersey Community Solar Pilot Program. In this analysis we classify the number renter occupied housing units, energy expenditures, and utility rates. These inputs are important in this model because they represent the individuals of a population that are less likely to be able to access the traditional residential net metering program described above. We than weight these inputs equally and perform the overlay analysis.

Figure 28: Community Solar Suitability Model Framework

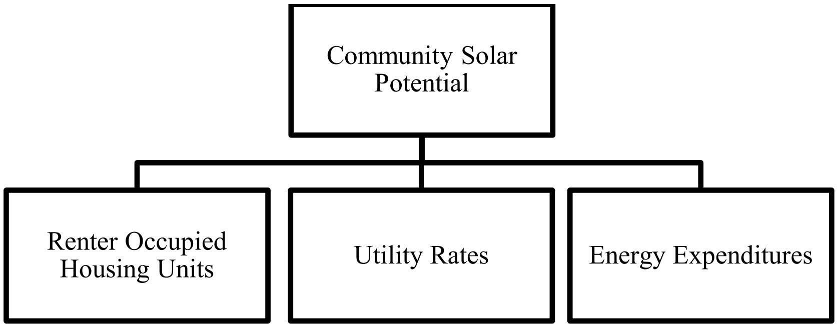
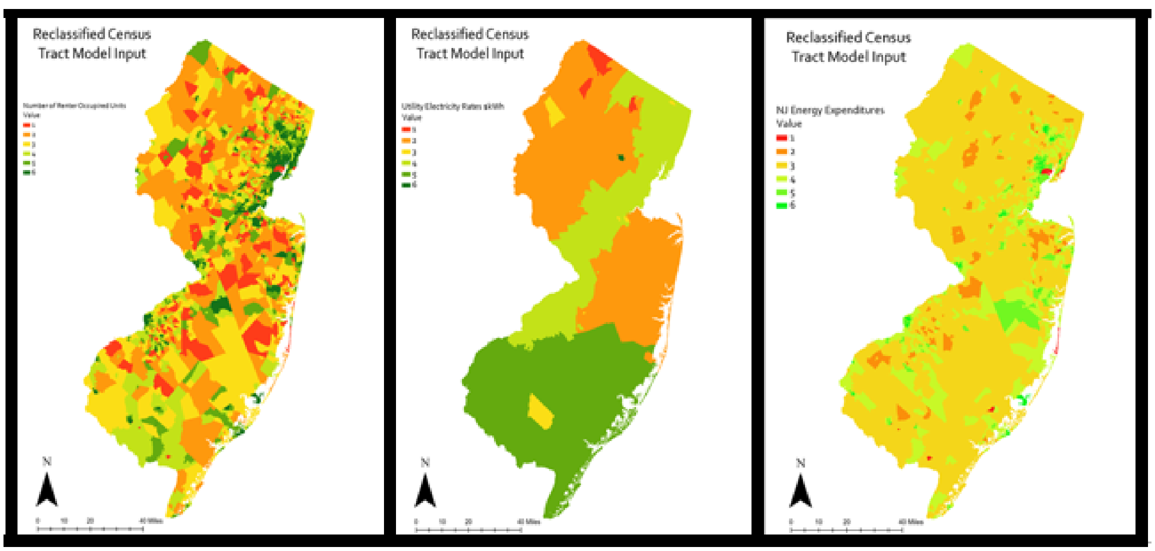


Figure 29: Community Solar Suitability Model Inputs



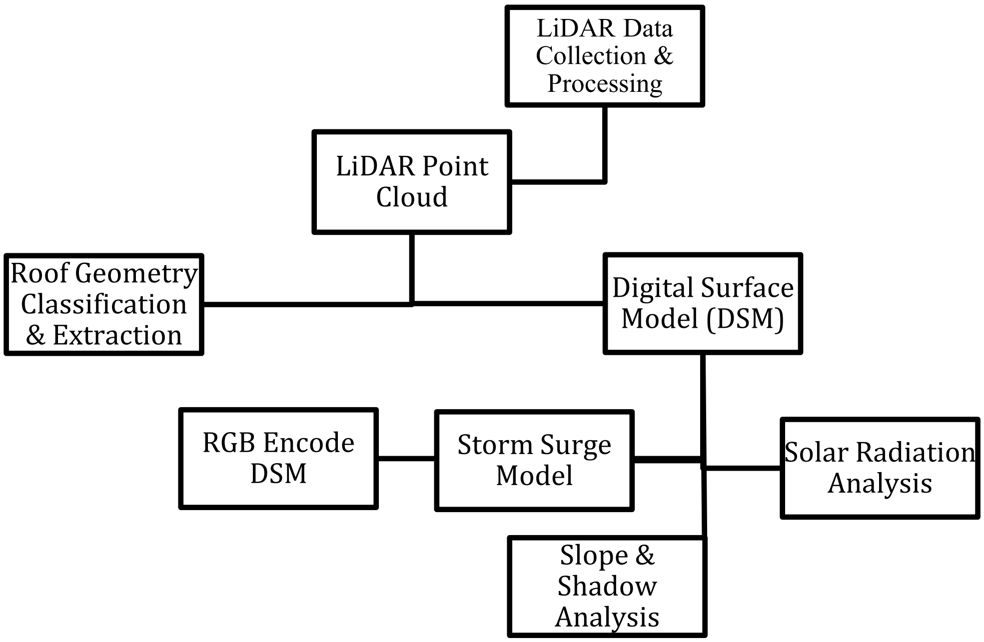
4.5.3 Municipal Remote Sensing Solar Analysis

In this section of our solar analysis we use remote sensing techniques to investigate solar potential as a case study of emerging clean energy evaluating approaches in the three municipalities of Camden, Newark, and Atlantic City, New Jersey. Due to the computational limitations associated with performing these processes, municipality scale is the largest coverage area practical with the computational power available to us at this time. We identify Newark, Camden, and Atlantic City for our analysis because of the potential for both net metering, and virtual net metering in the near future. Furthermore, the spatial interpolation methods for hosting capacity, and multi-market waited overlay suitability models highlighted these three municipalities for this higher resolution analytical approach.

The analysis workflow for these case studies begins with downloading publicly available LiDAR datasets from the NOAA digital coast and USGS Data clearing house. We than use remote sensing software, to classify and extract features from these point clouds. The classification process yields geometry of roof planes from the raw point cloud data. Additional analyses such as flood modeling, shadow identification, and solar radiation analyses are rooted in creating a digital surface model (DSM). A digital surface model is derived from LiDAR point cloud. The three-dimensional geometry of the surfaces in our analyses are calculated from hundreds of millions point locations with x, y, and z information representing their location is space. We begin our analysis of each municipality by downloading compressed LiDAR files (LAZ files) and extracting these compressed models into a functional LAS format. LiDAR data is published in a piece meal fashion, which requires the merging of several LAS datasets across the study area into a mosaic. The mosaic point cloud is the basis of our study. We used Quick Terrain Modeler (QTM v8.2.0) to merge the data and construct a digital surface model (DSM).

The DSM is a three-dimensional representation of the spatial geometry of all features collected by the fixed wing aircraft.

Figure 30: Remote Sensing Analyses Framework



4.5.2.1 Roof Plane Geometry

Identifying viable roof space is required for designing a photovoltaic system and evaluating solar energy potential across areas. Traditional methods of acquiring these measurements across an entire municipality would require a cost prohibitive amount of man hours in the field. To bridge this gap, we use LiDAR data to create three dimensional models and classify the geometry of these models to identify roof planes in the study areas. By adopting this process, we create new spatial information that would have been extremely time consuming and costly using traditional methods of human interpretation of imagery and manual computer aided design (CAD).

To isolate buildings and calculate the roof geometry we use the classification and extract functionality in the software. Additionally, we use imagery across the study area to create a colorized DSM encoding the RGB (Red, Green Blue) values to the LiDAR point cloud and DSM for Newark New Jersey. The results of this analysis allow us to visually inspect ground conditions with functional layouts of the actual roof space of the building yielding information on both potential shading obstructions and roof quality.

4.5.2.2 Storm Surge Model

For ground mounted systems in coastal environments, evaluating surface hydrology for evaluating flooding risks is needed to assess project feasibility. We use the LiDAR derived DSM described above to perform a storm surge flooding analysis for Atlantic City New Jersey. This process uses calculated elevation surfaces and simulates storm surge levels of 1 meter, 2 meter, and 3 meters. This approach is commonly referred to as a "bathtub approach" and is a way to perform a rapid assessment of flood hazards using the three-dimensional space of the study area.

4.5.2.3 Solar Radiation Model

Solar radiation estimates are needed for the design of a photovoltaic system. Throughout the solar industry, estimates of shading and solar resource availability are performed using in field measurement of sun paths for each individual roof plane of a potential project site. Tools such as the Solmetric *Suneye* require many hours of in situ observations and even more post processing time to remove errors within the images. We present an approach using ArcGIS Area Solar Radiation Tool to estimate solar radiation across the municipality of Camden. The tools using the DSM from the LiDAR data and predicted solar conditions for the entire year (2020). The result depicts potential energy sources per area with the unit of watts per square meter (W/m^2). This method calculated solar insolation and is computationally taxing. This particular model ran for several days to produce the final results.

4.6 Results

4.6.1 Solar Hosting Capacity Interpolation

The spatial distribution of the hosting capacity appears to be spatial heterogeneous. Based on other economic, demographic, and built environment considerations, we can infer that there is generally more capacity for new solar arrays in populated arrays. However, there is also considerations for higher utility electric rates and higher levels of available hosting capacity. Infrastructure upgrades are passed on to the consumer through a series of regulatory approvals and an eventual a component of the end retail utility rate for the customer. In the figures below, we show the distribution of hosting capacity among features within the EDC territories. It is evident that total number of features that may host a solar system various greatly among the territories. Additionally, the hosting capacity of these features is also diverse.

Figure 31: New Jersey Interpolated Hosting Capacity

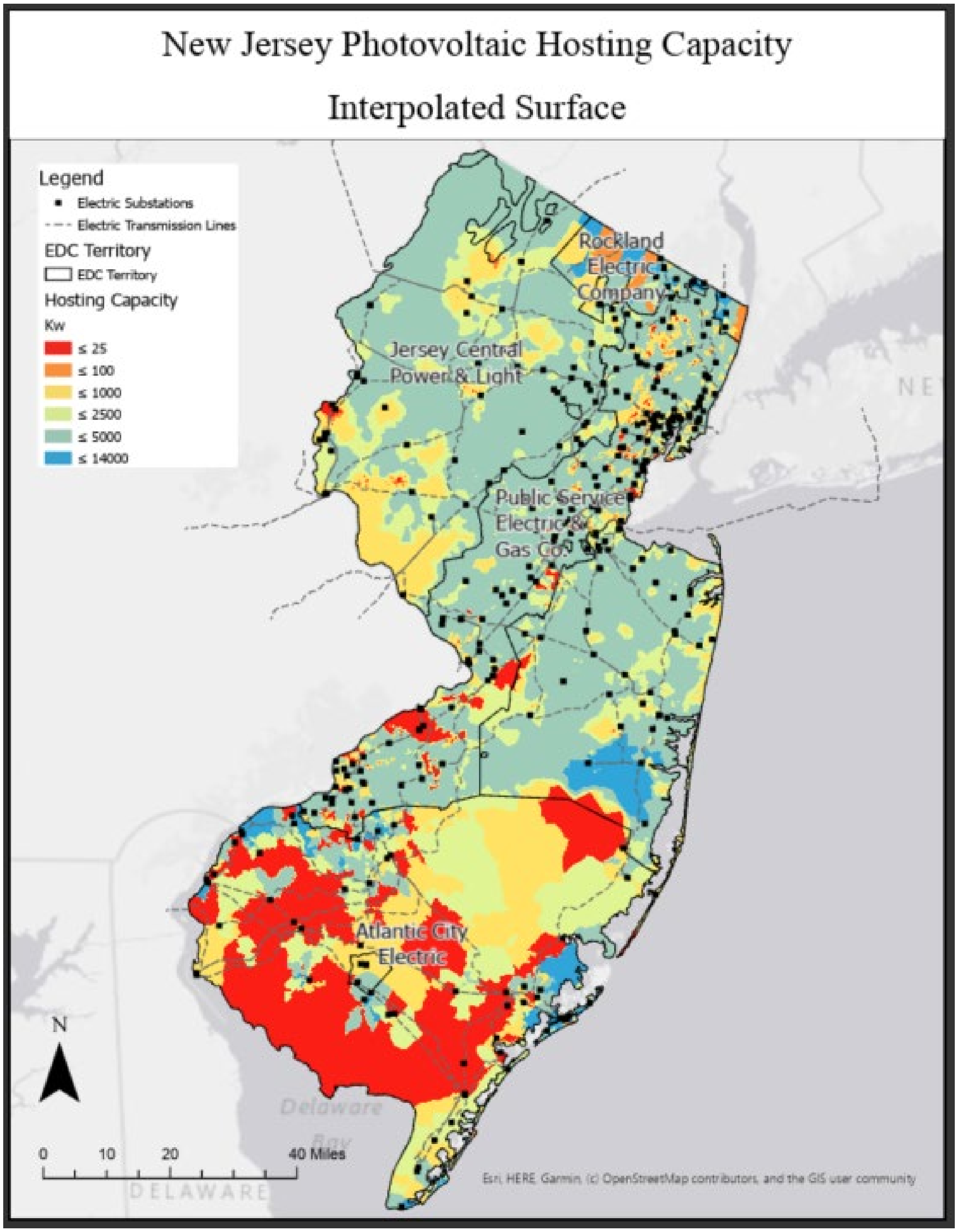


Figure 32: PSEG Feature Hosting Capacity

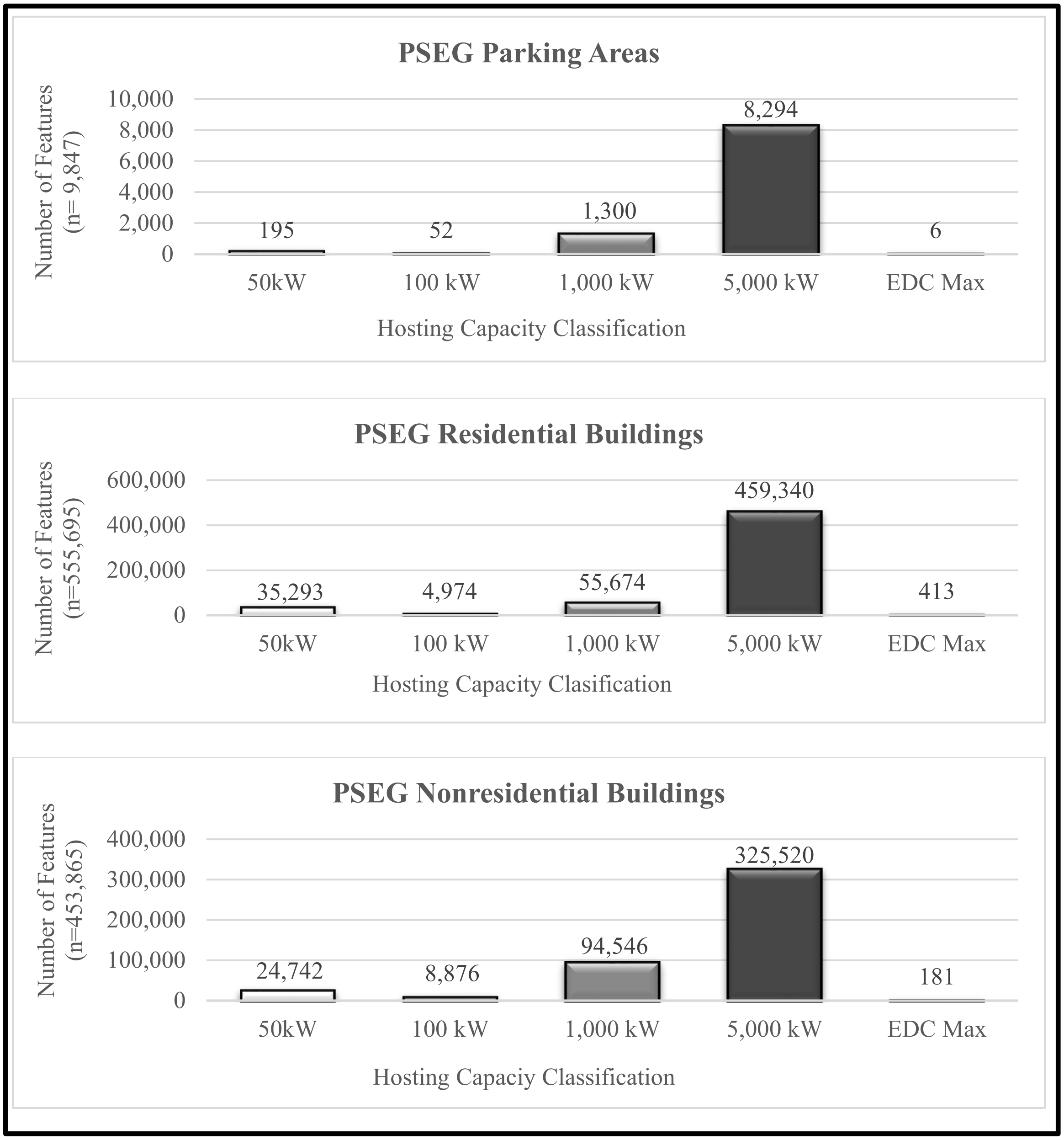


Figure 33: ACE Feature Hosting Capacity

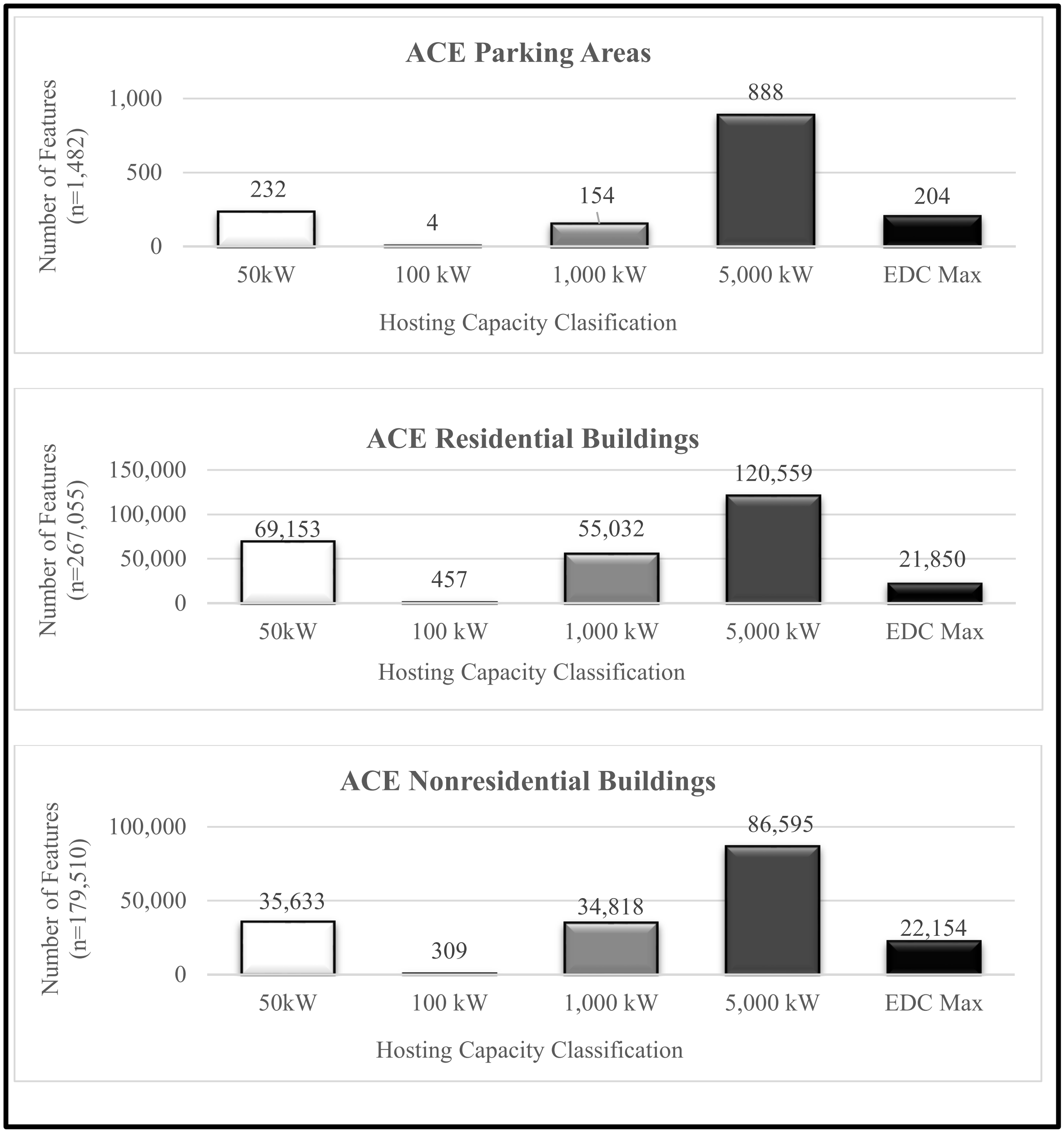


Figure 34: Orange & Rockland Feature Hosting Capacity

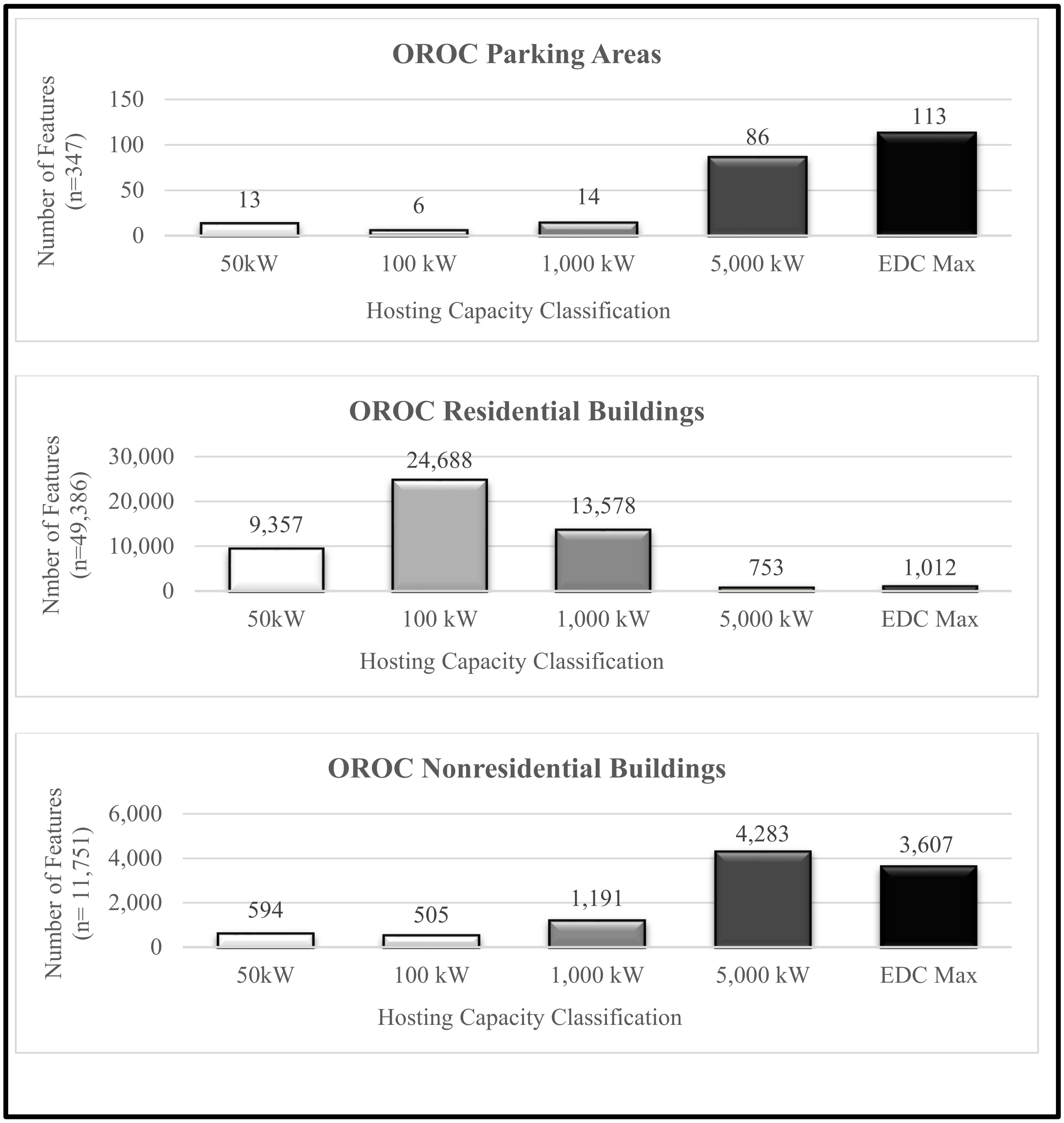
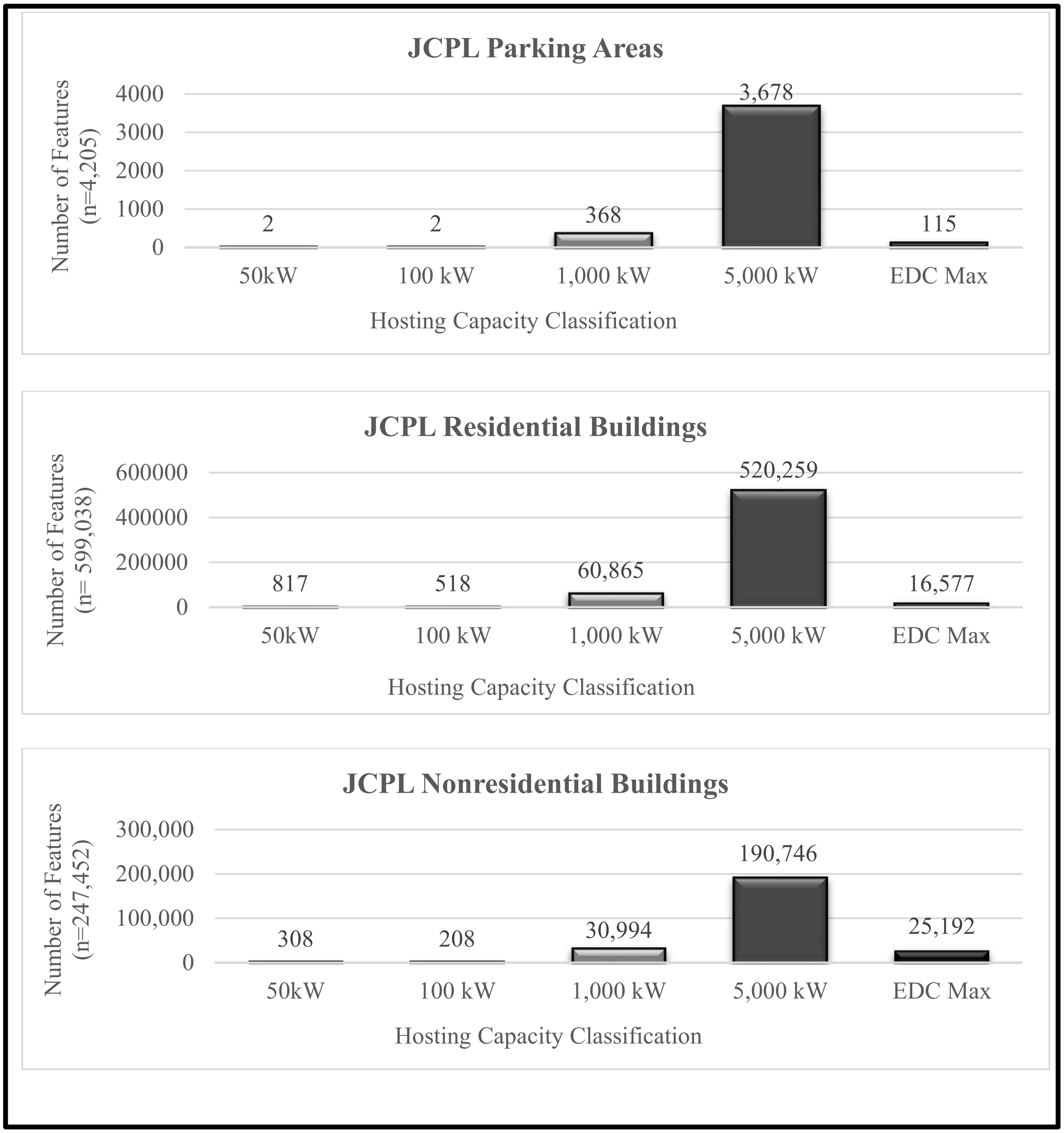


Figure 35: JCPL Feature Hosting Capacity



4.6.1.2 Multi-Criteria Weighted Overlay Suitability Assessments

In our multi-market analysis, we tailor a weighted over suitability model to the study area in the context for analyzing grid supply, commercial net metering, and residential net metering based on the siting criteria needed for each of these solar system types. In a similar fashion we identify locations where potential is greater for community solar projects. These three state-wide models use a raster overlay analysis based on demographics, land cover, building stock, and energy pricing spatial data. The results of the overlay solar suitability model analyses present a statewide interpretation of spatio-economic information that can be used in clean energy planning. Although coarse and relatively simple models, they provide new insights into the State's clean energy potential across multiple solar markets.

The visual results of our residential analysis show striking limitations throughout the study area. However, in our presentation of frequency and system size for the residential market, we know that these systems of numerous and relatively small in area. Therefore, the areas described as most suitable, suitable, and possible, can still proliferate a large amount of new systems in the future. It is also important to note that this model restricts areas of the State that are not listed as Single Family Residential, and Residential. The areas that are listed as residential are not restricted but are given a lower input score because there are some instances of multi-unit dwelling occurring in these classifications. The results of the residential model are driven by the utility rates as well, as seen by the diagonal strike across the stake of more suitable areas. This new information can be particularly useful in determining areas in need of hosting capacity upgrades, our provide solar developers location information on where to target new customers.

The results of the ground mount grid supply and large net metering weighted overlay analysis shows high spatial heterogeneity throughout the State, as seen in Figure 38. This model targets areas outside of residential classifications and avoids wetlands, forests, and natural areas. However, because these are not restricted specifically in solar policy, they are not omitted in our model. We can also see the lower scoring areas that fall within the spatial boundaries of the natural hazard inputs such as flooding and coastal hazards. This information can be used by policy planners and solar developers who are looking the expand within these larger sized projects throughout the study area.

The results of the community solar participant model, as seen in below, represents the results of the weighted overlay model used to identify areas where they may be potential clean energy customers that are unable to access clean energy in other means. As environmental managers are developing new community solar programs in the State, they can leverage this information to evaluate areas that might see stakeholders that would like to participate.

Figure 36: Residential Weighted Overlay Model Result

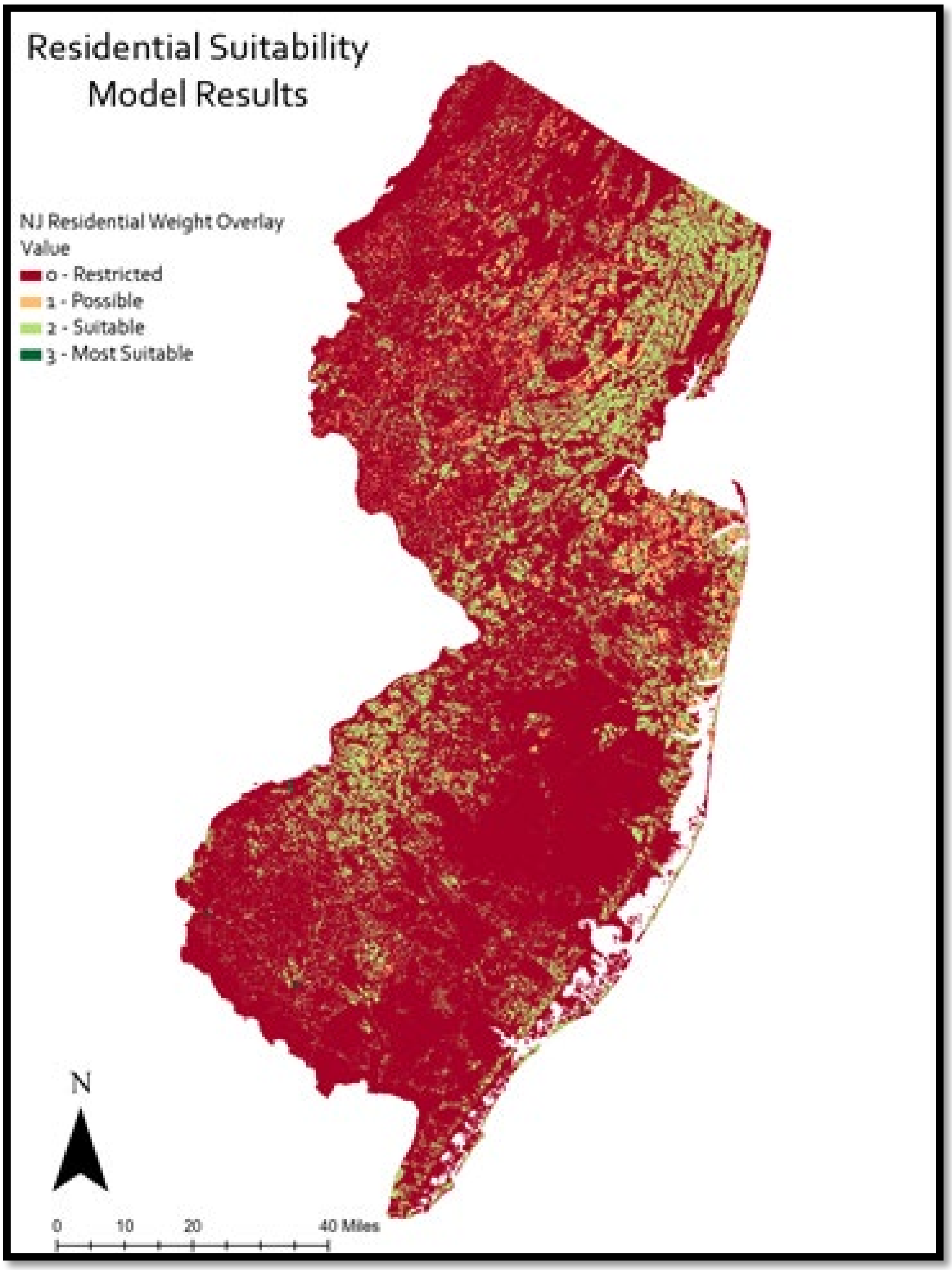


Figure 37: Ground Mount Grid Supply and Large Net Metering Model Result

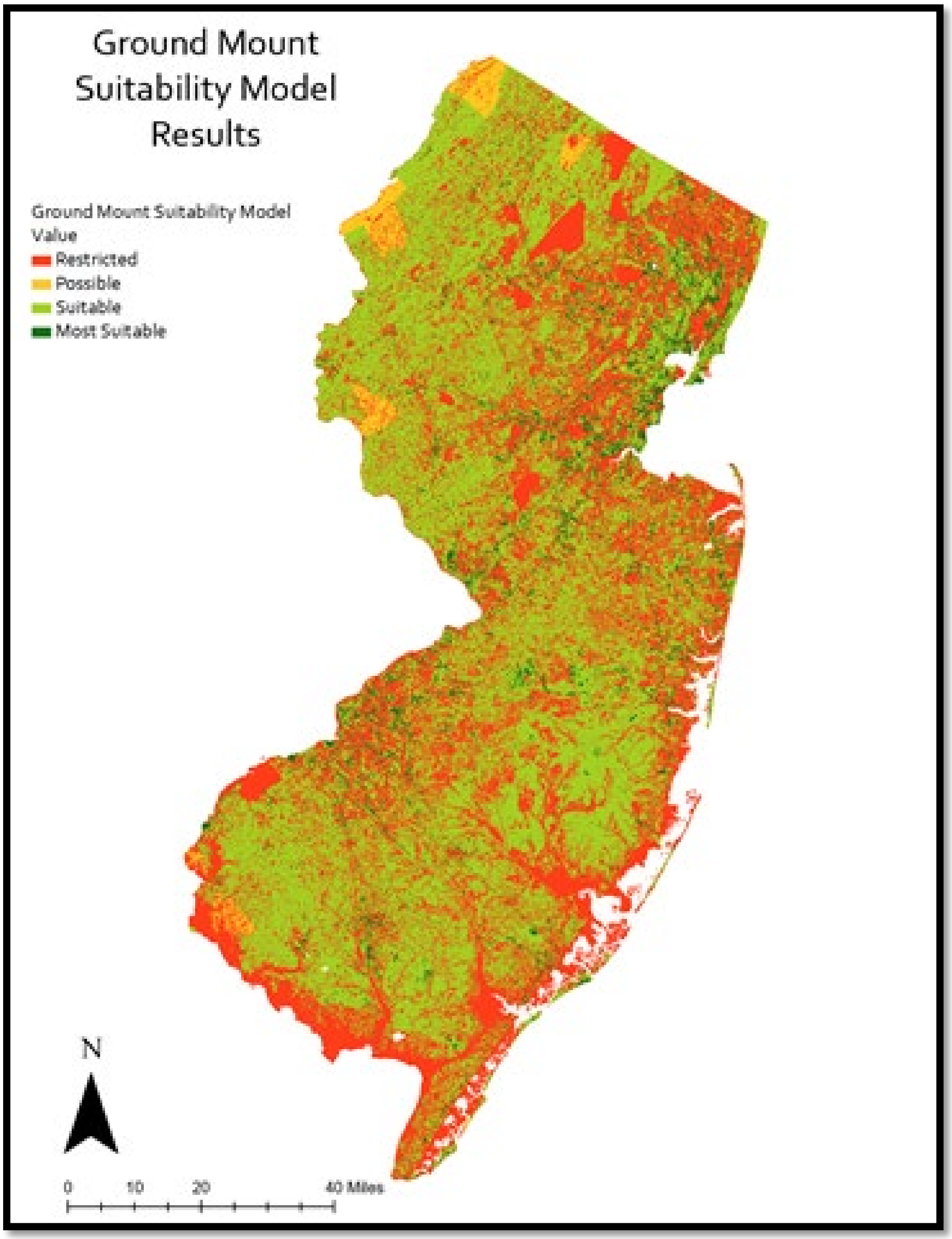
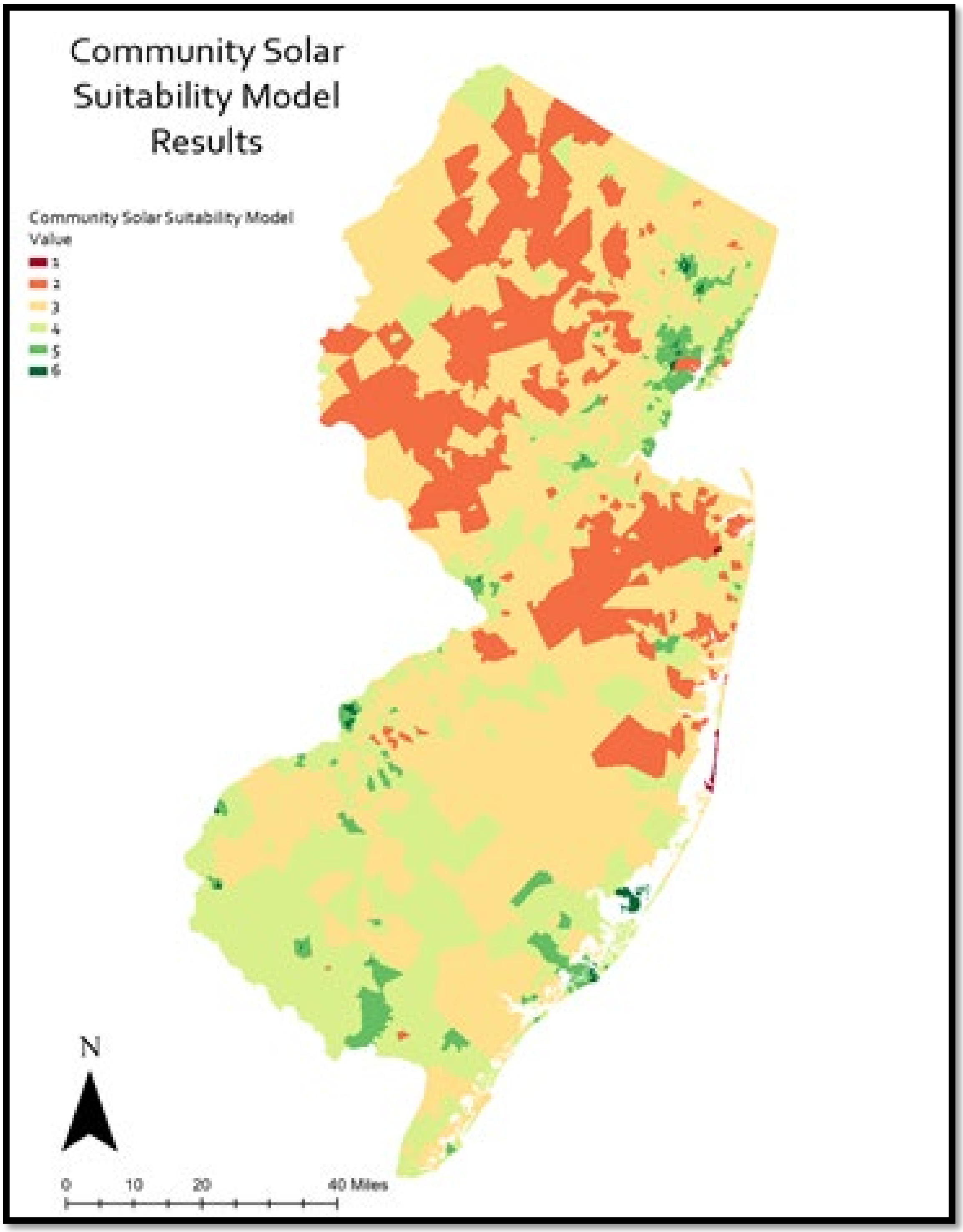


Figure 38: Community Solar Suitability Model Result



4.6.1.3 Remote Sensing

The results of our remote sensing analyses demonstrate applied three-dimensional modeling techniques that can be used to gather vast amounts of geographic information across a relatively large study area. After building our model with millions of points in three-dimensional space, we are able to highlight new opportunities and possible hazards for photovoltaic systems. The results produce visualization and quantification functionality in evaluating the municipalities. Visual results include the roof geometry and RGB color encoded surface for Newark, the storm surge, slope, and shadow analysis for Atlantic City, and the solar radiation analysis for Camden.

Figure 39: Newark RGB Color Encode and Roof Geometry

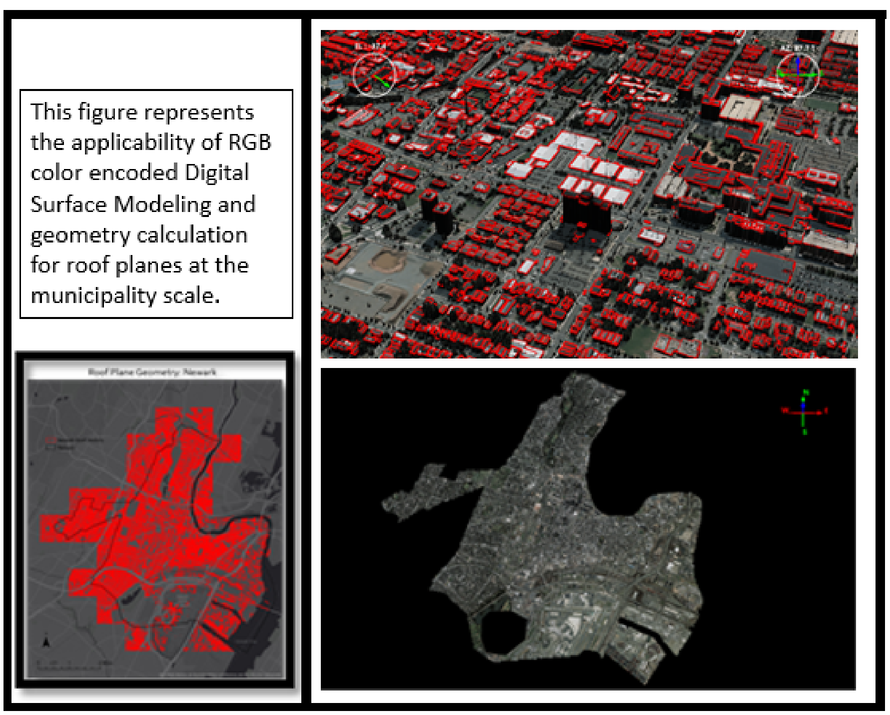
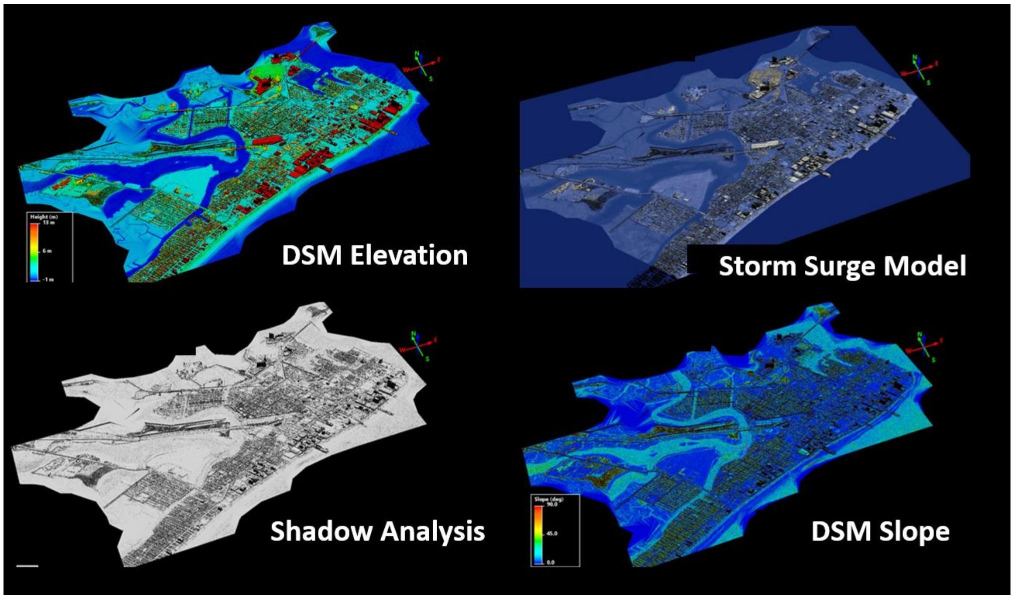
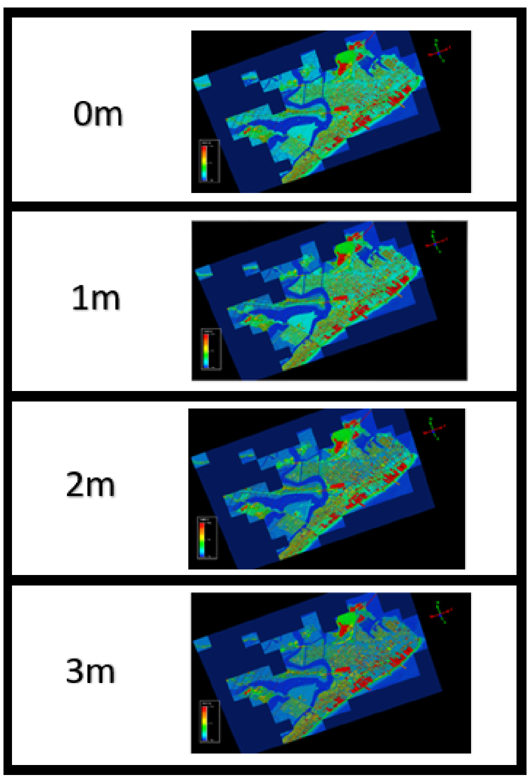


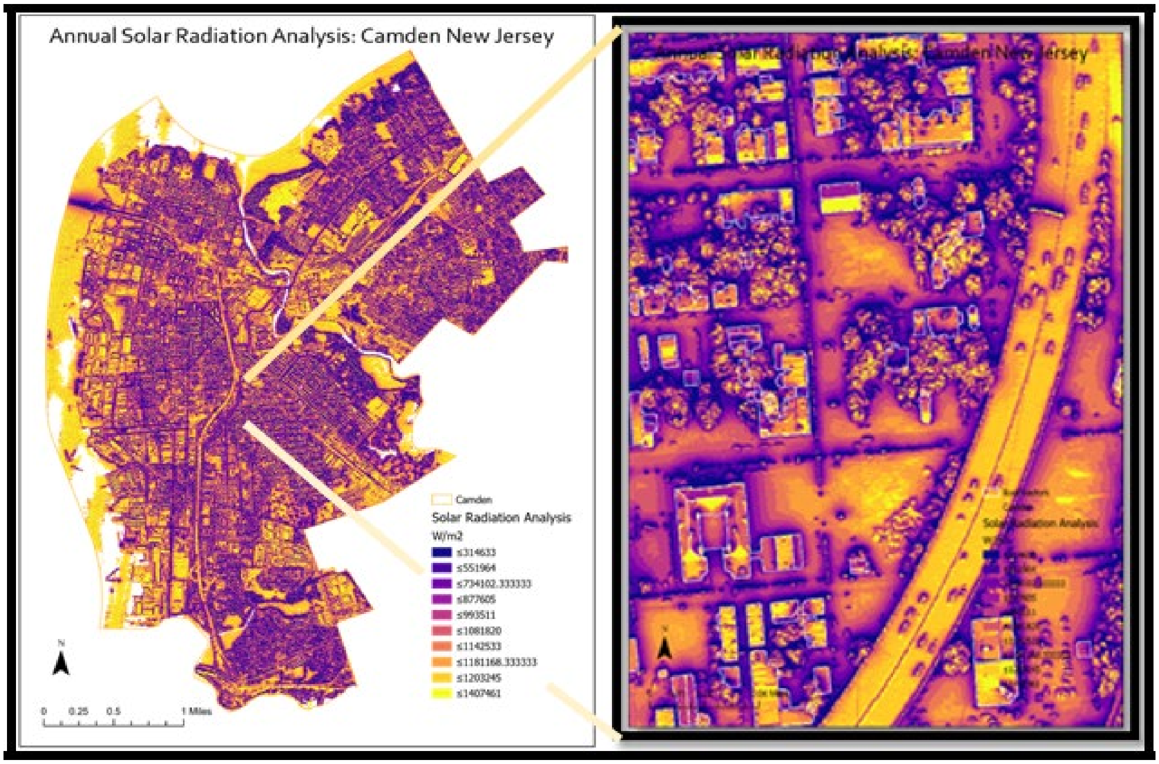
Figure 40: Atlantic City Local Models





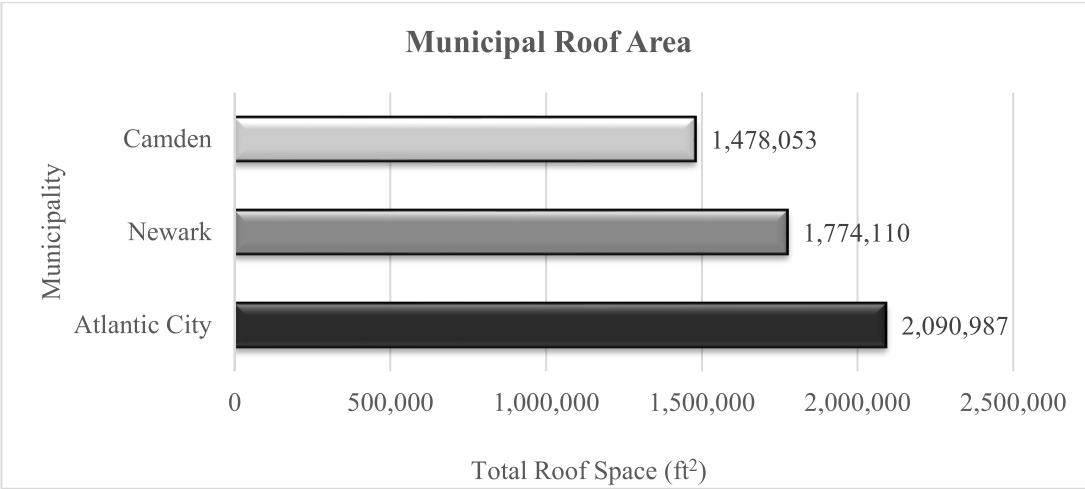
Coastal flooding poses threats to ground mounted solar systems. This provides new information for developers and policy makers for this location. In coastal states like New Jersey, it is likely that solar systems will be vulnerable to coastal flooding hazards. The results show areas that should be avoided for ground mounted systems.

Figure 41: Camden Solar Radiation Analysis Map Series



Evaluating solar radiation potential remotely will allow LCOE for solar projects to drop precipitously. Our resulting spatial model represents annual solar radiation analysis for the digital surface model of Camden, NJ. This represents the actual energy on the 3-dimensional surface for an entire year. The results of this show highly detailed shading and energy per unit area. These results provide new information for solar design and community expectations for photovoltaic potential.

Figure 42: Municipal Total Roof Space Estimation



Our analysis of roof plane geometry yields many new geographic features that can be used to fast-track the site inspection process and evaluate new solar potential. Current clean energy generation planning in New Jersey does not assume space limitations for roof mounted systems. In our approach, we calculate the total roof area within the three municipalities. This can be used for estimates for future solar system coverage.

4.7 Discussion

We can deduct from our literature review and preliminary research that evaluating future solar photovoltaic systems in New Jersey calls for cross disciplinary approaches in modeling the socioeconomic and physical attributes of the environment. Our results show differences in demographic and energy distribution infrastructure quality throughout the State. As future clean energy policies and designed and implemented, it may be beneficial to interpret policies differently across the distribution territories. Ratepayer impacts are an underlying theme in clean energy growth in New Jersey. The environmental benefits of increasing solar energy deployment must also consider the economic impacts that the ratepayers must bear. Due to the current interconnection and energy demand environment, one could argue that New Jersey ratepayers already bear a disproportionate burden of transmission upgrades throughout the ISO. Lowing the cost of clean energy through streamlined data collection and dissemination processes have potential to lower the LCOE of photovoltaics and improve new policy success likelihoods. In our multi-market analysis, we present a method for analyzing grid supply, commercial net metering, and residential net metering based on the siting criteria needed for each of these solar system types. As policies and socio-political priorities change over time, one can expect the interpretation of spatial data to also change. We may see more consideration given to projects that lower periods of peak demand and reduce locational marginal pricing (LMP) as a spatiotemporal approach to mitigate increased costs of electricity and reduce the solar industries dependence on government subsidy. We also perform an analysis for identifying locations where potential is greater for community solar projects. Increasing access to clean energy through distributed energy programs, such as virtual net metering and community solar will likely be harnessed in the future to improve regional environmental quality, address environmental justice issues, and reduce barriers to entry.

4.8 Conclusions

In this work we investigate the potential of solar photovoltaics across multiple scales using geographic information systems and remote sensing with the goal of evaluating deployment potential for this technology across the study area. The research performed in this chapter was designed to bring new insights into the current body of knowledge being used to predict the future of solar photovoltaic energy for environmental managers in New Jersey.

Furthermore, our methods can be adapted to be used to study other regions. Identifying and deploying methods to gain spatial intelligence on clean energy feasibility is an approach to gain insights into where potential technology adopters are located, quantifying suitable project locations, and evaluating future capacity assumptions. In our first analysis we present a method for analyzing grid supply, commercial net metering, and residential net metering array location. This is an effective way to evaluate to evaluate Statewide conditions at the census tract scale. In the second section of this analysis we present a spatial interpolation approach for estimating solar hosting capacity across the electric distribution territories of the State. Evaluating hosting capacity throughout the study area will have implications for future energy infrastructure development allowing for an increase in photovoltaic systems. In the final section we use remote sensing techniques to investigate solar potential in three municipalities. By taking this multi scaled technical approach we are able to evaluate this topic more holistically. Furthermore, the use of remotely sensed data yields high resolution outputs without costly and time consuming in field data collection. Future steps of this analysis will include expanding the coverage areas of the high-resolution remotes sensed data. This multifaceted approach adds to the current science being used in this region for policy development. We can use the results of this work to draw inferences on where solar interconnection infrastructure needs to be improved.

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5 Consumer Willingness to Pay for Community Solar in New Jersey

5.1 Introduction

In this study we leverage clean energy stakeholder survey in the form of a discrete choice experiment and multinomial logit (MNL) data analysis to evaluate consumer willingness to pay for community solar in New Jersey. Community solar programs present an innovative approach to increasing access to clean energy, particularly to those unable to participate in traditional solar markets such as residential net metering. Economic valuation methods such as those performed here, present robust insights on evaluating public perceptions on costs, benefits, and siting criteria used by state governments to develop solar programs and evaluate proposed projects.

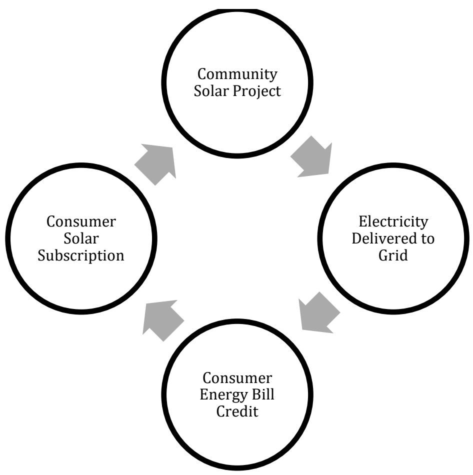
After reviewing recent clean energy policies in New Jersey, we identify an opportunity to present novel insights that can be used in future community solar program design. Furthermore, the importance of stakeholder engagement in clean energy policy, underscores the need for new investigations that can add to the current body of knowledge. Our goal is to utilize these approaches with additional New Jersey focused considerations to provide a holistic environmental management investigation on the public perception on community solar energy. In this chapter we test the hypotheses of: 1) Are known barriers to residential solar influencing clean energy access in New Jersey? 2) How do New Jersey energy consumers value community solar project attributes with respect to land use, environmental quality, community proximity, and energy savings?

The objective for our investigation is to provide new insights into common barriers in solar access and willingness to participate in community solar programs in New Jersey. Our rationale for this study is to improve the body of knowledge that can be used by policy makers to develop innovative clean energy policy to see increased success in climate mitigation through greenhouse gas reductions in the electric generation sector. There is a need to evaluate stakeholder's value of environmental benefits and siting locations for clean energy projects (Benioff, 2010). Community solar programs increase energy access among stakeholders (Chan, 2017).

Stakeholder processes are required of environmental law and policy making in the United States (Benioff, 2010; Petkova, 2014; Peterson, 2006; Brown, 2008). Engagement is often exhibited through public forums and public document commenting and response facilitated by a regulating government entity (Peterson, 2006). These traditional methods can fall short in terms of informing government on the social, environmental, and economic benefits and impacts of a new policy (Brown, 2008; Berardo, 2018). Leveraging more comprehensive public involvement and local knowledge can yield valuable information for policy design, particularly when coupled with spatial and economic methodologies (Ruggiero, 2014). The choice experiment approach is an economic valuation method that facilitates the estimation of trade-offs between goods (Kjaer, 2005). This allows for policy design scenarios to be evaluated in terms of survey participants' preference (Kjaer, 2005; Michaud, 2013).

Distributed power generation is growing in popularity in the United States (Thornton, 2011). This approach increases clean energy access to consumers by removing roadblocks of traditional net metering, such as home ownership, roof quality requirements, and long-term commitments to lease programs or equipment ownership (Darghouth, 2011; Eid, 2014). Community solar programs are distributed power generation policies which targets renters and low to moderate income (LMI) participants (Chan, 2017). In community solar, electricity customers subscribe to a solar company as they would other utilities similar to cable or telecommunications, and purchase electricity generated from a solar array in a location other than their residence which is credited to their electricity bill (Chan, 2017). This creates an opportunity for more individuals to access clean energy and creates added economic benefits for solar developers such as improved pricing schedules within the retail market and the economies of scale associated with larger photovoltaic systems (Chan, 2017).

Figure 43: Community Solar Framework



The State of New Jersey released its three-year Community Solar Energy Pilot program in the Spring of 2019 (N.J. A.C. 14:8-9). This pilot program sets requirements for proposed projects: These requirements include geographic boundaries of sale based on electric distribution company (EDC) territories in which the array and customers must be co-located, a capacity limitation of 5 MW, and land use restrictions protecting preserved agricultural lands. Additionally, projects were evaluated and awarded on the basis of utilizing impervious surfaces, serving low-to-moderate income participants, and utilization of compromised lands such as brownfields and landfills (BPU Community Solar Application form). Evaluating public perceptions on land use considerations, energy savings, and environmental improvements will be critical in future iterations of the New Jersey Community Solar Energy Program. After attending public stakeholder meetings and reviewing public document comments and State responses, we identify an opportunity to explore consumer evaluations of various community solar project scenarios. This can promote improved evaluation policies for future program years because evaluation criteria, as described in the program application documentation, can influence the likelihood of a project being successfully implemented. Maximizing stakeholder input combined with regulatory agency requirements can optimize consumer participation while reaching goals set my government. Characteristics of the New Jersey Pilot program are described in the figure below.

Figure 44: New Jersey Community Solar Program Characteristics

Choice experiment surveys are valuable in determining stakeholder ability to participate in clean energy programs, preference for siting new projects, and evaluating their willingness to pay for alternatives to the current carbon intensive fossil-based energy systems (Bergmann, 2008; Bergmann, 2006). We utilize this approach to determine how different environmental and geographic attributes of community solar photovoltaic systems impact the willingness of New Jersey residents to pay for alternatives. Currently, there is no information available on public preference for characteristics of clean energy alternatives. We focus on the environmental quality improvements, cost benefits, and proximity of arrays to residences to fill this gap and provide insights that can improve the evaluation of proposed community solar projects in the future.

5.2 Literature Review

As with most new government policies, stakeholder engagement is used to identify key issues and potential unintended consequences (Reed, 2008). Modern government stakeholder efforts often lack clear communication across government and public entities in the early stages of new policy development (Barletti, 2020). Particularly in climate related issues that are politically polarizing, there can be misinformation throughout media leading to inaccurate interpretations of climate issues and public mistrust in government decision making (Cook, 2014; Cook, 2017; Malone, 2010).

Throughout the literature, the use of place-based, geographically focused, discussions, such as the use of participatory geographic analysis and stakeholder survey, are a way to improve upon the current communication structures the government-public interface (Higgs, 2008; Abdollahain, 2013; Palmas, 2012; Dunn, 2007; McCall, 2003). Furthermore, this approach can proactively address public acceptance and other risks to the economic and ecological systems impacted by new policies (McCall, 2003; Mekonnen, 2015). Siting considerations are also evaluated when determining likely build out scenarios across solar markets (Van Hoesen, 2010; Dunn, 2007). Public perception derived from economic valuation can further enhance spatial suitability modeling (Brewer, 2015). This concept is known as participatory geographic information systems (PGIS) (Jankowski, 2009). PGIS can be applied to spatial analysis methods by engaging the public in surveys that have a geographic component, such as evaluating preference for clean energy project across landscapes (McCall, 2003; Mekonnen, 2015). Common practices in this area of literature often consist of allowing survey participants to identify areas of local importance on a map or being asked where they policy action to take place within their community (Mekonnen, 2015).

We see many solar incentive programs promoting photovoltaic systems that utilize impervious surfaces such as existing rooftops and new parking canopies (Chan, 2017). The reasoning behind this is to minimize development of open spaces. However, the associated additional costs as compared to ground mounted solar arrays can drastically increase the levelized cost of energy (LCOE) of these projects. Keeping costs down is important in driving economic feasibility of projects, government incentive schedules, and ultimate costs to the ratepayer (Comello, 2017; Taylor, 2015). Large building roof tops in commercial and industrial settings, can close this LCOE gap by capitalizing on larger systems and economies of scale (Comello, 2017; Taylor, 2015).

Landfills and brownfields are often prioritized for solar projects and the associated government generation incentives, as seen in the New Jersey Solar Act 2018, subsection t (New Jersey Solar Act 2018). Siting solar photovoltaics on landfills and brownfields is a functional means to re-purpose otherwise economically limited degraded lands (Szabo, 2017). The design requirements of photovoltaic systems call for open spaces with limited to no vegetation shading

(Goodrich, 2012). The gently slopes and low grasses/shrubs of properly closed landfills are often ideal in terms of potential to site solar installation equipment and available solar radiation potential (Goodrich, 2012; Szabo ,2017, Horowitz, 2017). Furthermore, the opportunity to capitalize on solar incentives may be a driving force in spending that is required to complete the capping and closing of an open landfill that is out of operation (Salasovich, 2011; Jacob, 2018).

Agricultural areas are a contentious landscape for the siting of new solar projects (Xiarchos, 2011). In New Jersey, farmland can be qualitatively classified as preserved farmland, agricultural development area, a qualified farm (tax incentive), or a degraded/low productive farm, with conservation efforts ranging from high to none respectively. Solar developers often seek to develop on farmland because they are very good locations in terms of ground slope and minimal shading (Chan, 2017). In some instances, we see financially struggling agricultural lands pivoting into clean energy and selling or leasing their land for solar development as an economically productive alternative to continued low financially productive farming (Xiarchos, 2011; Marcheggiani, 2013). This transition is common in parts of the northeastern U.S. (Funkhouser, 2015; Lichtenstein, 2017). Other states, such as Massachusetts are leading the way in developing incentive programs which take a mixed land use approach to manage this transition (Funkhouser, 2015; Lichtenstein, 2017). Successful community solar programs often promote this land use perspective with a mix of solar development collocated with single form of agriculture or a combination of pollinator support, confined feeding operations, and livestock grazing (Dinesh, 2016).

The problem of siting large solar projects is something many states struggle with in developing community and other solar programs (Stoms, 2013; Macknick, 2014). From an economic perspective, array development in underserved communities or economic development areas are thought to be better than others because of the potential to increase local economies and training of a new solar labor force (Pasqualetti, 2011; Friedman, 2011; Tulpule, 2013). However, areas that are characterized in this way may also have a history of being over developed, particularly in terms of fossil generation infrastructure, with implications of negative impacts to housing value, environmental contamination and poor air quality (Touche, 2005; McGranahan, 2000; Portney, 2013). Evaluating public perception of clean energy development within their community can be overlooked in traditional stakeholder processes (Chambers, 2007; Jenkins, 2016). Furthermore, increasing solar generation within close proximity to an existing fossil powerplant is unlikely to reduce the operating time and emissions of that powerplant in the short term because of the implications of load requirements of larger energy distribution systems which operate across regions (Jansson, 2008; Obi, 2016). Understanding public perceptions on the global and regional impacts that clean energy has on environmental quality can improve policies (Devine-Wright, 2005; Jones, 2015; Demski, 2014).

Many studies throughout the literature have utilized choice experiments in the context of renewable energy technology and their associated impacts using multinomial logit (MNL) and random parameter logit (RPL) models (Bergman et al, 2006; O'keefe, 2014). These studies evaluate aspects of different renewable energy projects including the negative and positive impacts on landscape conservation, wildlife, environmental quality, and employment (Bergman et al, 2006; O'keefe, 2014). Environmental attributes of renewable energy projects are found to be influential on public acceptability and willingness to pay (WTP) for alternative clean energy (Scarpa and Willis, 2010). The reviewed literature draws common conclusions on public preferences for siting and willingness to pay for solar photovoltaics across participants (Bergmann et al, 2006; Ku and Yoo, 2010; Scarpa and Willis, 2010).

5.3 Methodology

5.3.1 Theoretical Framework

The basis of this discrete choice experiment is on characteristics of Lancaster's random utility theory. This assumes that the utility an individual derives from a hypothetical community solar project depends on the characteristics of the solar array (attributes), individual characteristics, and the unobserved (stochastic) components (Lancaster, 1966; McFadden, 1976). Multinomial logit (MNL) assumes that unobserved factors affecting the choice of alternatives are strictly independent of each other (Independence of Irrelevant Alternatives, IIA). The description of the theoretical framework applied for deriving the respondent's willingness to pay was based on Bergmann *et al.,* (2006) protocols summarized below. In each choice set, the respondent faced a choice between a set of three alternatives: community solar program option A, community solar program option B (each defined with different attribute levels), and Option C representing the status quo option (no community solar program).

In general, a respondent *q*'s utility from choosing alternative *j* in choice situation *t* in a utility function with random parameters can be defined as

$$Ujtq = Vjtq + \varepsilon jtq \equiv \beta' qkXjtqk + \delta' kzqZjtqk + \varepsilon jtq \qquad (1)$$

Where respondent *q* (*q*=1,….*Q*) obtains utility U from choosing alternative *j* (Option A, B or C) in each of the choice sets t(*t*=1,....6). The utility has a non-random component (V) and a stochastic term (ε). The non-random component is assumed to be a function of the vector k of choice specific attributes: X_{jtqk}, with corresponding parameters $ß_{qk}$ which may vary randomly across respondents due to preference heterogeneity with a mean $ß_k$ and standard deviation δ_k. The utility function of the model without covariates, with the exception of the error term ε_{jtq} , can be expressed as a linear function of an attribute vector (X1, X2, X3, X4, X5, X6) = (Land use array, Proximity to your residence, reduction of fossil fuel generation, effect on environmental quality, and financial gain). It includes the alternative-specific constant representing a dummy for the respondent choosing the status quo option among two alternatives and all the attributes erringly excluded from X_{jtqk}. It is assumed that the individual chooses the option j that provides them with the highest utility (Kuu and Yoo, 2010).

$$V_{jq} = ASC_q + \beta 1X1_{qj} + \beta 2X2_{qj} + \beta 3X3_{qj} + \beta 4X4_{qj} + \beta 5X5_{qj} + \beta 6X6_{qj} \quad (2)$$

Hence, the probability function is defined over the alternatives which an individual is faced with the assumption that the individual will try to maximize their utility (Bergman et al., 2006). The probability that an individual q will choose alternative i over any other alternative j belonging to some choice set t of:

$$Prob_{iq} = Prob(V_{iq} + \varepsilon_{iq} > V_{jq} + \varepsilon_{jq} \qquad \forall j \in t$$

Which equals to

$$Prob\left\{\left(V_{in} - V_{jn}\right) > \left(E_{jn} - E_{in}\right)\right\} \quad (3)$$

To empirically estimate the observable parameters of the utility function (3), assumptions are made about the random component of the model. First assumption is that these stochastic components are independently and identically distributed (IID) with a Gumbell or Weibull distribution. This leads to the use of multinomial/conditional logit (MNL) models to determine the probabilities of choosing *i* over *j* options.

$$Probin = \exp(\mu V_{iq}) / \sum jexp\left(\mu V_{jq}\right) \qquad \forall j \in t \quad (4)$$

Where μ is a scale parameter, inversely related to the standard deviation of the error terms, and V_{iq} is the deterministic component of the utility function assumed to be linear in parameters:

$$V_{jq=} \sum k \beta_{jk} x_{jk} \qquad (5)$$

Where X_{jk} is the k^{th} attribute value of the alternative j and β_{jk} is the coefficient associated with the k'th attribute. The implications for this are that the estimated β values cannot be directly interpreted, since they are confounded with the scale parameter. However, the marginal rate of substitution (*MRS*) between any pair of attributes is obtainable, since the scale parameter cancels out, as shown:

$$MRS = -(\mu\beta attributea/\mu\beta attributeb) = -(\beta attributea/\beta attributeb) \qquad (6)$$

In cases where the cost of choosing an alternative has been included as an attribute as is the case for our model 2, then equation (6) can be used to produce an estimate of the "implicit price" or "part-worth" $P{*}a$ by replacing the denominator with the β estimate for this cost/price attribute:

$$P * a = (\beta a/\beta cost) \qquad (7)$$

The implicit prices express the marginal WTP for a discrete change in an attribute level, and thus allow some understanding of the relative importance that respondents places on attributes within the design

5.3.2 Attributes and optimal choice profiles

We considered literature on community solar and information gathers from the Pilot program stakeholder process to determine our attributes and respective levels. The attributes were selected to characterize community solar programs. For this discrete choice experiment, the respondents, traded-off five attributes described in the table below. *Land use of the array* explored the possible land-use options that could be utilized for community solar, that included *landfills, forestland, non-preserved farmland, commercial or industry buildings. Proximity to my residence* was an attribute looking into, how close to their respective residences are respondents willing to place the community solar project. This attribute had three levels that are *adjacent to my residence, within my community*, and *outside of my community*. Instead of the following the approach of most studies such as Bergman et al, (2006), that used distance measured in miles, we used generalizable, definition for ease of interpretation by the respondents. *Reduction of fossil fuel generation* was the third attribute that had the following levels, 20%, 50% and 100%. The fourth attribute was *environmental quality* that had the levels, *decrease, stays the same and improve*. *Financial gain* which also was the cost attribute had four levels these were a*dditional energy costs, no financial gain, 50% energy costs savings* and *100% energy cost savings*. It was anticipated that community solar may result in some form of financial gains that could be accrued through savings on the monthly utility bill, depending on the enrollment plan that an individual would undertake.

Table 17: Attributes & Levels

Attributes and Levels in The Choice Tasks	
Description	**Levels**
Land Use of Array	• Landfills • Farmland • Commercial buildings • Forestland
Proximity	• Adjacent to my residence • Within my community • Outside of my community
Reduction of fossil fuel generation	• 20% • 50% • 100%
Environmental Quality	• Decrease • Stays the same • Improve
Financial Gain	• Additional energy costs • No Financial gain • 50% energy cost savings • 100% energy cost savings

The associated levels resulted in 432 possible profiles (4*3*3*3*4) which is an unfeasible number to employ in the survey. An efficient design was applied to give an efficient combination for orthogonality, level balance, and minimum overlap using the JMP 14 statistical software package. We used a fractional factorial design to reduce the full factorial to 144 choice set profiles that were randomly paired to form 72 choice cards representing two community solar program alternatives and an additional fixed alternative described as "no community solar program", equivalent to the status quo alternative. Based on this design, the 72 different choice sets were blocked into six blocks of 12 choice tasks.

Table 18: Sample Choice Card

Sample Choice Card Including 2 Options for Community Solar Program and Opt Out			
Attribute	**Option A**	**Option B**	**Option C**
Land use array	Landfill	Forestland	No Community Solar Program
Proximity	Adjacent to my residence	Within my community	
Reduction of fossil fuel generation	50%	100%	
Environmental quality	Decrease	Improve	
Financial gain	No financial gain	50% energy cost savings	
Your choice (tick only one)	□	□	□

5.3.3 Questionnaire and Sampling Framework

The questionnaire consisted of three sections. The first section contained a brief introduction to the survey and background information on community solar and preliminary questions, on benefit valuation and preferences towards community solar. The second part of the survey was the choice experiment in which each respondent was presented with 12 tasks each consisting of two different community solar scenarios and the status quo. The final section contained socioeconomic information regarding respondent's characteristics such as gender, age, education, residence, occupation, household income, and monthly utility bill. The survey was administered to 630 New Jersey residents electronically in March 2020, from a third-party polling company.

5.4 Results

5.4.1 State Socio-Demographic Variables and Preliminary Questions

The survey was conducted during the month of February 2020 by the marketing firm Qualtrics that provides modest compensation to participants, which is not disclosed to scientists purchasing survey panels. The marketing firm collected a total of 797 surveys from which 630 were complete surveys resulting in a 79.04% response rate. The sampling points were randomly selected to consider the socio-economic characteristics of New Jersey.

The representativeness of the sample for the population of New Jersey was tested with the Pearson chi-square χ^2 independence test for the socio-demographic variables for both countries. The table below presents the average sample values of several socio-demographic characteristics and their corresponding average values from statistical data (US Census, Bureau (2018). At 1%, 5% and 10%, significance level, the evidence for failure to reject the null hypotheses of equality of means was found for age, education, gender, household size, and percentage owner occupied housing which is statistically representative of the New Jersey population

The resulting table presents the average sample values of several socio-demographic characteristic and their corresponding average values from statistical data. Overall, the chi-square tests indicate that the sample and population have a goodness of fit for most of the socio-demographic factors. At a 1% significance level, the evidence for rejection of the null hypotheses of the equality of means was found for annual household income, percentage rural population, and percentage electricity access for rural population.

Table 19: Respondent Characteristics

Characteristics of Respondents Compared to New Jersey Census			
Category	**Sample Population (n=630)**	**N.J Census**	**Pearson X^2 Test**
Gender (% Female)	51.73%	51.20%	Significance at 10%
Median Age	45.5	39.6	Significance at 10%
Education (H.S./GED)	97.90%	89.20%	Significance at 10%
Median Income	$59,999.50	$76,475	
Household Size	2.73	2.68	Significance at 10%
Percent Owner Occupied Housing	59.07%	64.15%	Significance at 10%

The results of the preliminary questions are shown in the figures below. This illustrates housing types and community characteristics of the respondents. Additionally, we are able to quantify current solar usage among the respondents. The barriers to solar energy access corroborate those commonly described throughout the literature. This re-enforces the need for new innovative programs such as community solar. We are also able to identify the dominance in television for clean energy information dissemination which is contrasted by the low usage of government websites.

Figure 45: Respondent Housing and Community Characteristics

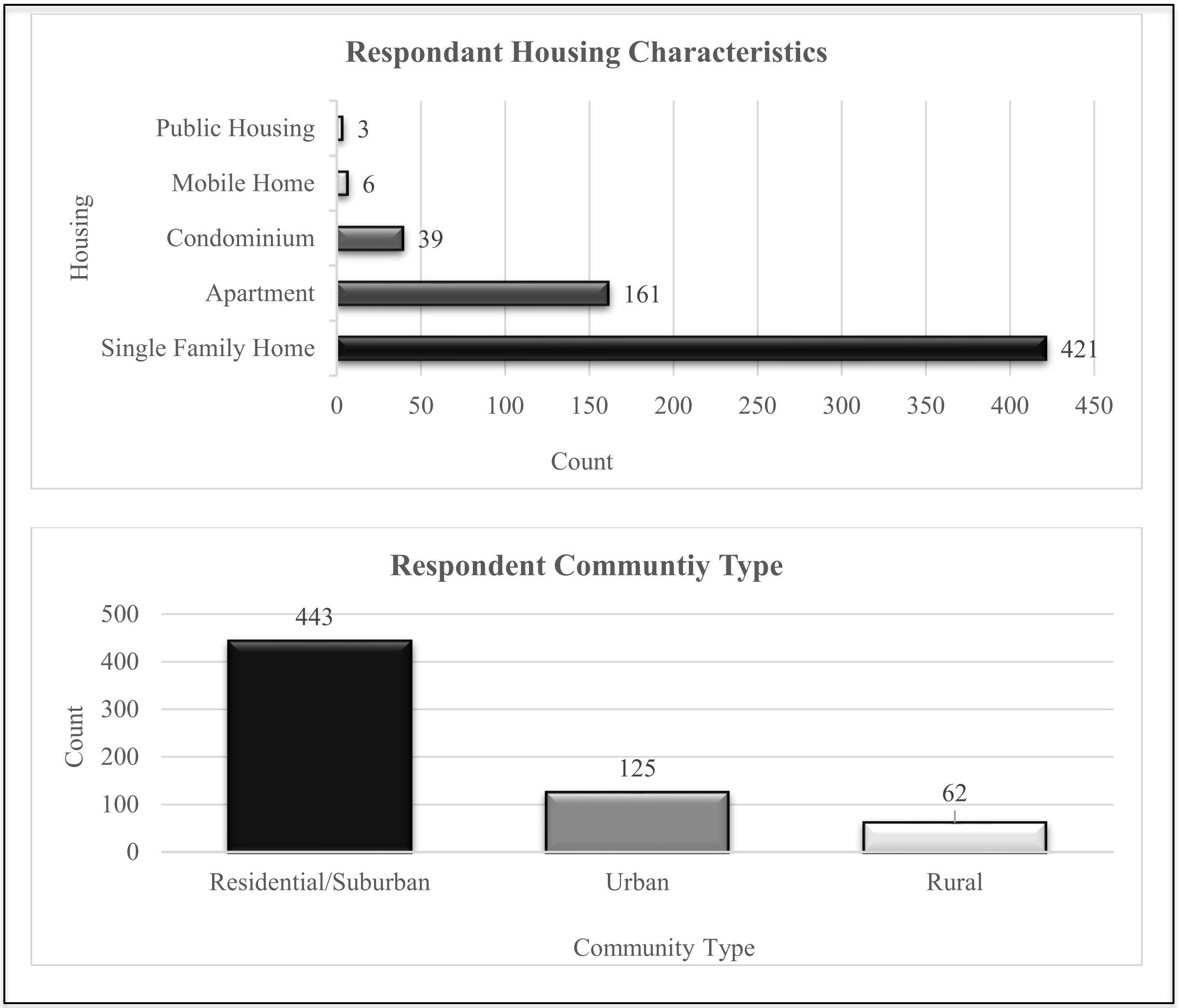


Figure 46: Barriers and Solar Use Among Respondents

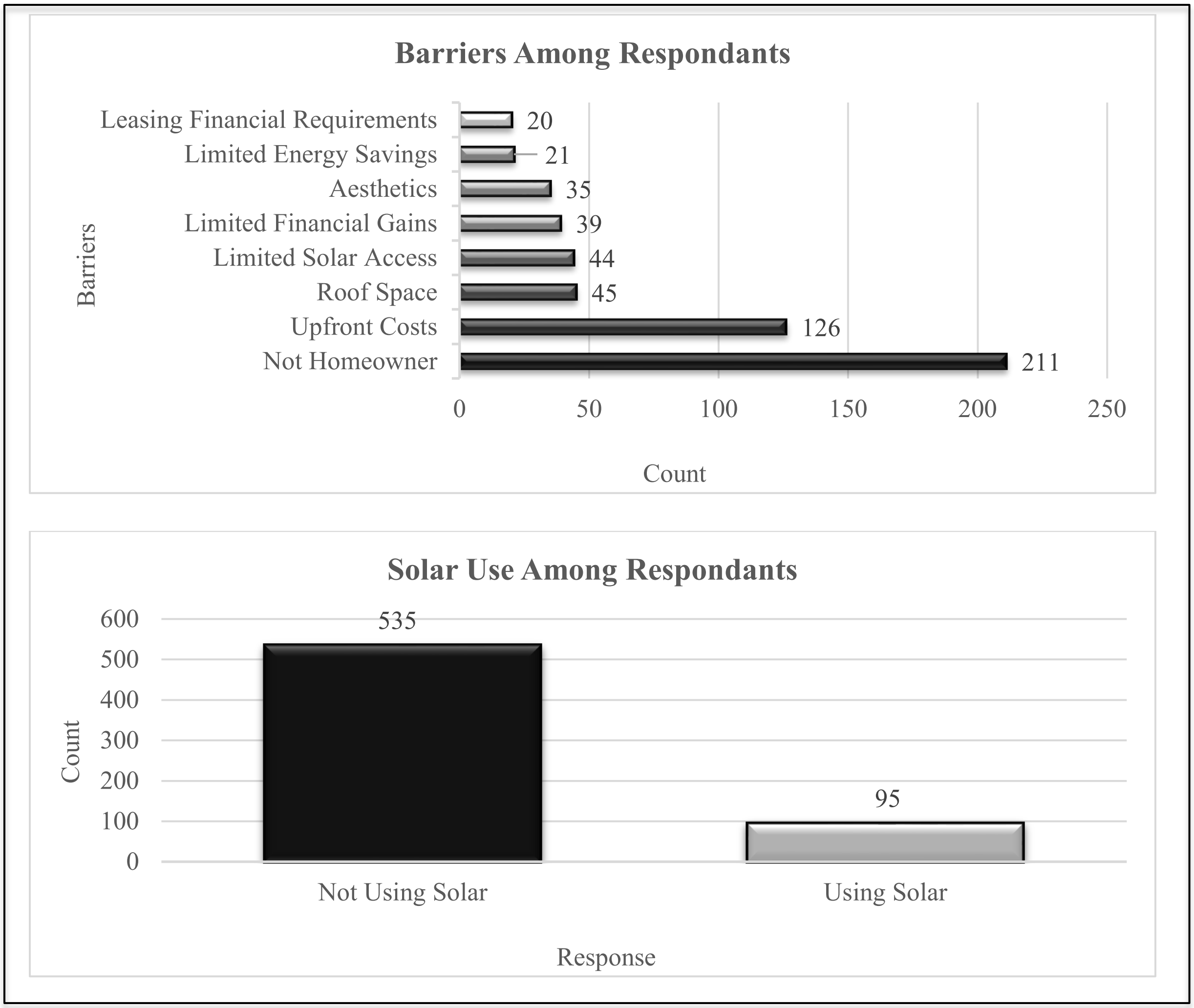
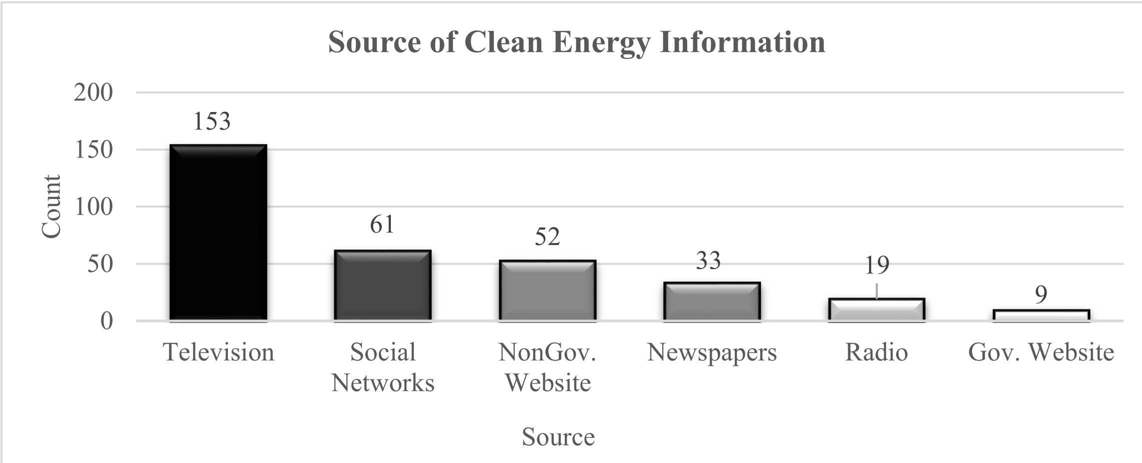


Figure 47: Clean Energy Information Sources



5.4.2 MNL Model 1

The estimated coefficients derived from the MNL with financial gain levels are shown in the table below. The coefficients of the utility function for the attribute levels had the expected outcome in the model. The model indicated a good fit with a Log likelihood of -4366.335 values at zero and at convergence, and a pseudo-R^2 = 0.4742. The non-preserved farmland level had the lowest utility as forestlands were the least preference location for community solar, hence we considered it as the baseline. All the land use array attributes (land fill, non-preserved farmland and commercial buildings) were statistically significant and exhibited positive utility to the respondents, suggesting significant support for all land use array by New Jersey residents. In the case of proximity attribute, *adjacent to my residence* was the baseline. The coefficients for *within my community* and *outside of my community* were both positive and significant, indicating that New Jersey residents prefer community solar that are both within and outside the community, with *adjacent to my residence* being the baseline. For reduction of fossil generation attribute, the baseline was 20%, both the 50% and 100% reduction of fossil fuel generation levels were positive and significant. For environmental quality attributes the baseline was decrease in environmental quality, with both levels staying the same and improvement of environmental quality having a positive and significant. In this model the cost attribute was the financial gain attribute was not considered as a continuous variable in order to assess the respondent preferences for the levels, no financial gain, 50% saving costs and 100% saving costs. We considered additional energy cost as our baseline, primarily because this would give the lowest utility among the other levels. Overall, all the financial gain attribute levels had positive and significant levels.

Table 20: Parameter Estimates

Parameter estimates for community solar program attributes	
Attribute levels	**MNL Estimate**
Land use array (Landfill)	0.757 (0.051) ***
Land use array (Farmland)	0.482 (0.051) ***
Land use array (Commercial)	0.819 (0.049) ***
Proximity	0.244 (0.042) ***
Proximity	0.284 (0.043) ***
Reduction of fossil fuel generation (50%)	0.402 (0.040) ***
Reduction of fossil fuel generation (100%)	0.690 (0.043) ***
Environmental quality (stays the same)	0.778 (0.042) ***
Environmental quality (improves)	0.137 (0.041) ***
Financial gain (No gain)	0.491 (0.050) ***
Financial gain (50% cost savings)	1.122 (0.055) ***
Financial gain (100% cost savings)	1.348 (0.054) ***
ASC	8.417(0.360) ***
Pseudo R^2	0.4742
Loglikelihood	-3874.30
Number of Respondents	630
Number of Observations	22,675

Note: ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Values in parentheses show standard errors.

5.4.3 MNL Model 2: Willingness to Participate

The parameter estimates in the second model was are consistent with the first model in terms of magnitude, signs and significant, as a result our focus will be in explaining the willingness to participate estimates. In our second model in-order to compute the marginal willingness to participate estimates, we converted the financial gain attributes into continuous cost variables. This was facilitated by considering the monthly utility bills from the respondents which was estimated at $240.08. As result the financial gain attribute level, additional energy cost being equivalent to $ 244.8, no gain being equivalent to $ 240.08 monthly bill, whereas the level 50% cost savings was $ 120.08 monthly bill, 100% cost saving resulting in $ 0 monthly bill (or no monthly bill). The marginal WTP measures are presented in the table below.

Table 21: WTP Parameter Estimates Community Solar

Parameter estimates and willingness to participate in community solar programs		
Attribute Levels	**MNL Estimate**	**WTP (USD)**
Land use array (Landfill)	1.074 (0.049) ***	579.88
Land use array (Farmland)	0.908 (0.048)***	490.44
Land use array (Commercial)	1.082 (0.047) ***	583.82
Proximity (Within the community)	0.552 (0.040) ***	298.25
Proximity (Outside the community)	0.639 (0.042) ***	344.99
Reduction of fossil fuel generation (50%)	0.535 (0.040) ***	289.23
Reduction of fossil fuel generation (100%)	0.627 (0.042) ***	338.67
Environmental quality (Stays the same)	0.712 (0.044) ***	384.31
Environmental quality (Improves)	1.111 (0.043) ***	600.03
Financial benefit	-0.002 (0.001) ***	
ASC	7.853 (0.358) ***	
Pseudo R^2	0.4316	
Loglikelihood	-4664.53	
Number of Respondents	630	
Number of Observations	22,412	
Note: ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Values in parentheses show standard errors.		

For the land use array attribute the level commercial/industrial building elicit the highest increase in willingness to participate. This indicates that conversion of the land use array from landfill to commercial building would result in an expected increase of $ 3.94 per month in financial gain by the program participants. Similarly, conversion from farmland to landfill would elicit an increase of $89.44 per month in financial gain by program participants.

For the proximity attribute program participants indicated preference for community solar arrays, outside their community. Furthermore, the conversion of the location of the community solar array from within the community to outside the community is expected to increase the financial gain by $46.74 per month.

Similarly, program participants prefer community solar arrays that results in 100% reduction of fossil fuel generation, this is evident as an increase of the capability from 50% to 100% reduction of fossil fuel generation will attract an increased financial gain of $ 49.44 per month. Finally, community solar array programs that result in improving environmental quality are more preferred by program participants, as conversion from a program that has no change in environmental quality to a one that results in an improved environmental quality will attract financial gain to the tune of $215.72, which is the highest change in utility for all attributes.

5.5 Discussion

In this chapter we execute a discrete choice experiment based on characteristics of random utility theory to examine how 630 New Jersey residents perceive utility of a hypothetical community solar project based on attributes of land use, environmental quality improvements, proximity to their residence, and potential energy savings. Based on our analyses we can deduce that individuals within the population prefer solar photovoltaics to be developed in commercial areas, followed by landfills. We found that farmland was least desirable. We also found that individuals preferer arrays to be further away from their residences outside of their communities. This brings to light how people would rather not see their clean energy source and would prefer for it to be located on environmentally degraded lands. In our willingness to participate analyses, we are able to see that individuals are willing to incur additional energy costs and less energy savings to see community solar projects located on their preferred land uses and with maximum reductions in fossil fuel electric generation and improved environmental quality. The improved environmental quality describes the importance of local air and water quality that are negatively impacted by fossil electric generation.

The strengths of this work include gaining novel insights specific to New Jersey. This information improves upon the current body of knowledge at a time when environmental policy dynamics are advancing rapidly in this area of research. Also, in the context of future ratepayer analyses, the WTP results can provide insights into where stakeholders are willing to spend more on energy if they are able to benefit from improved environmental quality and climate change mitigation.

5.6 Policy Implications

Advances in renewable energy generation technology, particularly solar photovoltaics are improving greenhouse gas mitigation efforts (Brown, 2001; Carpejani, 2020). The overall success of solar photovoltaics is highly dependent on available policy support regimes, technical design of the array, land use planning, energy demand, and quality of available grid interconnection infrastructure (Sen, 2017). Understanding where these technologies may be deployed, quantifying the anticipated benefits, and mitigating risks are required for successful policy success (Pindyck, 2017). In New Jersey, the socio-economic characteristics of the population span a wide range, making traditional clean energy programs not accessible to all. With over 40 % of New Jersey residences not owning their own home, and nearly 10 % living below the national poverty line (U.S. Census), it becomes apparent that many individuals are not eligible for traditional incentive programs such as residential net metering solar (Comello, 2017). As clean energy policies advance in the United States, access can be increased, as demonstrated in distributed energy programs such as community solar (Funkhouser, 2015).

New community solar policy in New Jersey has created exciting opportunities to apply information from this study to future program iterations that expand access to clean energy. The State's community solar pilot program was introduced in late 2019 with the goal of evaluating opportunities and challenges associated with a statewide virtual net metering policy. The program calls for a site host, a project developer, and an energy subscriber. The pilot program solicited 75 MW of solar capacity across 45 new solar projects that were evaluated and selected based on geographic, demographic, and economic factors. The pilot program is structured to promote siting projects on impervious surfaces and degraded lands such as brownfields and landfills. Additionally, projects are required to serve low-to-moderate-income (LMI) communities within the same electric distribution company (EDC) territory (N.J. Community Solar Pilot Program Application). Providing location-based insights into potential project locations with considerations of interconnection, conservation, and public preference will be critical in the development of future iterations of community solar in New Jersey which are anticipated to be further integrated into long term solar policies and possibly renewable portfolio standards. This study and future survey approaches targeting New Jersey, will improve the dissemination of information from stakeholders to the policy developers, thus leading to increased participation and overall benefits.

5.7 Conclusions

Stakeholder perceptions and valuation of solar photovoltaics will always have strong influence over public acceptance of changing utility systems. If policy makers expect ratepayers to allocate more of their income to support renewable energy and avoid the environmental and economic impacts of climate change, fully understanding where these projects are desired will be critical. We conducted this investigation to answer our questions on how New Jersey residents perceive community solar energy in terms of land use, energy savings, impacts of reducing fossil generation, environmental quality. As we anticipated, we say positive perceptions on climate change mitigation, energy savings, and local environmental quality improvement. We also saw negative perceptions of locally sited arrays, with preferences being on marginal lands outside of communities. As community solar and other net metering programs advance in New Jersey and throughout the United States, economic valuation methods with geographic considerations will bring new and useful information to be used in policy development.

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6 Qualitative Policy Analysis for Evaluating Generation Shifting Approaches in The Regional Greenhouse Gas Initiative Emission Trading Scheme

6.1 Introduction

In this chapter we explore the issue of generation shifting in the Regional Greenhouse Gas Initiative (RGGI) from a qualitative policy analysis perspective. This carbon dioxide trading program targets greenhouse gas reductions in the fossil fuel section of the grid supply energy sector in the northeastern United States. As with other cap and trade programs the underlying economic and environmental rationale is straightforward, de-incentivize emissions in a targeted sector by requiring firms to internalize costs of the associated emission. However, competitive energy market dynamics can complicate the process and pose risks of undermining the greater goal of reducing GHGs and mitigating climate change (Chan, 2019).

RGGI is a state and nongovernment-organization collaboration among RGGI Inc. and New York, Maryland, Massachusetts, Connecticut, Vermont, New Hampshire, Maine, Rhode Island, Delaware and most recently, New Jersey. This program commenced development in the early 2000s and first saw revenue in 2009. The RGGI program has additional potential for expansion into Virginia and Pennsylvania (Fell, 2018). As these state governments begin the early discussion and investigations on how they can participate, and what the environmental and economic ramifications may be, additional research is needed to identify new opportunities and mitigate risks associated with a growing carbon emission trading program (RGGI Inc, 2007; Fell, 2018).

In our analysis we look to other emissions trading schemes for insights into how competitive energy markets and GHG cap and trade market driven programs interact. In doing so we define generation shifting, discuss how it is evaluated, and propose recommendations for mitigating with respect to RGGI. Political drivers at the state level have influenced participation in RGGI over time (Huber, 2013), as seen in New Jersey's involvement in the RGGI program. Although the State was a founding member, they departed from the program due to political pressures in 2009. In early 2017, the political tides of the state had shifted once again, and New Jersey to re-enter the program. New Jersey exiting the program forced the other participating States to adjust the regional cap. This is an example of how dynamic the program is. As external factors, such as changing fuel availability and prices and other air quality regulation, influence electric generation efficiencies and emission rates, low hanging fruit for emission reductions are becoming sparse (Fell, 2018). As seen in the shifts in New Jersey's generation portfolio transitioning from coal and oil boilers, to more efficient and economical simple cycle and combined cycle generating units (De Gouw, 2014). Although these factors have positive implications for GHG emission reduction as a whole, they do limit the possible reductions associated with cap-and-trade programs.

As the program undergoes a scheduled re-design in late 2020 the program will be considering how to optimize re-investment proceeds, maximizing carbon dioxide reductions, and minimize ratepayer impacts. Furthermore, with the potential of expanding to additional state's there is value in illustrating and evaluating strategies to mitigate generation shifting (Chan, 2019, Fell, 2018; Viskovic, 2019). The goal of our work is the synthesize the main concepts in this topic and communicate them to inform our audience. The hypotheses we test in this chapter include: 1) How are interconnected competitive energy markets impacted by the RGGI ETS? 2) Are these impacts creating risks of generation shifting? 3) What program specific mitigation measures can be used to mitigate generation shifting in this ETS?

6.2 Literature Review

In the United States, carbon dioxide is the largest contributor to greenhouse gases and global warming (EPA, 2018). The two sectors in which these gases are produced the most include electricity generation and transportation (EPA, 2018). In the U.S. emissions are controlled under air quality regulation (Crandll, 1983; Kolstad, 2018), which most frequently operates as a command-and-control regulation (Kolstad, 2018). The emission trading approach has been conceptually developing since the 1960's (Coase, 1960; Dales, 1968) and has seen implementation as an alternative across a variety of pollutants in the United States starting in the 1980's and 1990's (Borghesi, 2014; Kolstad, 2018). Most notable early emission trading programs in the U.S. include the lead trading program (Elleman, 2005) targeting gasoline composition, and the acid rain program targeting fossil fuel power plants (Elleman, 2005). Literature suggests that when implemented with appropriate program design, emission trading programs can reach goals more rapidly, and with greater success rates than their command-and-control counterparts (Elleman, 2005). This is attributed to allowing compliance entities to independently determine the lowest-cost compliance strategy, often realized by utilizing new technologies or switching to a more efficient fuel source (Elleman, 2005).

Historically, efforts to mitigate GHG emissions reduction efforts have focused on expanding clean energy generation such as solar and wind (Bazmi, 2011; Brown, 2001). Because U.S. energy markets are so heavily driven by reliability and reducing rates of increased energy costs to the consumer, directly restricting fossil fuel generation can be challenging (Brown, 2001). However, as the hazards associated with climate change have gained global public awareness and political traction over the last twenty years, we have seen a slow but gradual trajectory in global policy to transition from strictly air quality regulation directly related to human health and environmental quality towards more encompassing climate regulation (Maser, 2011).

The European Union's Emission Trading Scheme (EU ETS) is regarded as a pioneer program to bridge this GHG regulation gap (Elleman, 2005). The EU ETS is recognized throughout the literature as the first international GHG cap-and-trade program and has evolved since the early 2000s in terms of growth in participants, and design improvements bolstered by other international GHG maxims such as the Kyoto Protocol (Grubb, 2014; Babiker, 2003; Aichele, 2013). This ETS program includes over 30 countries and regulates more than 11,000 compliance entities (Burghesi, 2016). Encompassing such a large emission market presents an abundance of opportunities for technological advances and large amounts of emission reduction (Burghesi, 2016). The EU ETS program is the basis of several other national programs such as the United Kingdom ETS, New Zealand ETS, Australian ETS, Korean ETS, China ETS, and the Switzerland ETS (Aldy and Stavins, 2008; Smith and Swierzbinksi, 2007; Elleman ,2005).

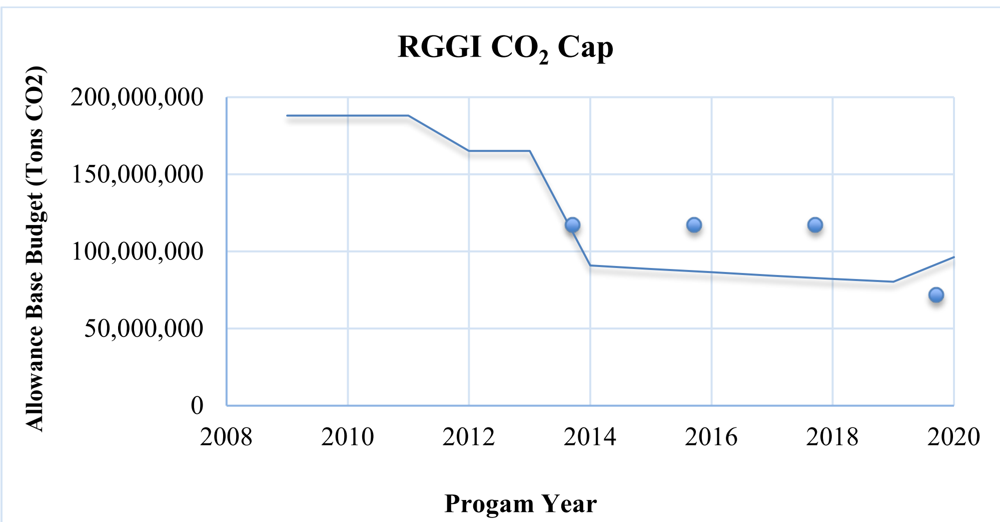
The EU ETS program regulates electricity generation and other industrial activities, which are required to purchase carbon dioxide allowances based on their emissions (Elleman, 2005). However, notable shortcoming of this ETS include challenges in monitoring emissions and maintaining consistent allowance allocation planning across political boundaries (Burghesi, 2016). Both of these issues have resulted in significant allowance price volatility and uncertainty among regulated firms (Burghesi, 2016). Regional ETS efforts such as the Tokyo ETS and the China ETS (Elleman, 2005) emulate the EU model and make appropriate adjustments to avoid monitoring and market issues prevalent in larger international schemes (Elleman, 2005). The largest regional GHG ETS program in the U.S. is the California Cap and Trade Program operated by the California Air Resources Board (Elleman, 2005). The California ETS includes multiple sectors, originally regulating electricity generation, and later expanding into large industrial operations, and fossil fuel distributors (De Perthuis, 2014). Due to the energy distribution system markets in the region, the program has recently expanded internationally with participation into the Canadian provinces of Ontario and Quebec thus merging with the Quebec Cap-and-Trade Program (Flachsland, 2009).

The Regional Greenhouse Gas Initiative (RGGI) is discussed in the literature as a means to regionally reduce greenhouse gasses from the electricity generation sector while simultaneously reinvesting emission auction proceeds into energy efficiency and renewable energy, and supporting state environmental justice improvement priorities (Huber, 2013; RGGI Inc, 2009; Bifera, 2013; Burtraw, 2006; Holt, 2007; Ruth, 2008; Hibbard, 2015). Some works, such as Huber et al 2013, highlight the success of the Regional Greenhouse Gas Initiative, while others such as Burtraw et al (2006), describe the challenges of establishing the state allocations and the broader economic pressures on electric generators which ultimately impacts rate payers (Huber et al, 2013; Burtraw et al, 2006).

This initiative is facilitated by program administrators of RGGI Incorporated and environmental regulators across the participating states. The goal of this collaborative effort is to gradually reduce greenhouse gasses (GHG) by creating a carbon dioxide market in which the owners and operators of qualifying electric generation units (EGUs) are required by state regulation to internalize the cost of carbon by purchasing allowances equivalent to the amount of emissions they produce (Fell, 2017). In turn, the state agencies re-invest the realized proceeds of these sales into the clean energy economy through funding mechanisms determined by a state-by-state legislative process (RGGI Inc, 2008; Hibbard, 2018). The cumulative emissions produced by these generators will determine the regional demand (Fell, 2017; RGGI Inc, 2008).

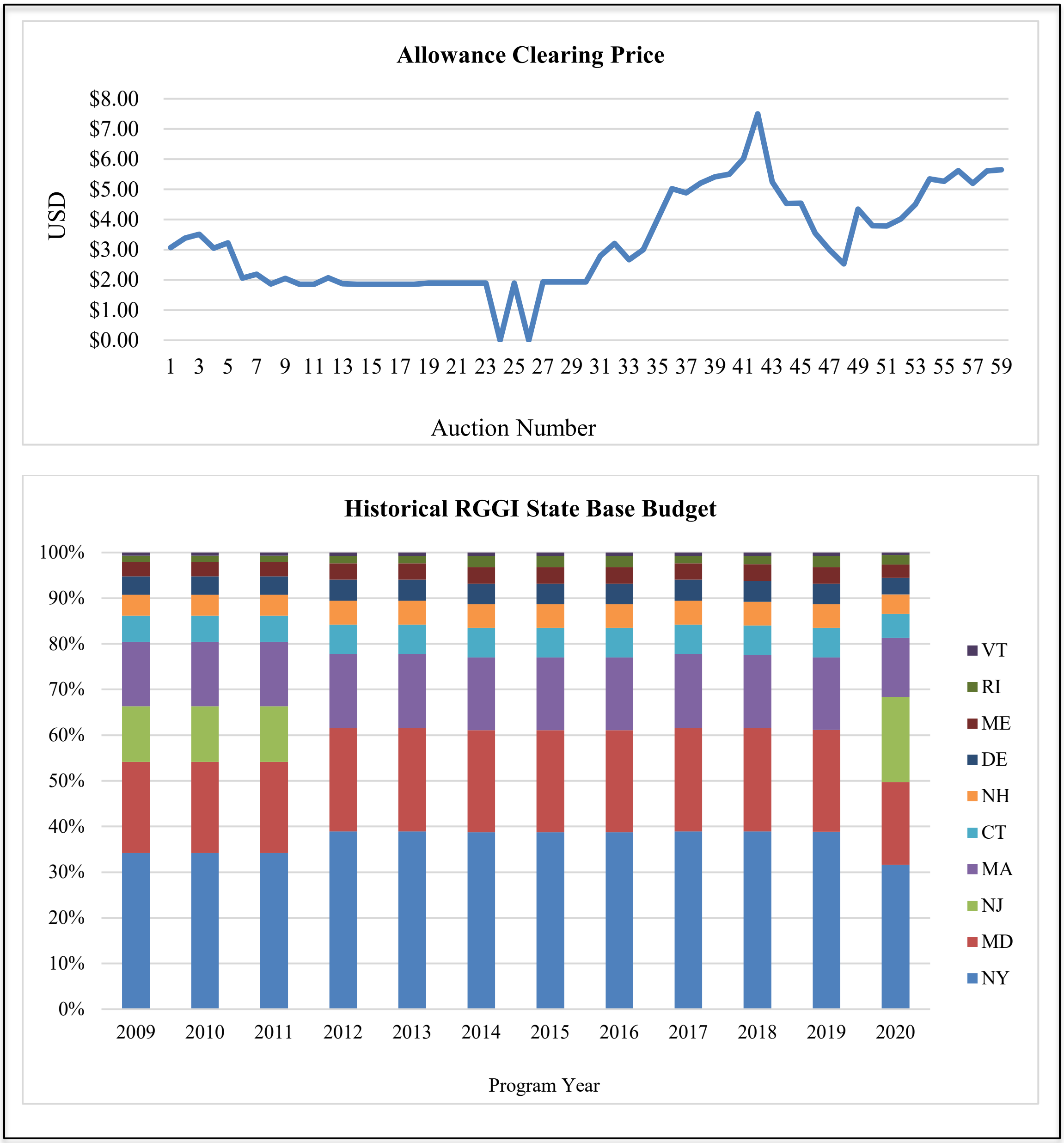
The value of the allowances fluctuates over time as supply and demand influences the market (Fell, 2017). The overall supply of allowance is a result of the regional allocation cap, which is determined by the participating states and is based on the aggregated amount of carbon dioxide emissions across the region (Fell, 2017). The sharp noticeable drops in the total budget is a result of regional cap adjustments, most notably when New Jersey temporarily departed from the program. The current RGGI region is defined as the state boundaries of Connecticut, Delaware, Massachusetts, Maryland, Maine, New Hampshire, New Jersey, New York, and Rhode Island.

Figure 48: RGGI Total Allowance Budget



The figure below represents trends in the carbon dioxide base budget for RGGI participating states for the year 2009 to 2020 collected from RGGI Inc. These values are indicators for potential economic investment in climate mitigation projects determined by the State regulatory agencies. The allowances are auctioned quarterly with the proceeds reinvested in the clean energy economy by providing funds to renewable energy programs and incentives (RGGI Inc, 2008). The allowance budget for each state is proportional to the amount of auction proceeds each state realizes. Proceeds from RGGI auctions have driven large capital investments throughout the participating states in clean energy development and climate change mitigation (Bush, 2020). Between 2009 and 2017 the program has generated $315 million (RGGI Investment Report. 2019). Furthermore, since its inception the total reduction in emissions is estimated at 20 million tons (RGGI Investment Report. 2019). The historical investments have been in the areas of energy efficiency, clean and renewable energy, greenhouse gad abatement, and direct bill assistant at rates of 51%, 14%, 14%, and 16% respectively (RGGI Investment Report. 2019). Energy efficiency investment compounds the emission reduction of the program, with a cumulative energy savings of over $800 million on energy bills through the life of the program (RGGI Investment Report. 2019). The figure below represents quarterly auction allowance clearing prices, collected from RGGI Incorporated and is a function of total emissions and allowance supply. Taking lessons from the larger ETS approaches, RGGI utilizes strategies to provide predictable market signals including a pre-established rate of reduction in the regional cap over time, floor and ceiling allowance prices, and frequent program redesigns. This program specifically targets grid supply fossil fuel generation with a nameplate capacity of 25 MW or greater. By targeting larger capacity EGUs, the program avoids impacting smaller generators, which are mostly utilized by an ISO during peak demand periods. This reduces impacts on reliability and risks of economically terminating low operating time marginal units (Bush, 2020).

Figure 49: RGGI Clearing Prices and State Budgets



The RGGI program crosses multiple interconnected system operators (ISOs), meaning electric generators subject to RGGI regulations can be competing at an economic disadvantage against other generators that are not impacted by the program within the same energy market (Fell, 2017; Chan, 2019). Carbon dioxide emissions produced by fossil fuel grid supply power generators with a nameplate capacity of 25 MW or greater are not uniform across RGGI State borders. A generator's bid in price is a function of many fluctuating inputs, the risks of generation shifting occurring is spatiotemporally dynamic. When ISO territories are small or contains within the boundary of a participating state this issue is absent or negligible (Fell 2017). However, in larger ISO's that cross several political boundaries, there is an increased likelihood that the additional costs of RGGI compliance can influence where and how electric generators are dispatched (Fell, 2017).

In a competitive power market, just as PJM ISO, NYISO, New England ISO, generation dispatch is determined by the ISO on the basis of acquiring lowest cost reliable energy to meet load demands across the transmission system (Fell, 2017). Considering the variability in generator technology and fuel types used within the ISOs of the RGGI region and outside the region in other areas of the United States, changes in dispatching can create implications of increased levels of less efficient electricity generation and associated emissions (Fell, 2017). This phenomenon is defined as generation shifting, also referred to as leakage (Babiker, 2003). More specifically, these means that there may be, and potentially has been, changes in the geographical locations of where energy is entering the electric power market, based on economic forcing's as a result of the RGGI program (Fell, 2017). Generation shifting is most likely to occur in ISO's with diverse generation and partial participating in RGGI, such as PJM (Fell, 2017). As political tides within the RGGI region and the surrounding states shift to favor the expansion the program, the associated risks of generation shifting must be evaluated and addressed through mitigation strategies (Fell, 2018).

In the energy economic literature, there have been many been many studies discussing leakage as an issue related to regional ETS systems (Fell, 2018). The analytical approaches used in these investigations uses quantitative numerical simulation models such as the computable general equilibrium (CGE) modeling to evaluate economic impacts on large scales and carbon pricing approaches such as border adjustment taxes or generation-based costs adders (Fell, 2018; Carbone, 2014; Fischer, 2012). Studies of this nature focusing on RGGI and California ETS leakage specifically include (Fowlie, 2009; Bushnell, 2012; Chen, 2012; Caron, 2015). Recent studies applying these, and other quantitative approaches have suggested that there is leakage occurring as a result of the RGGI program and similar sub-national regional programs (Lee, 2013; Kindle, 2011; Chan, 2019)

6.3 Study Rationale and Objectives

Based on our review of relevant policies and literature, we identify the need for additional research to be conducted on evaluating options for mitigating generation shifting within regional greenhouse gas emission trading programs. There is consensus that emission trading programs spanning multiple political and interconnection (ISO) borders are at risk of negatively influencing generation dispatch resulting in net increases in global emissions. We identify an opportunity to evaluate generation shifting mitigation strategies than can be used to improve GHG mitigation in an expanding Regional Greenhouse Gas Initiative program. The objective of this research is to describe and assess generation shifting approaches that have been historically proposed by the RGGI program and compare them to those used to mitigate generation shifting in other ETS programs and those proposed by the PJM ISO.

6.4 Mitigation Approaches

Among the available approaches described throughout research and energy market literature, we can organize the potential generation shifting mitigation methods into three overarching categories. These approaches include:1) Improving monitoring and modeling methods to better quantify leakage risks and occurrences 2) Promote efforts which target reducing energy demand overall within the program states, and thus reducing leakage by proxy. This would be primarily achieved through increasing energy efficiency across sectors. 3) The development and implementation of carbon adders and emission rate regulation mechanisms, which would effectively incorporate environmental costs into the total costs of generation. 4) Incorporating a load-based emission cap, which would directly place an emissions allocation obligation on electricity load serving entities (LSE), or utility companies associated to their power purchases, as compared to the status quo generator obligations. 5) Foster increased participation among states within leakage prone ISOs and explore linkage opportunities with other ETSs. By expanding the RGGI program within areas of interests benefits such as increased potential for emission reduction and auction revenue can be incorporated into leakage mitigation.

The approaches listed above, or an interpretation of, has been proposed by the RGGI program, discussed by PJM ISO, and implemented within other GHG ETSs. At this time, the RGGI program does not utilize any generation shifting mitigation approaches. However, during the development of the program, RGGI Inc. and a working group of regulatory agents across the participating states, put forth documentation in which they described their evaluation of perceived risk and recommendations for future polity action to reduce leakage (Potential Emissions Leakage and the Regional Greenhouse Gas Initiative (RGGI): Evaluating Market Dynamics, Monitoring Options, and Possible Mitigation Mechanisms 2008) . Although the program has made some significant changes is its design over the past twelve years, all documentation referring to leakage point back to this report.

Improving data availability can promote additional analyses to evaluate leakage conditions across an ETS. In the RGGI Market Dynamics Report (2008), the priorities of improving the PJM GATS and New England ISO GIS (generator attribute information system tools) to include additional information regarding emissions mixes and adding additional generator attributes for smaller units. Similar improvement has been added to the E.U. ETS program in recent years (Dixon, 2015). This approach does not directly impact reduction in leakage; however, it opens the door for future analyses to do so (De Giovanni, 2014).

Developing policies that reduce energy demand are beneficial for many reasons but are highlighted by providing maximum benefits to energy consumers through energy savings. This approach would be manifested as improved standards for appliances and buildings codes, in addition to developing energy efficiency portfolio standards, and promoting innovative technology such as combined heat and power (RGGI 2008). This use of these approaches can indirectly reduce leakage by reducing overall load demand while simultaneously providing additional benefits realized by the RGGI proceeds re-investment. However, the relationship between improved energy efficiency and reductions in energy prices is indirect. Therefore, this approach would certainly be beneficial, but its impact of future leakage is uncertain (RGGI, 2008). This approach can also be manifested on the state scale, as seen in New Jersey's zero costs allocation approach to combined heat and power operations in their regulations as the re-joined the program (NJ RGGI Rule). Although there is a limited number of CHP facilities that fall into this category in the State, it is a step in the right direction.

Carbon adders can target leakage more directly by increasing costs associated with procurement, emission rates, and portfolio standards (RGGI, 2008). A carbon procurement adder creates a shadow price of carbon on load serving entities (LSE), also commonly referred to as, utilities, or electric distribution companies. In this approach risks of future carbon regulation risks are internalized by the LSE and can influence their choices in procuring generation. This approach targets power purchase agreements from specific power generation units/power plants. This approach would make the adder equivalent to the clearing price of a RGGI allowance and would impact generators within the region more than the ISO and thus have limited leakage impacts that scale with direct sales. Carbon procurement emissions rate would also influence power purchase agreements based on energy-emission efficiencies thus driving down the generation of high emitting generation and would see limited impacts in areas where state of the art combined cycle natural gas generation occurs. Emission rate portfolio standards (EPS) is another carbon adder approach that would set a standard emission rate that an LSE would procure energy. Carbon adder approaches have recently been undergoing evaluation from the PJM ISO to better understand potential future energy markets in which they participate.

The most effective approach for reducing generation shifting is expanding the RGGI program with additional states, particularly those with generation portfolios that consist of inefficient generation such as coal. Although this process takes place over the long term and would be potentially politically challenging, it would be the most effective in alleviating factors that drive leakage described in the literature. Recent discussions with Virginia and Pennsylvania pose significant opportunities for the program to expand into much larger territories with higher generation and coal intensive units. Furthermore, linking with non-interconnected ETS programs, as seen in California pose additional opportunities to expand.

6.5 Discussion

Based on the reviewed applications of best options for adapting generation shifting mitigation would be a combination of increased energy efficiency programs with fostering favorable conditions to expand into other states within the PJM ISO. This would be an optimize approach in bolstering energy efficiency strategies, with come with their own befits, and targeting the most direct approach to reducing leakage. Increasing the RGGI market would directly reduce impacts on economic competition among EGU's, while increasing the regional cap. This would drastically drive up the revenue potential and the climate mitigation associated with investment of auction proceeds. Furthermore, this would create new opportunities for technology improvements such as the transition from coal to more efficient natural gas, as seen in Pennsylvania and Virginia. Also, pursuing linking systems and expanding RGGI to collaborate with other ETS programs, can prove strategically useful across stakeholder groups as future climate policy influences the region. Recent oil market fluctuations may have an impact on clean energy programs in the near future. However, these forcing are likely to impact mitigation efforts focused in the transportation sector as potential consumers electric vehicle consumers see lower gasoline prices. In the Unites States, particularly within the PJM ISO, low crude oil prices are unlikely to have major direct impacts on how energy is dispatched. Oil electric generation is minimal and is mostly used for generators to meet reliability requirements. In the context of generation shifting within the RGGI ETS, the price difference between natural gas and coal will have much more of an influence. This is due to minimal usage of oil generation as discussed above, in addition to domestic shale gas sourced within relatively close proximity to the generators in the region. Local sources of cheap natural gas, and massive efficiency differentials between the two technologies have resulted in oil generation exiting the market.

6.6 Conclusions

The Regional Greenhouse Gas Initiative is a successful program which allows for a collaboration among several State agencies to reduce energy emissions that contribute to climate change. In our analyses we describe generation shifting techniques that can be used to minimize addition net carbon dioxide emission as a result of the RGGI program. Based on the reviewed applications of best options for adapting generation shifting mitigation would be a combination of increased energy efficiency programs with fostering favorable conditions to expand into other states within the PJM ISO.

Particularly as states enter, the risk of generation shifting, also known as leakage is likely to occur. As political drivers among various states change over time, the risks associated with generation shifting will likely be elevated slighted, e.g. Pennsylvania possible entering the program. However, due to the historical and continued use of low efficiency fossil fuel generation throughout portions of PJM it is unlikely that RGGI will be a silver bullet in the attempts to decarbonize the grid of the eastern U.S. Fortunately, other large-scale clean energy programs are likely to be injected into the national grid such as development of large-scale offshore wind project along the eastern coast. The results of this chapter provide timely information as the State of New Jersey enters this initiative and finalizes plans to make the most of the benefits while minimizing the negative economic impacts of this cap and trade system. In our analyses we investigate generation shifting mitigation approaches. This information can be used to inform policy decision making in the near future, particularly during the program redesign taking place later this year. Next steps and future efforts of this research will include dispatch modeling to better extrapolate leakage risks across a series of scenarios.

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Worland, J., (2017). A new U.S. environmental alliance is trying to take Trump's place on the world stage. Time Magazine.7 Conclusions, Limitations, and Future Work

7.1 Conclusions

As society is faced with present hazards and future risks associated with anthropogenic climate change, clean energy policy that promotes end use energy reduction, renewable generation, and emission reductions in the fossil generation sector become increasingly important. The objective of this research is to leverage spatial economic investigation methods to provide new insights that can be used to support new clean energy policy in New Jersey by disseminating technical potential and stakeholder input from an environmental management perspective. Understanding where these technologies may be deployed, quantifying the anticipated benefits, and mitigating risks are required for successful policy implementation and further clean energy transition. This dissertation targets geothermal heat pumps (GHP), solar photovoltaics, and the Regional Greenhouse Gas Initiative (RGGI).

We identify geothermal heat pumps as an underutilized efficiency strategy to reduce energy end use in New Jersey. Based on the new information provided in our place-based analysis, we determine that GHP is most frequently used in the residential segment of the building sector and systems show significant spatial clustering which alludes to driving forces influencing current levels of deployment. Additionally, the results of our suitability model identify areas for targeted site-specific feasibility investigations based on socio-economic, energy economics, and physical geographic factors. These approaches speak to future policy improvements that would be enhanced with a segmented market approach of government incentivization and support regimes that makes determinations among building sectors and prioritizes residential adoption.

Our life cycle assessment of residential geothermal heat pumps yields new insights into the cradle-to-grave environmental and human impacts across the categories of climate change, ozone depletion, photochemical ozone creation, human toxicity, ecotoxicity, eutrophication, acidification, land and water stress, and resource depletion. Furthermore, comparing location-based generation portfolio parameters we can deduce that geothermal heat pump systems have lower impacts within New Jersey as compared to the rest of the United States, as well as compared to other building space heating and cooling technologies. This underscores the untapped co-benefits of these systems which complement the emission reductions attributed to their energy efficiency paybacks.

Maximizing renewable energy generation while minimizing development of conservation landscapes will be an essential component of climate mitigation strategies to reduce fossil-based electric generation. We fill a knowledge gap for predicting solar photovoltaics potential in New Jersey across multiple scales using geographic information systems and remote sensing in New Jersey. This chapter was designed to develop spatial intelligence on clean energy feasibility to gain insights into where potential technology adopters are located, quantifying suitable project locations, and evaluating future capacity assumptions. In the first section of this investigation we present a spatial interpolation approach for estimating solar hosting capacity across the electric distribution territories of the State. Evaluating hosting capacity throughout the study area will have implications for future energy infrastructure development allowing for an increase in photovoltaic systems. In the second section we present a method that analyzes residential net metering, ground mounted systems, and community solar customer potential based on geographic, demographic, and economic inputs using suitability modeling in a geographic information system environment. This is an effective way to evaluate to evaluate statewide conditions at the census tract scale. The key findings improve upon commonly used metric for evaluating future solar development. In the final section of our solar investigation we use remote sensing techniques to examine solar potential in three municipalities which yields high resolution outputs without costly and time consuming in situ data collection. We present new information on flooding risks, roof geometry, and solar radiation potential for the municipalities of Atlantic City, Camden, and Newark. By taking this multi-scaled technical approach we are able to evaluate this topic more holistically while providing policy makers with a foundation to inform anticipated new solar generation assumptions and policy incentive structures.

As future policies advance with the goal of improving clean energy access, determining stakeholder willingness to participate in solar programs will be needed to design new programs. In our consumer willingness survey for community solar, we verify common barriers to residential net metering in New Jersey and evaluate stakeholder's valuation of community solar projects based on their geographic attributes and environmental benefits. As community solar is a new and developing incentive program in New Jersey, there is a demand for stakeholder input that strengthens traditional policy making stakeholder contribution as seen in stakeholder meetings. Our survey questions target how New Jersey residents perceive community solar energy in terms of land use, energy savings, impacts of reducing fossil generation, environmental quality. As we anticipated, we see positive perceptions on climate change mitigation, energy savings, and local environmental quality improvement. We also saw negative perceptions of locally sited arrays, with preferences being on marginal lands outside of communities. These findings contribute to the body of knowledge on which policy makers gauge future proposed community solar projects and prioritize dissemination of clean energy information.

The Regional Greenhouse Gas Initiative is an emission trading scheme that targets the grid supply electric generating units along the eastern United States with the goal of reducing carbon dioxide emissions to mitigate climate change. This program crosses multiple interconnection system boundaries and can result in generation shifting, also known as leakage. In our qualitative policy analysis, we investigate generation shifting mitigation approaches. We identify the optimal mitigation approaches for this expanding program to be a combination of increased monitoring and modeling, promoting load reductions through efficiency, and expanding the RGGI program to states within distribution systems that have partial state participation. As political drivers among various states change over time and drive participation among regions of competitive power markets, the risks associated with generation shifting may be alleviated slighted. However, due to the historical and continued use of low efficiency fossil fuel generation throughout portions of PJM, it is unlikely that RGGI will be a silver bullet in the attempts to neutralize carbon in the grid of the eastern U.S. The results of this chapter provide timely information as the State of New Jersey enters this initiative and finalizes plans to make the most of the benefits while minimizing the negative economic impacts of this cap and trade system.

7.2 Limitations and Future Work

In our place-based analysis of geothermal heat pumps, we make assumptions to draw conclusions between tax parcels, building sectors, and system occurrence. These assumptions are limited by the accuracy and precision on the spatial data inputs. As noted in the discussion above, tax parcel data is at some level incomplete and is changing over time. Additionally, the GHP well records are limited in the information present to draw broader conclusions on use. In the suitability model of this chapter we base the weight of our inputs on industry standards and literature review. In future iterations of this procedure, we plan to engage with stakeholders, particularly in the geothermal workforce to better identify barriers and local drivers that may be contributing the system use. Furthermore, our initial exploration of our model inputs included state-wide spatial regression analyses. Unfortunately, these did not yield informative results regarding unknown spatial relationships between borehole records and geographic characteristics. In future iterations specific to identifying and weighting suitability model inputs, we will revisit the regression approach at more local scales, particularly in the areas identified as GHP hotspots. This may help us identify a more concrete foundation to inform the model.

In our life cycle assessment of geothermal heat pumps, we use assumptions on future PJM generation portfolios based on information published by the ISO and energy regulators which describes near and long-term increased generation from renewables, particularly solar photovoltaics. Our analyses are limited in these assumptions due to uncertainty regarding the spatiotemporal realization of new renewable generational cross the region. In future iterations of this work, we will perform a more detailed scenario-based series of impact assessments to identify additional co-benefits associated with renewable energy. Additionally, we plan to explore using a Life Cycle Cost Analysis (LCCA) to evaluate cost effective options for increasing GHP deployment in segmented heating and cooling markets. This can further validate our suggestions for a segmented market approach to future incentive programs.

In our geographic investigation of solar photovoltaics, we improve upon established methods used in the regulatory realm to estimate solar capacity potential to inform policy decisions. In our analysis of hosting capacity within the distribution territories we make assumptions on the limitations of the energy system to create the interpolated surface. More detailed investigations on future planned infrastructure upgrades, and additional characteristics of the current system on local scales, would yield a more detailed model with a forward-looking approach. Additionally, exploring locational marginal pricing and areas of congestion to draw linkages between photovoltaic growth and associated impacts on local energy prices would very useful in regulatory planning and prioritization of targeted clean energy strategies. Although outside of the scope of this research, we plan to explore the feasibility of such studies in future work.

In our multi-market suitability model, we provide a statewide hierarchical output which identifies solar build out potential on a sliding scale. As with all raster overlay models, it is limited by the rationale behind the input raster data used and their influence. Our residential suitability model is most robust because it is informed by the prescriptive policy requirements which can be easily transcribed within the spatial data. However, we were forced to be more general in our ground mount and community solar suitability models due to the wide range of environments commercial net metering and community solar arrays can be sited. In future investigations we plan to further explore existing grid supply and large net metered projects to produce new models. Furthermore, as the New Jersey Community Solar Pilot program advances over the next two years, location information on projects successfully accepted into the program can better inform our future models.

In our remote sensing analyses of the selected municipalities, we were limited by the available coverage of high-resolution LiDAR data. Additionally, processing requirements of the analytical procedures are demanding, making the municipal scale the largest practical study area. Within the next year, the New Jersey Department of Environmental Protection is expected to release Quality Level 2 (QL2) high resolution LiDAR data that would establish full New Jersey coverage. This will allow us to perform the same analyses in any location within the state. We plan to explore the feasibility of a state-wide remote sensing analysis to generate additional solar radiation and roof geometry estimate. Furthermore, we plan to investigate the impacts on the levelized cost of energy (LCOE), if such information was publicly available to solar developers across the study area.

In the consumer willingness to pay section of this research, we sample a population of over six hundred New Jersey residents to evaluate their potential participation of community solar. Using the discrete choice experiment approach, we are able to extrapolate survey responses to paint a more complete picture of how the public values clean energy and where in their community they would prefer to have new projects installed. Future iterations of this approach can be used to explore additional participatory geographic information models (PGS), particularly those that investigate future build out potential at lowest levelized costs. This could potentially be integrated within the stakeholder process to inform project evaluation. Understanding where the low hanging fruit are for increased community solar generation will be highly valuable to environmental managers within the State,

In the final segment of this research we perform a qualitative policy investigation to make suggestions for future generation shifting mitigation strategies for the Regional Greenhouse Gas Initiative emissions trading scheme. We were limited in the evaluation of strategies there has yet to be any mitigation action taken, which we could cross-reference. Because the program is unique in how it impacts the competitive energy market, extrapolating from other emission trading schemes has limitations. Additionally, there are several other external factors than may influence frequency and scale of leakage such as dynamics in federal regulation and domestic fuel markets. As policies continue to expand within the climate change discipline of regulation, our future investigations will consider these new state and federal policy scenarios coupled with dispatch modeling.