Assessment of the Environmental Performance of Household Solar Photovoltaics

By

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Abstract

The majority of energy in the U.S. comes from traditional fossil fuel sources (80%) while only 11% is from renewable sources. The availability and reliability of sunlight makes solar energy one of the most viable renewable energy options. Additionally, it has lower carbon dioxide emissions compared to fossil fuels, which is relevant from the standpoint of global climate change. Solar photovoltaics (PV) are the most widely known and adopted solar technology today, especially in sunny locations. However, a variety of factors, such as economic/policy, geographical/location, and environmental impacts, may impact the suitability of PV for large-scale adoption and the associated environmental benefits that are achieved. One concern is whether the raw materials and manufacturing impacts of PV are offset by the impact savings from offsetting grid electricity.

This research focuses on Los Angeles (LA) County as a case study to evalulate the environmental impacts and benefits of residential PV adoption and use. The work will 1) develop an agent-based model to evaluate policies intended to advance the adoption of residential PV systems by residents in the county 2) use life-cycle impact data on PV and fossil fuel sources to evaluate the potential environmental impacts and savings of PV adoption in LA County 3) assess the environmental payback period for PV use in multiple United States

locations. The methods that are used will include life-cycle assessment (LCA), agent-based modeling (ABM), and environmental payback period (EPBP). Chapter 1 outlines the specific research objectives and questions that are addressed through this research. It also describes the methods in more detail.

In the second chapter, the ABM literature on residential PV adoption was reviewed to understand the current state of knowledge and identify gaps for further analysis. Analysis highlighted that studies found certain policies to have increased the overall number of PV adopters. In addition, the opportunity to combine ABM with the methodology of LCA to provide the environmental impacts of adoption over a variety of environmental impact categories was highlighted for further research.

The third chapter is an environmental payback period analysis of solar panel use in five major US cities with differing solar potential and electricity mixes. This evaluation finds that the larger the current portion of renewables is in the electricity mix, the longer the environmental payback period is. It also estimated the environmental impacts of PV manufactured in three major manufacturing regions: China, Europe and US across ten environmental impact categories, including acidification, global warming, fossil fuel depletion, respiratory effects, ecotoxicity, eutrophication, smog, carcinogenics, non-carcinogenics, and ozone depletion.

The fourth chapter is an ABM on residential solar panel adoption in Los Angeles County, California. It was found that the policies evaluated (changes to grid electricity costs and solar panel costs, federal tax credit, and new homes policy) all increased adoption as compared to a business as usual scenario over the time period of 2018-2050. It was found that adoption reached a critical mass in the model by the first 5 years under all scenarios, resulting in approximately 98% of LA County homeowners adopting residential solar panels.

The fifth chapter is on an ABM-LCA model in Los Angeles County, California. It was found that adoption of PV increases environmental impacts in the short term, due to the raw materials and manufacturing portions of the life-cycle of PV. However, it results in savings in the long term, due to PV offsetting grid electricity. Additionally, it was found that the raw materials and manufacturing of PV account for a small portion of life-cycle impacts (~0.3%) when considering the entire life-cycle (raw materials and manufacturing through use).

The sixth chapter expands the initial analysis in chapter three to evaluate the environmental payback period in all US states. It resulted in average, maximum and minimum environmental payback periods across ten environmental impact categories in all 50 states (and District of Columbia). The results were compared to solar potential of each state to find that the ranking is different compared to environmental payback period. Additionally, recommendations were made for which impact categories would be useful from a policy perspective. It was found that in four impact categories, in addition to global warming, fossil fuels (coal, natural gas, petroleum) exceed PV impacts: ozone depletion, smog, acidification, and fossil fuel depletion. Therefore, including these additional impact categories, in addition to global warming, can be used to illustrate the additional benefits of PV over fossil fuels from a policy perspective.

Overall, this work provides a comprehensive assessment of solar PV technology adoption and use as a substitute for conventional electricity generation technologies. It includes the impact of policies on adoption and geographical and temporal variations on the overall life- cycle environmental impacts and benefits of PV use

There are several limitaions of this work, as with all work. For example, the intermittency of PV electricity generation was not considered (including battery storage). Further work would be needed to understand how to best include intermittency in the environmental impact analysis as well as the the end-of-life of PV.

Acknowledgments

I would like to thank all of the people and funding organizations that made this research possible. Specifically, the Sustainable Los Angeles – University of California-Los Angeles Grand Challenges program for the funding for this work. I would like to thank my committee members for serving on my thesis committee: Gregory Nemet, Tracey Holloway, James Schauer, and Timothy Malloy, especially Dr. Andrea Hicks for advising me throughout the PhD process. She helped support this work through her training and expertise in agent-based modeling and life-cycle assessment. I am grateful for the love, support and encouragement from my parents, Lori and Jeff Grant. Thanks to my boyfriend, Adam Jablonski, for his support as well.

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1. Introduction

1.1 Research Summary and Goals

Electricity consumption is increasing in the United States due to global population expansion, which also intensifies the overall environmental impacts. In 2018, the US electricity sector generated 4,178 million megawatt hours (MWh) of electricity (Energy Information Administration 2019). Sixty-three percent of US electricity consumption was from fossil fuel sources, such as petroleum, natural gas, and coal, while only 17% was from renewable sources (Energy Information Administration 2018). Using solar photovoltaic (PV) panels represents an opportunity to reduce the environmental impacts from the US electricity sector. PV panels are a renewable source of electricity, which does not generate environmental impacts during use. In addition, PV electricity displaces carbon-intensive electricity, resulting in environmental benefits.

Figure 1-1 shows the average annual solar potential in the United States (National Renewable Energy Lab 2012). Arizona, California or Texas have higher than average solar resources, while states, such as Minnesota, Maine, New York, and South Dakota, have below average solar resources. Los Angeles (LA) County is used in the majority of this work, as a case study. LA County is the most populous county in the US, with more than 10 million inhabitants (US Census: American Fact Finder 2017). The daily solar potential is high in LA County throughout the year and averages 4.5-6.5 kilowatt hours per square meter per day (kWh/m^2/day) (National Renewable Energy Lab 2012). The current portion of fossil-fuel electricity in LA County's grid is 62%, while 27% is from renewable sources and the remaining

11% is from unspecified sources (California Energy Commission 2017). Therefore, there is a potential for solar PV to provide environmental benefits from offsetting the current electricity grid. In addition to environmental benefits, saving money on utility bills has been identified as a primary contributor to the value of solar in California because of its high electricity prices.

Residential PV systems, averaging around 5 kilowatts (kW), represent the largest market in California. In 2018, LA County had approximately 370 megawatts (MW) of residential capacity (California Solar Initiative 2018). However, the California Energy Commission recently approved new building energy efficiency standards that will take effect in January 2020. As part of the new standards, all newly constructed single-family residential homes are required to have solar panels installed. This is estimated to represent roughly 410 MW of installed solar capacity per year (Dong 2017).

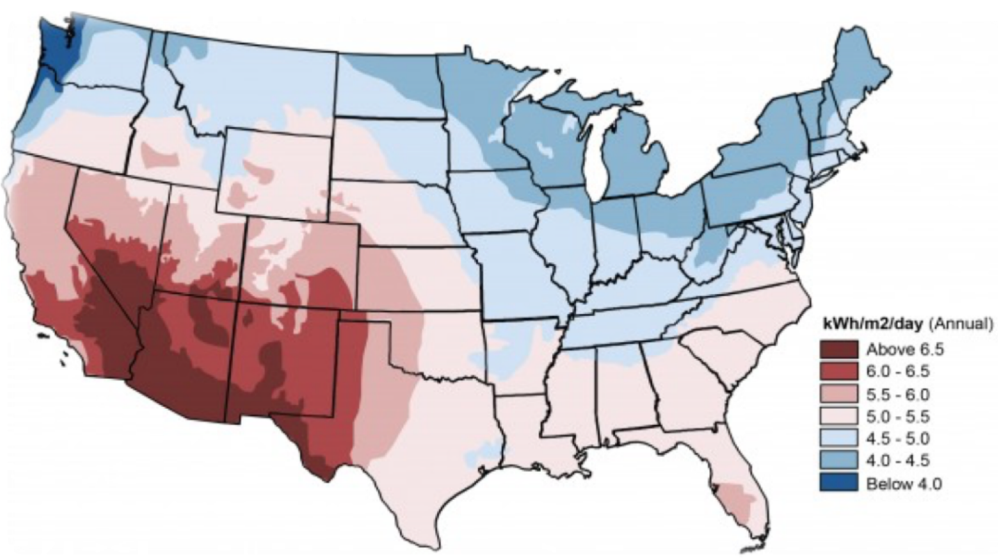


Figure 1-1 Average annual solar potential

(National Renewable Energy Lab, 2012)

The main goal of this research is to provide a comprehensive assessment of solar photovoltaics (PV) technology adoption and use as a substitute for conventional electricity generation technologies at a household level. Life-cycle assessment (LCA), agent-based modeling (ABM) and environmental payback period (EPBP) are the methods used to analyze the environmental implications of PV.

This work seeks to add to the body of literature surrounding the environmental impacts of household PV adoption and use. Specifically, a framework for using LCA and ABM to analyze the environmental implications of solar PV is presented (Chapter 2). A prioritization of residential solar PV installations in the United States (US) is developed through environmental payback period analysis (Chapters 3 and 6). An agent-based model of solar PV adoption in Los Angeles (LA) County, California is constructed and the impact of policies on the adoption of PV are explored (Chapter 4). Using the methodology of LCA, the ABM results are combined with life-cycle impact data to generate environmental impact data at the societal-level for LA County (Chapter 5).

1.2 Research Objective and Questions

The primary objective of this research is to evaluate solar PV adoption and the environmental impacts of solar PV technology compared to grid electricity technologies throughout their life cycles, with a specific emphasis on rooftop PV in LA County, California. The research is also broadened to explore the impact of location on environmental payback period within the United States. The specific research questions examined in this dissertation are:

1) How do consumers in LA County make choices about solar PV? What are the most important characteristics for adoption? (Chapter 4)

2) What is the impact of policies and evolutions in technology on solar PV adoption in LA County as compared to business as usual? (Chapter 4)
3) What are the environmental impacts and benefits of solar PV adoption and use in LA County as compared to grid electricity use? (Chapter 5)
4) How does the environmental payback period of solar PV change, based on variations in location in the United States? (Chapter 3 and 6)

1.3 Crystalline-Silicon PV Panels

While PV panels can achieve significant environmental benefits, there are also environmental burdens throughout the PV life-cycle, particularly in the raw materials and manufacturing processes. Most PV panels installed in the United States are made from crystalline silicon (c-Si), which is considered to be the most established PV technology (Energy Information Administration 2009). There are four major steps to manufacture c-si PV panels: silicon manufacturing, wafer manufacturing, cell manufacturing and panel manufacturing. Silicon manufacturing, in particular, is a step that has high energy requirements during the processes of metallurgical grade (MG) silicon smelting, and purification from MG to solar grade silicon (Alsema and de Wild-Scholten 2011). The panel manufacturing process includes the materials and adhesives to connect the cells, frame, back foil, glass and junction box. Figure 1-2 shows the various components of a complete c-Si PV panel (Naumenko and Eremeyev 2014).

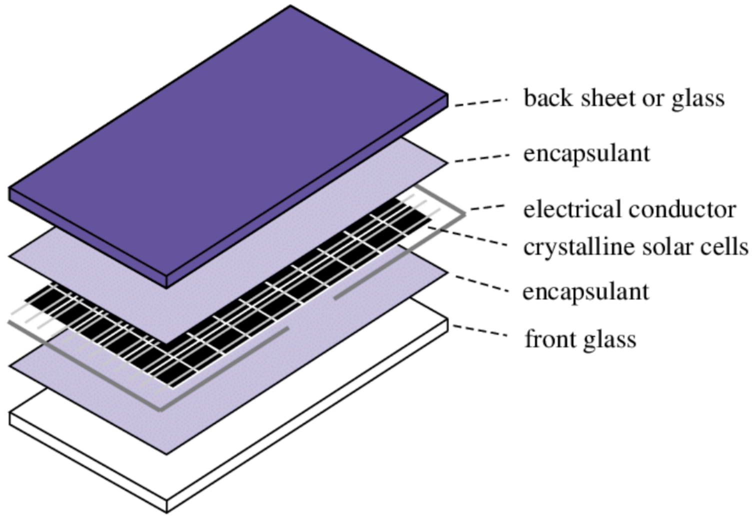


Figure 2-2 c-Si PV Panel Components

(Naumenko & Eremeyev, 2014)

Multiple PV panels are connected together, with the balance of systems (BOS) to form an array. Balance of system components are those used for installation, including mounting structures, and the inverter (Gerbinet et al. 2014). The inverter converts direct current (DC) output of the PV panel to alternating current (AC) electricity that can be used by a home. After the electricity is used for the various applications within a home, any excess can be exported back to the electricity grid. A current policy at the state-level is net metering, which credits owners for the electricity they add to the grid (Energy Sage 2019).

1.4 Life-Cycle Assessment

While it is generally known that solar PV electricity is an improvement from fossil fuel electricity with respect to environmental impact, several tools can be used to quantify the environmental impacts. A standard methodology to evaluate the environmental impact of products and processes is life-cycle assessment (LCA). LCA can be used to identify hotspots in the product life-cycle, compare product alternatives or evaluate the environmental impact of product or process design changes. Environmental impacts are analyzed by considering the inputs and outputs throughout the life-cycle stages including raw material extraction, production, use and end-of-life (Williams 2009)

There are three typical approaches to conduct an LCA: process LCA, economic input-output LCA (EIO-LCA) and hybrid LCA. In a process-based LCA, the guidelines and principles are set forth by the International Organization for Standardization (ISO 14040 and 14044) and consist of four phases: Goal and Scope Definition, Life-Cycle Inventory Analysis, Life-Cycle Impact Assessment and Interpretation (International Organization for Standardization 2006). In defining the goal and scope, there are several items that are described, such as the functional unit (measure of the performance of the product) and system boundary (the processes that are included in the LCA). The inventory analysis phase involves data collection and calculations to quantify the inputs (e.g. energy, water, materials) and outputs (e.g. waste and emissions) throughout the product life-cycle. During the life-cycle impact assessment phase, the inputs and outputs are characterized to environmental impacts. One common impact assessment method is the Tool for the Reduction and Assessment of Chemicals and other Environmental Impacts (TRACI) (Bare 2011). It provides impacts in ten different impact categories, and it will be used in this work to analyze the raw materials and manufacturing impacts of c-Si PV.

1.5 Agent-Based Modeling

LCA can generate environmental impacts of solar PV per a functional unit. Environmental impacts can be scaled up with insight on the potential adoption of PV technology. The adoption of solar PV provides the basis for the “pull” of materials and energy through the life-cycle. One drawback of LCA, however, is that it does not have the ability to model human behavior. When LCA is combined with social science methods, technology adoption scenarios can be grounded in real human behavior (Gutowski 2018), which allows for an evaluation of the environmental implications of solar PV adoption decisions.

Agent-based modeling (ABM) is a simulation methodology that models the decisions and actions of agents, which leads to macro-scale trends and impacts. An agent is an autonomous individual or object with particular properties and actions, such as fish, homes, people or companies (Wilensky and Rand 2015). Compared to traditional equation-based modeling (EBM), individuals are modeled in an ABM, and therefore, it can be used to model heterogenous populations. An agent's actions are determined by a decision-making process (Wilensky and Rand 2015). A common type of process used is a utility-based function, in which agents maximize a utility function that is composed of multiple characteristics and weights for the relative influence of each characteristic in their decision. ABM has been applied to a wide variety of processes and systems, such as building energy performance (Azar and Menassa 2012), travel demand modeling (Zhang and Levinson 2004) and urban expansion (Guzy et al. 2008). It has been used to model rooftop solar PV adoption in the past for several locations (Alyousef et al. 2017; Borghesi et al. 2013; Macal et al. 2014; Palmer et al. 2015; Rai and Robinson 2015; Zhang and Levinson 2004; Zhao et al. 2011). ABM is used in this work to model the effect of policies on adoption of rooftop solar PV panels in LA County. In addition, ABM and LCA were combined for an evaluation of the environmental impacts and environmental benefits of PV at the population scale.

1.6 Environmental Payback Period

Traditionally, payback period is defined as the length of time needed to recover the cost of an investment. Similar to in capital budgeting, this concept has been used in the energy sector to estimate the environmental and energy payback period of energy technologies (Hesser et al. 2017). Environmental payback period, with respect to PV, represents the point at which the investment in environmental impacts for PV during its life cycle is compensated by its electricity production output. Two influential variables in calculating the electricity production output, and environmental benefits of PV, are the solar potential and electricity mix, which change based on location. This work investigates how the environmental payback period of solar PV changes depending on where PV is installed in the US.

2. Modeling the environmental impact of electricity generation using agent-based modeling and life-cycle assessment

The following chapter is a reproduction of an article published in Integrated environmental assessment and management, with the citation:

Grant, C.; Hicks, A., The Environmental Impact of Electricity Generation: Agent-Based Modeling of Residential Solar Adoption. *Integrated environmental assessment and management.* 14 (5), 660-663, 2018

The article appears as published, although style and formatting modifications have been made.

The generation of electricity comprises nearly 30% of United States (U.S.) carbon dioxide (CO_2) emissions due to the use of fossil fuels. Transitioning to solar power is a topic of much interest, as it is a renewable resource and has lower CO_2 emissions compared to fossil fuels, which is relevant from the standpoint of global climate change. Life-cycle assessment (LCA) is a systematic tool used to analyze the environmental impacts of a product over its life-cycle, comprising raw materials, manufacturing, use and end-of-life. LCA has been used in the past to study the environmental impacts of solar technologies. Compared to fossil-powered generation, solar technologies have reduced environmental impacts with respect to global warming potential, acidification and ecotoxicity. Previous LCA studies, however, assume that the utility of electricity options is interchangeable, or that solar electricity and the electricity generated from the grid is the same. However, consumer willingness to accept new technologies for generation of electricity is more complex than previously estimated.

Agent-based modeling (ABM) is a tool that can be coupled with LCA to better understand the rate of adoption of solar power and its environmental benefits compared to fossil power. ABM is a bottom-up methodology used to model the decisions of individuals or actors within a simulated network and across various spatial and temporal scales, to generate macro scale results. ABM can model large, heterogeneous populations of interacting agents. Differences in technology preferences, demographics, and current technology are often factors that drive human behavior and can be captured in the agent-based model. ABM has also been used in the past to model stock markets and supply chains, predicting the spread of epidemics and modeling the immune system (Macal and North 2010).

In light of the growing applications of ABM to solar power, this paper reviews previous models on solar power adoption. The main objective is to survey the ABM literature on solar adoption, with a focus on identifying the technology characteristics and scenarios used to model solar photovoltaic (PV) adoption at the residential scale. In addition, future research opportunities and opportunities for integration with LCA are described.

There have been a number of ABMs applied to residential solar adoption (Alyousef et al. 2017; Zhao et al. 2011; Robinson and Rai 2015; Palmer et al. 2015; Borghesi et al. 2013). Studies have commonly utilized a “desire factor” threshold, or a utility threshold, to represent the point at which an individual homeowner will decide to install a solar technology. This threshold represents all of the relevant technology characteristics, which are weighted according to their relative influence. Borghesi et al. (2013) focused on the economic characteristics influencing the household adoption decision, namely payback time (PBT) of the investment, the return on equity and the net present value (NPV) of the investment. They examined how incentives and loans increase the total installed solar power in Italy by reducing the total system cost. This fairly simplistic model was able to predict the adoption levels over time but it was missing the validation process, a necessary step in ABMs to determine if a model is an accurate representation of the real-world. Robinson et al. (2015) included social and behavioral characteristics, such as the influence of peers, in an ABM developed for the Austin, Texas area. The resulting model included both spatial and demographic validation.

Zhao et al. (2011) and Palmer et al. (2015) considered additional economic and behavioral characteristics. Zhao et al. (2011) developed an ABM to compare solar adoption in New York City and Tucson, Arizona using the characteristics of income, payback period, residential location, and advertising. Overall, they found that smaller cities are more likely to incentivize solar PV adoption. Palmer et al. (2015) simulated residential solar adoption in Italy by gathering data on consumer household income, environmental attitude, payback period, and social influence. Based on the results, income influenced solar PV adoption more than other utility characteristics.

Solar PV is limited by its intermittency, which also represents a barrier to adoption. Complimentary technologies such as battery storage may make solar PV more valuable, beyond electricity bill savings or environmental benefits. Alyousef et al. (2017) explored how battery storage affects the adoption of solar PV in Germany. Scenarios that simulated higher than average electricity prices and decreasing PV system and battery costs resulted in the largest number of adopters. Similarly, residential demand may increase in the future due to the development of complementary technology, such as electric vehicles. These new technologies may make solar PV a more attractive investment and result in more adopters.

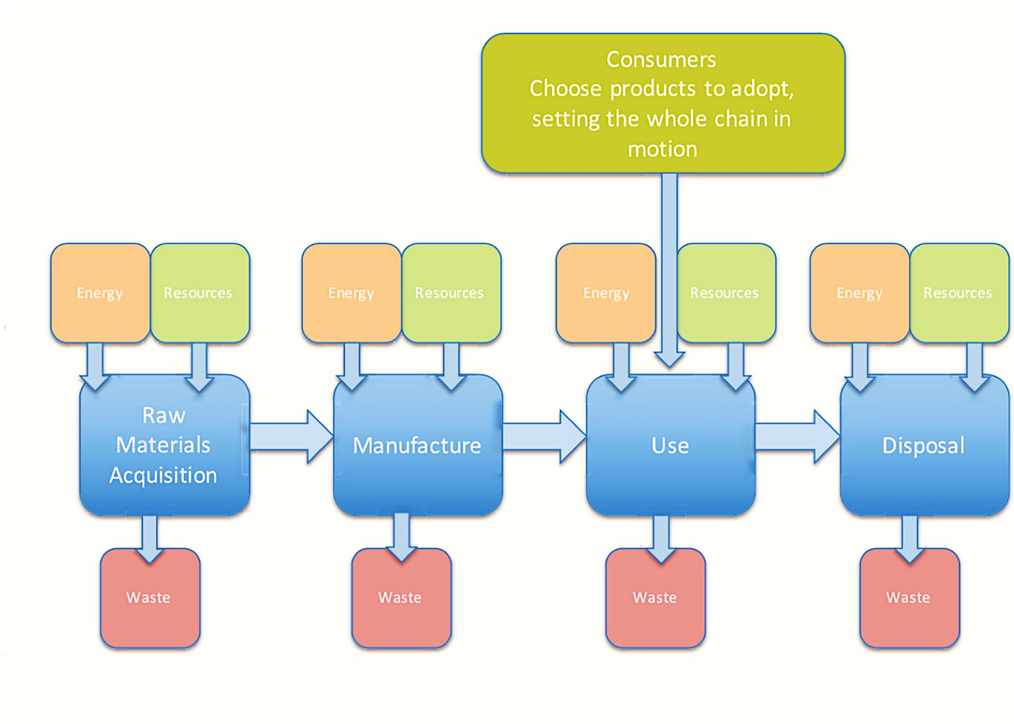


Figure 2-1 Role of Consumer Adoption in LCA

ABM is a common tool for modeling consumer adoption of new technology in the solar sector. Figure 2-1 presents the integration of the role that consumer adoption plays in LCA at the population level. Adoption of new technology may be considered a “pull” that moves the system and its corresponding environmental impacts forward. With respect to residential PV, adoption is the pull that generates the corresponding life cycle environmental impacts. Combining LCA and ABM allows for the opportunity to generate environmental impact data at the societal level, with respect to the tradeoffs of PV versus fossil fuel sources of electricity. Policy scenarios, such as those simulated in ABMs allow for better understanding of the potential efficacy of those policies in promoting or discouraging the adoption of PV as an electricity source in a household setting. Coupling ABM with LCA allows for a population-level assessment of the tradeoffs of solar adoption for electricity generation.

3. Effect of manufacturing and installation location on environmental payback time of solar power

The following chapter is a reproduction of an article published in Clean Technologies and Environmental Policy, with the citation:

Grant, C.A.; Hicks, A.L., Clean Techn Environ Policy (2019). https://doi.org/10.1007/s10098-019-01776-z

The article appears as published, although style and formatting modifications have been made.

3.1 Abstract

Solar photovoltaic (PV) systems are a promising technology to reduce the environmental impacts of electricity production. Several locations in the United States are favorable for solar PV deployment due to having a high solar potential. This study evaluates the environmental impact payback time (PBT_I) for installing multi-crystalline silicon PV systems in multiple US cities, Seattle, Miami, Los Angeles, Phoenix and Indianapolis, with varying electricity mixes and solar potential, using life-cycle inventory data and the Tool for the Reduction and Assessment of chemicals and other environmental impacts as the impact assessment method. China, United States and European manufacturing scenarios were analyzed to compare the effect of the electricity mix used during manufacturing on PBT_I. The results show that the PBT_I ranges between <1 year to 3000+ years across all impact categories. A Chinese manufacturing scenario increased the PBT_I in some impact categories (i.e. global warming) compared to United States and Europe manufacturing, but had no effect for others. The PBT_I is within the solar panel lifespan for the impact categories of global warming, acidification and fossil fuel depletion, but is longer than the lifespan for other impact categories (i.e. eutrophication and ozone depletion). According to the global warming PBT_I, policies should incentivize solar panels in the following order: Phoenix, Indianapolis, Miami, Los Angeles, Seattle. This work provides guidance to policy makers and manufacturers on the PBT_I when the manufacturing location, solar potential and electricity mix are known.

3.2 Introduction

Recently the sales of photovoltaics (PV) have grown rapidly within the United States (US), with a compound annual growth rate (CAGR) at 52% for the sector over the past decade

(Goodrich et al. 2013). Global solar PV shipments were approximately 92 gigawatts (GW) in 2017 and 98% of shipments came from Asian countries, with China supplying 57% (Feldman et al. 2018), while the US supplied approximately 0.5% of global PV modules in 2017. Most PV systems installed in the US are made from crystalline silicon (c-Si) and it is considered to be the most established PV technology (Energy Information Administration 2009). c-Si PV cells use two types of silicon: monocrystalline or multicrystalline. Mono-Si cells typically have higher efficiencies but are also more costly to manufacture than multi-Si cells (Hegedus and Luque 2003).

Life-cycle assessment (LCA) is a methodology used to analyze the environmental impacts of products and processes, such as c-Si solar PV, throughout its life-cycle (Guinee 2002) (International Organization for Standardization 2006). A large body of literature has addressed the LCA of c-Si solar PV systems from a “cradle-to-gate” perspective. In addition, more recently, other forms of PV have been a focus of LCA studies, such as building-integrated photovoltaics (BIPV) (Carvalho et al. 2019). Hsu et al (2012) performed a meta-analysis of the solar PV LCA literature and found the “cradle-to-gate” carbon dioxide equivalent (CO_2e) impacts for mono-crystalline and multi-crystalline to be 30 -100 grams carbon dioxide equivalent/kilowatt hour (g CO_2e/kWh), and 20 – 217 g CO2e/kWh, respectively (Hsu et al. 2012). The CO_2e impacts vary based on several factors, such as solar potential, efficiency, performance ratio, system lifetime and mounting type.

Recently, an increasing number of LCA studies on Chinese c-Si PV manufacturing have been conducted. Yue et al. (2014) compared manufacturing in China to manufacturing in Europe and found that the carbon footprint of China c-Si manufacturing was double that of the

European scenario for installation in Europe (Yue et al. 2014). Another study compared the environmental impacts of c-Si manufacturing shifting from Germany to China and found that the eutrophication (EP) and freshwater ecotoxicity potential (FAETP) decreased by 13–19 % and 9–14 %, respectively, as a result of production in China (Stamford and Azapagic 2018). This was due to the differences in EP and FAETP impacts of the countries' electricity mixes. Overall, the environmental impacts of c-Si panels can shift depending on manufacturing location and the LCA impact category considered.

LCA data has commonly been used to evaluate the environmental performance of solar PV. The most common metrics evaluated are energy payback time (EPBT), carbon payback time (CO_2 PBT) and energy return on investment (EROI) (Bhandari et al. 2015). CO_2 PBT quantifies the time needed for the CO_2 emissions over the life cycle of a system to be offset by the CO_2 emission reductions obtained from the system itself (Hyoungseok et al. 2014). EPBT is the length of time a PV system must operate before it recovers the energy invested throughout its lifetime (Bhandari et al. 2015). Compared to the EPBT, EROI is used to understand an energy source's long-term viability. EROI is a unitless ratio of the energy obtained from a system of an energy source to the energy required to make that energy (i.e. embedded energy). A meta-analysis of the EPBT and EROI of solar PV systems found that the EPBT is 1- 4.1 years and EROI varied from 8.7 to 34.2. Table 3-1 summarizes the CO_2 PBT from previous c-Si systems in the literature, with a range between 0.39 - 7.8 years. The CO_2 PBT varies by location, technology type and installation type, among other factors.

Filho et al (2016) performed a CO_2 PBT analysis to compare the CO_2 emissions of manufacturing to the CO_2 emission reductions from installation in multiple production and installation locations (i.e. Brazil, Japan, Germany, United States, Brazil and China). It was found that the greater the CO_2 emission factor of the panel's production country, the greater the time needed for use phase emissions reduction to recoup the CO_2. Differences in the energy mix of each installation country were included to compare emission reductions. However, the study assumed a representative solar potential value of 1700 kWh/m^2/year for all countries, which is typical of Southern Europe and the southwestern US (Filho et al. 2016). This is a limitation of the study, as electricity mixes and solar potential may vary significantly within the same country while the environmental impacts of solar PV vary as a function of solar potential at the place of installation (Sherwani 2010).

A less common metric analyzed in the literature is environmental impact payback time (PBT_I) using life-cycle impact assessment results. The single metric of CO_2 or energy PBT is easier to perform and communicate, but LCIA can provide a wider perspective on environmental impacts. PBT_I is defined as the time needed for the life-cycle environmental impact generated from the PV system to be offset by the annual environmental impact saving associated to energy generation. Chen et al. (2016) evaluated the PBT_I for Chinese solar PV manufacturing for the impact categories of climate change, human toxicity, marine ecotoxicity, metal depletion, and fossil fuel depletion. It was found that the PBT_I varies significantly according to impact categories and coal electricity generation technologies in China. The overall payback time ranges were from 3.31×10^{-2} years to 34.48 years.

Table 3-1 – CO_2 PBT Results from Previous Studies

Study	PV Technology	CO_2 PBT (years)	Mounting System
Kim et al. (2014)	multi-crystalline Si	1.53-1.91	Ground-mounted
Kim et al/ (2014)	mono-crystalline Si	2.53	Ground-mounted
Tripanagnostopoulos et al. (2005)	multi-crystalline Si	2.70	Rooftop
Garcia-Valverde et al. (2009)	mono-crystalline Si	7.77	Rooftop (Stand-alone)
Marimuthu and Kirubakaran (2013)	multi-crystalline Si	0.39	Rooftop

This current work increases the body of knowledge with the respect to the solar LCA literature and the environmental payback time literature by evaluating the environmental impact payback time (PBT_I) for mc-Si PV in multiple production and US installation locations and for multiple impact categories. PBT_I is defined for the purposes of this work as the quantify of time necessitated to recoup the environmental impacts due to the investment in the raw materials, manufacturing, installation, and transportation of the PV. It is recouped by quantifying the environmental impacts saved through using the PV at the installation location, instead of purchasing electricity from the grid. The location of production and installation are critical factors to analyze because of the three parameters in an LCA that are location dependent: the environmental impact of the electricity used in production, the environmental impact of the displaced electricity mix at the place of installation, and the solar potential in the place of installation. Multiple impact categories are necessary to evaluate changes in the environmental impact payback time in a holistic manner, and to evaluate trade-offs in the environmental performance of solar panels.

China, Europe and US supplied 92% of solar panels in 2017 (Feldman et al. 2018). Therefore, all three major production locations (China, US and Europe) were chosen. Five installation locations within the US with differing solar insolation and electricity mixes were selected, including Los Angeles (LA), California (2051 kWh/m^2/year), Phoenix, Arizona (2810 kWh/m^2/year), Seattle, WA (1314 kWh/m^2/year), Miami, Florida (1934 kWh/m^2/year) and Indianapolis, Indiana (1463 kWh/m^2/year (National Renewable Energy Laboratory, 2012). The cities were selected as they have a diverse electricity mix, which will allow for the assessment of the relative influence and importance of these factors on the environmental performance of solar PV and how they might vary geographically.

Figures 3-1 and 3-2 display the solar potential and CO_2e of the electricity grid, respectively, of the locations considered. The CO_2e impacts of the grid were calculated using SimaPro version 8.0.1, which is an LCA modeling software. They are also compared to a US average solar potential of 1800 kWh/m^2/year and average US grid mix (Fthenakis et al. 2008). Seattle and Los Angeles receive a large proportion of their electricity from renewable fuel sources, making their electricity mixes the least carbon intensive. Washington is the leading hydroelectricity producing state in the nation, which comprises 91% of Seattle's electricity mix, while Los Angeles has a larger quantity of non-hydroelectric renewables, including solar, biomass and wind. Phoenix, Miami and Indianapolis have a higher proportion of non-renewables in their electricity mixes. As such, they have more carbon intensive electricity mixes. Indianapolis is largely supplied with coal (71%). Nuclear power, coal, and natural gas provide almost equal shares of Arizona's electricity generation, comprising 90% of the state's electricity mix in 2018. Florida relied on natural gas for 76% of its electricity generation in 2018, with coal supplying 12%.

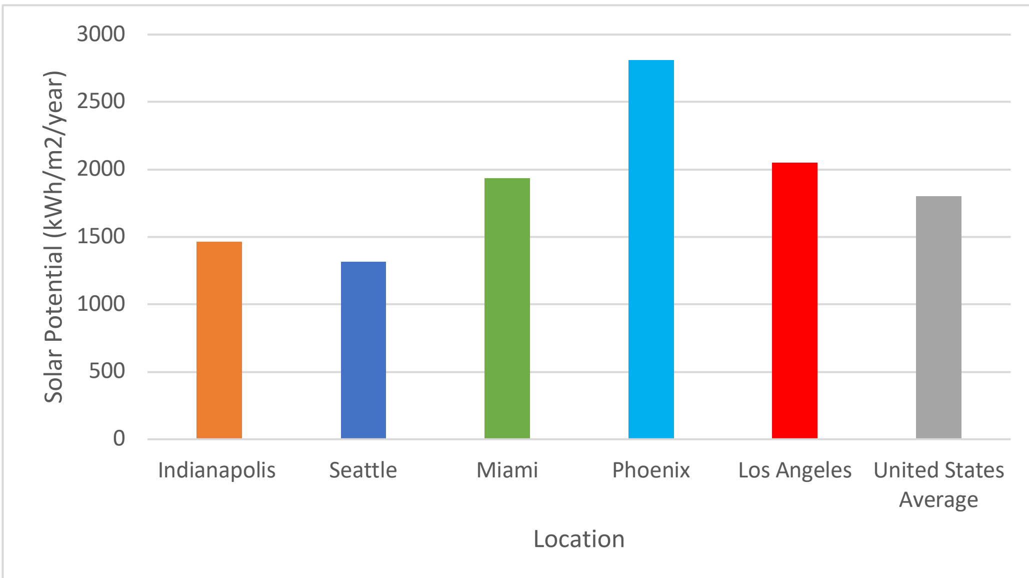


Figure 3-1 Solar Potential of Installation Locations (National Renewable Energy Laboratory 2012; Fthenakis et al. 2008).

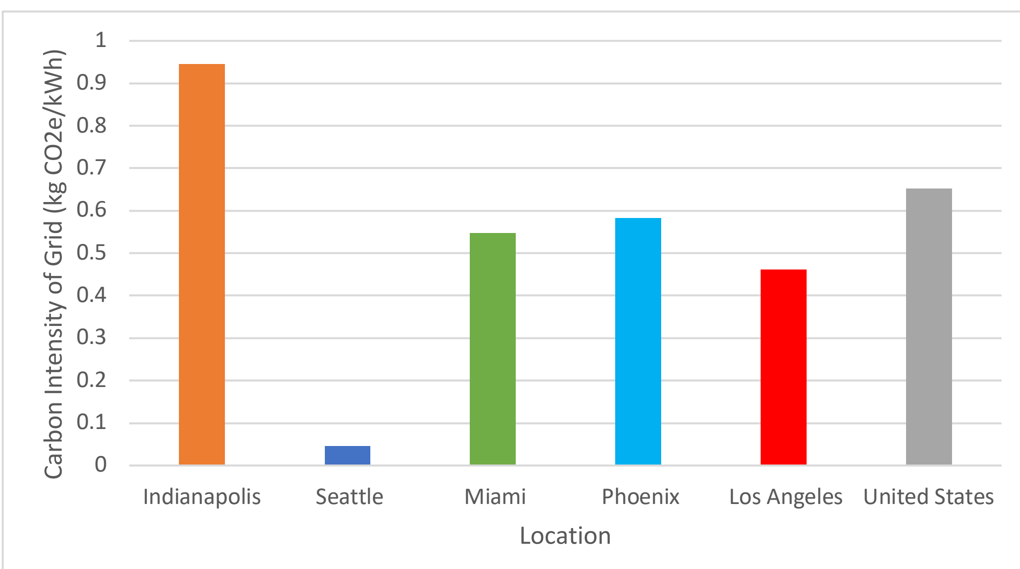


Figure 3-2 CO_2e Impacts of Electricity Generated from the Electricity Grid by Installation Location

3.3 Methods

In this section, an overview of the goal of the work is presented in Section 3.3.1 The data and methodology used to calculate life-cycle environmental impacts of mc-Si PV production and transportation is described in Section 3.3.2. The data sources and methodology to calculate environmental impact savings from mc-Si PV use are described in Section 3.3.3.

3.3.1 Goal of Study

The metric of environmental impact payback time (PBT_I) is used in this study to evaluate the environmental performance of solar panel use in multiple production and installation locations. PBT_I can provide a comparison of the environmental performance of solar panels among the chosen scenarios and for different impact categories. This metric was applied to multiple impact categories generated by the Tool for the Reduction and Assessment of Chemical and other environmental impacts (TRACI) 2.1 impact assessment method, because of its relevancy for a US context (Bare 2011). TRACI 2.1 generates impacts in the following ten impact categories (followed by their unit of measure): ozone depletion (kg CFC-11 eq), global warming (kg CO2 eq), smog (kg O3 eq), acidification (kg SO2 eq), eutrophication (kg N eq), carcinogenic (CTUh), non-carcinogenic (CTUh), respiratory effects (kg PM2.5 eq), ecotoxicity (CTUe), and fossil fuel depletion (MJ surplus)

PBT_I, in years, is calculated using the following equations (Kim et al. 2014).

$$PBT_I = \frac{I_{EM}}{I_{SV}} \qquad (1)$$

$$I_{SV} = E_{OUT} * I_{MIX} \; (2)$$

where I_{EM} are the environmental impacts over the solar panel life cycle (impact category unit/m^2), I_{SV} are the annual environmental impacts associated with electricity generated by the solar panel system (impact category unit/year), I_{MIX} is the environmental impact of the electricity mix in each installation location (impact category unit/kWh), and E_{OUT} is the annual electricity generation of the panel (kWh/year).

The electricity output of the panel was calculated as follows, where IR = solar insolation (kWh/m^2/year), PR = performance ratio of the system, A = area of the module (m^2), and CE = conversion efficiency of the PV panel (16%).

$$E_{OUT} = PR * IR * CE * A \qquad (3)$$

3.3.2 Life-cycle environmental impact

The life-cycle environmental impact of the solar panel can be estimated by adapting the equation from Cucchiella et al. (2012) for environmental impacts:

$$I_{EM} = I_M + I_T + I_D \ (4)$$

Where I_{EM} is the total environmental impacts emitted during the lifetime of the system, I_M are the environmental impacts of the manufacturing phase of a PV system, I_T are the environmental impacts from the transport of the PV system from the factory to the installation site and I_D are the environmental impacts from the disposal of the panel at the end of its lifetime. Figure 3-3 displays the scope of the LCA analysis, and more details on the material inventory can be found in the Appendix A.

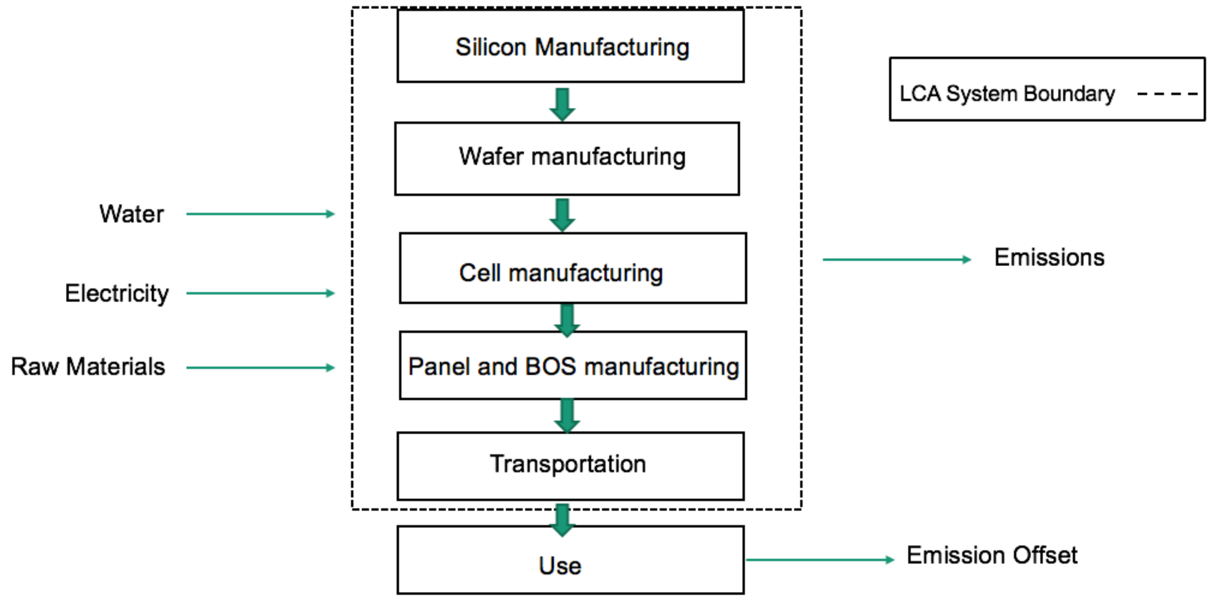


Figure 3-3 LCA Stages in Present Study

I_M includes manufacturing of the PV panel and the balance of systems (BOS). BOS components are those used for installation, including mounting structures and the inverter (Gerbinet et al. 2014). In the current work, the panel and BOS environmental impacts for 1 m^2 of a mc-Si PV panel were analyzed using SimaPro version 8.0.1. The inventory data for the panel used in this work, from the Ecoinvent database, aggregated from many factories in Europe, was industry-level data representing Europe manufacturing from 2005-2015 (Ecoinvent database 2019). The major process steps investigated include poly-silicon manufacturing, wafer and cell manufacturing and module manufacturing. Module manufacturing process includes the materials and adhesives to connect the cells, frame, back foil, glass and junction box. The data used for European manufacturing was modified to represent US manufacturing scenario, by substituting a US electricity mix throughout all processes.

Data from Ecoinvent was supplemented with inventory data from the literature for a mc-Si panel manufactured in China, as China is the leading manufacturer of mc-Si systems and has been shown to have relatively high manufacturing emissions due to its reliance on coal-based electricity (Yao et al. 2014; Fu et al. 2014). An inventory from Yao et al. (2014) was used, also including poly-silicon manufacturing through module manufacturing. Yao et al. (2014) aggregated inventory data from major manufacturers in China, representing industry-level data.

As the locations in this work are major metropolitan areas of the US, it's assumed that the panels are installed on a slanted residential roof. Inventory data for the BOS components (mounting structure and inverter) are from the Ecoinvent database. The inverter was assumed to have capacity of 0.5 kW and was chosen based on available Ecoinvent data.

To calculate I_T, the environmental impacts to transport the PV systems, it was assumed that PV systems manufactured in China and Europe were transported from major manufacturing locations in each country to the Port of Los Angeles by ocean freighter. This was followed by rail and then truck transportation to the US city where it is used (Union Pacific 2019; Sinovoltaics 2014). For PV systems produced in the US, truck transportation was assumed to the installation location from California, a major manufacturing location in the US (Energy Sage 2019). The distances from manufacturer to the installation location was calculated using SeaRates and Google Maps and environmental impacts per weight distance from the US Life Cycle Inventory (LCI) database (SeaRates 2019). The US LCI database was created by the National Renewable Energy Lab (NREL) and provides the energy and material flows into and out of the environment that are associated with transportation modes in the US (National Renewable Energy Laboratory 2012). It was assumed that the PV system weighed 16.8 pounds (Fu et al. 2015).

End-of-life of the panels was not considered in this current work. Three industrial or pilot scale recycling processes are available at present, and one is for c-Si PV (Tao and Yu, 2015). First Solar, in the US and Germany, and ANTEC Solar GmnbH, in Germany, have developed processes for thin-film PV module recycling. Deutsche Solar, in Germany, has a full-scale process for recovery of c-Si modules and recycling of glass and metals. Muller et al. (2005) performed an LCA on Deutsche Solar's process and found that the recycling of modules can reduce the life-cycle impact by 30% (Muller et al. 2005). Other LCA studies have included recycling and recovery processes that are under development, but the data is either incomplete or unavailable (Berger et al. 2010). For example, Kim et al. (2014) made assumptions on the recycling and disposal rates in China and Berger et al. (2010) removed several recycling steps from their work due to unavailable process data.

The lifetime expectancy of PV panels, with respect to performance warranty, ranges from 25-30 years (Fu et al. 2015). Energy output of solar panels degrades by 0.8% per year, on average, but this rate of decline will vary depending on the manufacturer. Regular maintenance of the solar panel system can lead to a lower degradation rate. Preventing any physical damage from weather can also lead to a longer lifetime expectancy (Energy Sage 2019). The majority of solar panel disposal at present is due to physical damage during transportation, installation or weather (Illinois Sustainable Technology Center 2019).

However, with the expected lifetime of PV systems, there is anticipated to be a spike in disposal beginning in 2030. In addition to development and improvement of current recycling processes, policy and incentives can be strong drivers for recycling of PV systems at the end-of-life. Currently, Europe is the only market with PV-specific waste regulations, which cover the economic aspects of recycling and ensure PV modules will be collected (Kadro and Hagfeldt 2017). No policy currently exists in the US for end-of-life management of PV.

3.3.3 Energy output of solar panels and environmental impact savings

The energy output of the PV panel in each location was calculated using equation 3 and the parameters in Table 3-2. Data on the average annual solar potential for each city was taken from National Renewable Energy Lab (NREL) Solar Maps (National Renewable Energy Laboratory 2012). The PV module efficiency of 16% was recommended for multi-Si systems based on an analysis of PV LCA studies (Gazbour et al. 2018). The performance ratio, or system losses, vary based on the operating temperature of the panels and the panel efficiency under different solar potentials (Gazbour et al. 2018). However, since the PR values are difficult to estimate, the average used in prior PV LCA studies of 0.8 was chosen in this analysis.

Table 3-2 – Solar Potential of US Cities (National Renewable Energy Laboratory 2012).

Location	Average Annual Solar Potential ($kWh/m^2/year$)
Los Angeles, CA	2 051
Seattle, WA	1 314
Phoenix, AZ	2 810
Miami, FL	1 934
Indianapolis, IN	1 463

CA = California, WA = Washington, AZ = Arizona, FL = Florida, IN = Indiana

It is common practice to predict emission savings from the use phase of renewable energy technologies, like solar PV, using a market-based or simple averages approach with respect to the electricity grid that is displaced (Connors et al. 2004; Denholm et al. 2009). In this analysis, a weighted average approach was used to calculate the environmental impacts, in each TRACI impact category, from 1 kWh of electricity generated from the current electricity mix in each location. Data on the electricity mix for the cities was compiled from the utilities servicing the cities or from the Energy Information Administration (EIA), and is shown in Table 3-3. Environmental impact data for each electricity type in Table 3-3 was generated from SimaPro and several databases (Ecoinvent database 2019; National Renewable Energy Laboratory 2012; European Commission 2019). Additional information can be found in the Appendix A.

Table 3-3 - Electricity mixes used in each installation location (Energy Information Administration 2019; Seattle City Light 2017; University of California Los Angeles 2019; Florida Power and Light 2018; Azusa Light and Power 2017; Los Angeles Department of Water and Power 2017; Burbank Light and Power 2017; City of Cerritos 2017; Glendale Water and Power 2017; Pasadena Water and Power 2017; Southern California Edison 2017; Verona Light and Power 2017).

Electricity Source	Miami	Seattle	Phoenix	Los Angeles	Indianapolis
Coal	2%	1%	25%	18%	71%
Natural Gas	71%	1%	42%	30%	23%
Nuclear	23%	4%	23%	6%	0%
Hydroelectric	0%	91%	5%	6%	0%
Non-hydroelectric renewables	1%	2%	5%	29%	6%

Unspecified	2%	1%	0%	11%	0%

The percentages above are presented as rounded to the nearest whole number percentage. Non-hydroelectric renewables include solar, wind, biomass and geothermal.

3.4 Results and Discussion

The PBT_I results for China, Europe and United States manufacturing and installation in multiple US cities are found in Tables 3-4, 3-5 and 3-6, organized by installation location with low (Seattle) to high solar potential (Phoenix).

Table 3-4 - PBT_I for Chinese manufacturing scenario (years)

Location	Seattle	Indianapolis	Miami	Los Angeles	Phoenix
Solar Potential (kWh/m²/year)	***1 314***	***1 463***	***1 934***	***2 051***	***2 810***
Ozone depletion	817	418	1383	68	296
Global warming	81	5	5	5	3
Smog	132	25	13	6	11
Acidification	117	2	3	4	2
Eutrophication	1018	61	114	47	56
Carcinogenics	902	166	58	<1	58
Non carcinogenics	913	87	26	35	28
Respiratory effects	456	32	9	15	10
Ecotoxicity	636	76	28	25	27
Fossil fuel depletion	72	4	<1	2	1

Gray shaded boxes = 0-10 years, orange shaded boxes = 11-20 years, green shaded boxes = 21-

30 years, Blue shaded boxes indicate when the PBT_I is greater than the expected lifetime of panels (>30 years)

Table 3-5 - PBT_I for Europe manufacturing scenario (years)

Location	Seattle	Indianapolis	Miami	Los Angeles	Phoenix
Solar Potential (kWh/m²/day)	***1 314***	***1 463***	***1 934***	***2 051***	***2 810***
Ozone depletion	1866	955	3159	155	675
Global warming	39	2	2	3	2
Smog	72	14	7	3	6
Acidification	59	1	2	2	1
Eutrophication	1083	65	122	50	60
Carcinogenics	1050	193	68	<1	70
Non carcinogenics	930	88	27	36	29
Respiratory effects	353	25	7	12	8
Ecotoxicity	616	74	27	24	26
Fossil fuel depletion	65	3	<1	2	<1

Gray shaded boxes = 0-10 years, orange shaded boxes = 11-20 years, green shaded boxes = 21-30 years, Blue shaded boxes indicate when the PBT_I is greater than the expected lifetime of panels (>30 years)

Table 3-6 - PBT_I for United States manufacturing scenario (years)

Location	Seattle	Indianapolis	Miami	Los Angeles	Phoenix
Solar Potential (kWh/m²/day)	***1 314***	***1 463***	***1 934***	***2 051***	***2 810***
Ozone depletion	1643	841	2782	137	595
Global warming	47	2	3	3	2
Smog	90	14	9	3	6
Acidification	60	1	2	2	<1
Eutrophication	1643	99	185	76	90
Carcinogenics	960	176	62	<1	62
Non carcinogenics	894	85	26	34	28
Respiratory effects	284	20	6	9	6
Ecotoxicity	569	68	25	22	24
Fossil fuel depletion	73	4	<1	2	1

Gray shaded boxes = 0-10 years, orange shaded boxes = 11-20 years, green shaded boxes = 21-30 years, Blue shaded boxes indicate when the PBT_I is greater than the expected lifetime of panels (>30 years)

Overall, the PBT_I varies with impact category, manufacturing location and installation location, with the range in PBT_I of <1 to 3159 years. The PBT_I for Seattle, across all impact categories, is longer than the average solar panel lifespan of 30 years, indicating that the environmental impacts from manufacturing are higher than the environmental impact savings from solar PV generation. This result can be attributed to Seattle having both the cleanest electricity mix, relying largely on hydropower, and the lowest solar potential compared to the other locations. These factors combined result in Seattle having the least environmental impacts from grid electricity and the lowest energy generation of 168 kWh/m^2/year as shown in Table 3-7. Considering both the differences in solar potential and electricity mixes when evaluating the environmental performance of solar PV is critical in providing a more realistic analysis.

Table 3-7 – Electricity Output of PV Panel

Installation Location	**Electricity Output of PV panel (kWh/m^2/year)**
Los Angeles	263
Miami	248
Seattle	168
Phoenix	360
Indianapolis	187

The PBT_I changes significantly for different environmental impact categories in the analysis. The global warming, acidification and fossil fuel depletion PBT_I is faster than the solar panel lifespan for all locations considered (besides use in Seattle), while the eutrophication, carcinogenics, and ozone depletion PBT_I is longer than the solar panel lifespan for all locations. This result demonstrates the importance of considering multiple impact categories to evaluate trade-offs in the environmental performance of solar PV. Although the more common payback time metrics seen in the literature, such as energy and CO_2, may be easier to communicate, impact categories can provide a wider perspective of environmental impacts. Excluding Seattle, the PBT_I for the impact categories of fossil fuel depletion (0.8-3.6 years), acidification (0.9-3.8 years) and global warming (1.4-5.2 years) are within the same time needed to payback other environmental indicators commonly seen in the literature, such as energy and CO_2.

A Chinese manufacturing scenario doubles the PBT_I in global warming, smog and acidification compared to Europe and US manufacturing. Chinese manufacturing also doubles the PBT_I for respiratory effects compared to US manufacturing. The PBT_I is similar between the three countries for other impact categories (i.e. eutrophication, carcinogenics, non-carcinogenics, ecotoxicity, and fossil fuel depletion). These results are due to the differences in environmental impacts per m^2 of panel between the three manufacturing countries and the contribution of electricity to the raw materials and manufacturing impacts. Further details can be found in the Appendix A. Electricity had a significant contribution (>60%) to the Chinese raw material and manufacturing environmental impacts in the categories where the PBT_I was double. The Chinese electricity mix contributed to 22% of ozone depletion impacts, 67% of global warming, 62% of smog, 60% of acidification, 42% of eutrophication, 43% of carcinogenics, 23% of non-carcinogenics, 64% of respiratory effects, 21% of ecotoxicity, and 21% of fossil fuel depletion. In 2016, coal made up 62 percent of China's electricity mix. According to energy projections by the EIA, the share of coal in China's electricity mix is expected to decrease by 2040, while renewables are expected to increase (Energy Information Administration 2017).This may shift the contribution of electricity to the raw materials and manufacturing impacts and change the PBT_I results for China compared to US or Europe. Future work could explore these electricity mix shifts. PV technologies are continually improving, and subject to federal and state-level policies, which may shift the environmental impacts as well.

The results in this analysis are useful for policymakers when considering solar panel deployment. Policy makers should not only focus on locations with high solar potentials (i.e. Phoenix), which can create a faster economic payback period, but also consider locations that have a significant portion of coal in the electricity mix, such as Indianapolis, which may result in a faster environmental payback period. According to the global warming payback period analysis, policies should incentivize solar panels in the following order for the fastest to slowest payback periods: Phoenix, Indianapolis, Miami, Los Angeles, Seattle.

3.5 Conclusion

This study provides an analysis of the environmental performance of mc-Si panels installed in Phoenix, Los Angeles, Miami, Seattle and Indianapolis and manufactured in China, Europe and US using the metric of environmental impact payback time. The PBT_I was found to be less than the average panel lifetime in most scenarios in this study, but varied significantly by impact category, solar potential and electricity mix. Multiple impact categories are necessary to evaluate trade-offs in the environmental performance of PV. The variation in solar potential and electricity mixes between various locations should also be considered in solar PV studies to account for the influence of geographical factors on the environmental performance of solar PV.

This analysis considered one type of PV panel of multi-crystalline silicon due to its dominance in the solar market and due to data availability. Future work could expand this analysis to other PV types, such a building-integrated PV or emerging thin-film technologies. Future work might also include additional PV components or additional life-cycle phases, such as the end-of-life. As an example, the use of a battery for electricity storage may increase the environmental impacts of solar PV systems, and therefore, increase the PBT_I. Finally, in practice, the electricity mix that solar PV will displace often depends on local circumstances, such as technical constraints or cost, which were not considered in this analysis.

4. Agent-based modeling of rooftop solar panel adoption – LA County as a case study

4.1 Abstract

Rooftop solar photovoltaic (PV) is a promising option for renewable electricity generation. This paper analyzes how policies and evolutions of technology may impact the adoption of rooftop solar PV systems and consumption of solar PV electricity in Los Angeles (LA) County, California over the time period of 2018-2050. Using data from a survey of LA County residents regarding decision-making characteristics around PV, this work uses an agent-based model to simulate the adoption of residential solar PV by homeowners in LA County. Agents, representative of households, select between one of two solar PV systems or consuming electricity from the grid using a probabilistic utility. Agents are heterogenous in nature, with each having unique preferences towards solar PV. The adoption of solar PV systems was compared under five scenarios, including the investment tax credit, a falling cost of solar due to technological improvements, an increase in grid electricity prices, and two variations of the California Energy Efficiency Standards (which mandates that new homes be built with PV). All five policy scenarios showed a significant increase in solar adopters and solar electricity consumption by 2050 compared to 2018 levels. However, there were minor differences in the total percentage of solar adopter owner-occupied homes by 2050 and cumulative solar electricity consumption (8.5-9.7 billion kilowatt hours) among the five scenarios. This study suggests that more costly policies, such as the investment tax credit, may not be necessary to increase adoption if rooftop solar prices are expected to fall on their own.

4.2 Introduction

Rooftop solar photovoltaics (PV) are a promising alternative energy technology to reduce the greenhouse gas emissions associated with electricity production. Solar PV harnesses sunlight to generate electricity using photovoltaic cells. This is done through the PV effect, which is the process of converting light photons to electricity using semiconducting materials in the PV cells (National Renewable Energy Laboratory 2019).

Rooftop PV is well suited for a large portion of the United States (US), which has an average solar potential between 3.5-6.5 kilowatt-hours per square meter per day (kWh/m^2/day) (National Renewable Energy Laboratory 2016). Arizona or Texas have higher than average solar resources, while states like Minnesota, Maine, New York, and South Dakota have below average solar resources. According to a 2012 report by the National Renewable Energy Lab (NREL), the total annual technical potential for rooftop PV in the US is estimated at 818 terawatt hours (TWh) (National Renewable Energy Laboratory 2012).

In addition to alternative energy production, rooftop solar PV adoption has a number of potential benefits for a homeowner, including helping the environment, saving money on electricity bills, and increasing property values (Kabir 2018). Saving money on utility bills is a primary contributor to the value of rooftop solar in US states with higher than average electricity prices, such as California (Nemet 2017). The Solar Energy Evolution and Diffusion Studies (SEEDS) program at the NREL was developed to understand adoption barriers and motivations for adopting PV in residential markets (National Renewable Energy Laboratory 2019). Analysis of surveys administered to households in Arizona, California, New Jersey and New York by SEEDS indicated that economic factors, such as the ability to afford solar, are the largest barriers to adoption. The decision to adopt a rooftop PV system often requires a significant upfront cost (Kabir 2018). The upfront cost depends on the solar panel system size and the price per watt of solar panels. According to EnergySage, the average cost of installing solar panels is $3.05 per watt (Energy Sage 2019). With an average rooftop solar panel system size of 6 kilowatts (kW), the average upfront cost is $18,300 before any tax incentives, and $12,810 after tax credits are applied. The federal tax credit deducts 30% off the upfront cost of the system, but other state or local incentives and credits may further reduce the upfront cost of rooftop PV adoption.

Agent-based modeling (ABM) is a relatively new, bottom-up, modeling technique that can be used to model rooftop solar PV adoption (Alyousef et al. 2017; Borghesi et al. 2013; Macal and Graziano 2014; Palmer et al. 2015; Rai and Robinson 2015; Zhang 2016; Zhang and Vorobeychik 2014; Zhao et al. 2011). ABM has also been used to study other issues such as the flows of metals through an economy (Bollinger et al. 2011), cropping systems (Schreinemachers 2009), and travel demand models (Zhang and Levinson 2004). ABM models the decisions and actions of individual agents, which contribute to macro-scale trends (Hicks et al. 2015). Agents also commonly interact with each other. The agent's decision rules are either based on theory or empirical data on the population of interest (Rai and Robinson 2015). After the ABM is constructed, a large number of simulations are often run to understand the likely patterns, due to the stochastic nature of these models. A common function used to model decisions by the agents is the utility function, where agents are either seeking to maximize or minimize a certain value or score. And take the corresponding individual action, which leads to macroscale impacts.

Los Angeles (LA), California is a favorable location as a case study for studying rooftop solar PV adoption due to its high solar potential of approximately 1600 kilowatt-hours per kilowatt-year (kWh/kW-year), and higher than average electricity prices (National Renewable Energy

Laboratory 2016). In 2018, LA County had approximately 370 megawatts (MW) of residential capacity (California Solar Initiative 2018). However, the California Energy Commission recently approved new building energy efficiency standards that will take effect in January 2020. As part of the new standards, all newly constructed single-family residential homes are required to have solar panels installed. This is estimated to represent roughly 410 MW of installed solar capacity per year (Dong 2017).

4.2.1 Literature Review

In light of the growing applications of ABM to solar photovoltaics (PV) adoption, a review was conducted on previous literature. The main objective was to survey the ABM literature on residential solar adoption, with a focus on identifying the functions and technology characteristics chosen to model adoption and the policy scenarios explored. Table 4-1 provides a summary of the literature review. Studies have most commonly used a utility function to represent how individuals decide to install a solar technology. In some cases, an agent decides to install a system when one's utility exceeds a decision threshold value. The threshold value is determined by matching the ABM simulation results with the actual adoption during the calibration of the model (Palmer et al. 2015).

A maximizing utility function is useful when a large amount of complex information may need to be considered to make the best decision (Carpenter 2011). Logistic (Mohandes 2019), heuristic (Macal et al. 2014), and the theory of planned behavior (Rai and Robinson 2015) have also been used to model the decision to adopt solar. The logistic model is a widely used statistical model that uses a logistic function in its basic form (Mulligan 2006). The logistic model is computationally easier to use than other types of functions. However, individuals having different attributes (e.g. age, income) and motivations are all grouped together in the estimation. Heuristics are decision-making strategies people use that are based on little information and the use of mental short-cuts that reduce the burden of decision-making. Reliance on heuristics is useful in decision-making for convenience and speed (Dietrich 2010). The key component to a model using the theory of planned behavior is behavioral intent. Behavioral intentions are based on attitude toward the behavior and a person's subjective norm (Rai and Robinson 2015).

Borghesi et al. (2013) focused on the economic characteristics influencing the household adoption decision. Two economic characteristics were used: payback time (PBT), or time needed to "break-even" on the solar panel investment, and net present value (NPV), considering both investment costs and savings on electric utility bills. They compared the installation behavior of solar PV over four different incentive scenarios and found that the total installed solar power can be enhanced in Italy by improving the financial attractiveness of adoption.

Robinson et al. (2015) included social and behavioral characteristics, such as the influence of peers, in an ABM developed for the Austin, Texas. The resulting model included both spatial and demographic validation. Validation is still in its infancy in ABM due to the inherent stochasticity of the models and is typically used to determine the structural validity of the model (Hicks et al. 2015). Although financial characteristics were important in predicting adoption, they found that social interactions were critical to predict spatial and demographic patterns of adoption. Social interactions were modeled as households close in space to the agent's location in the model.

Zhao et al. (2011) and Palmer et al. (2015) also considered both economic and behavioral characteristics. Zhao et al. (2011) developed an ABM to compare solar adoption in New York City (NYC) and Tucson, Arizona due to their differences in size, solar potential, electricity prices, demographics, and available incentives. The model evaluated two incentives: investment tax credit and feed-in tariff. Adoption of solar was impacted by the two investigated incentives in both cities, but NYC was less sensitive to the changes due to the differences in solar potential and grid electricity price. Palmer et al. (2015). simulated residential solar adoption in Italy using household income, payback period, influence of peers, and attitude toward the associated environmental benefits of adopting a solar PV system. The scenarios of feed-in-tariff and decrease in investment cost of solar PV changed the NPV of adoption, resulting in more adopters compared to the baseline.

Zhang et al. (2016) evaluated “seeding” policies in San Diego, CA to leverage the impact of peer effects on adoption. This policy involves giving away solar panel systems subject to a budget constraint over a specific time period. The model found that, compared to subsidies that reduce the cost of solar panels, adoption was more sensitive to “seeding” policies.

Solar PV is limited by its intermittency, which represents a barrier to adoption, in addition to its high upfront cost. Complimentary technologies such as battery storage have the potential to increase the environmental and/or economic benefits associated with solar PV adoption. Alyousef et al. (2017) explored how battery storage affects the adoption of solar PV in Germany. Scenarios that simulated increasing electricity prices and decreasing PV system and battery costs had the strongest impact on PV adoption, suggesting that cost of solar PV and grid parity are critical adoption factors.

Table 4-1 – ABM Literature on Residential Solar Adoption

Author/Year	Location	Survey Used?	Adoption Process	Scenarios Considered
Zhao et al. (2011)	Tucson, Arizona and New York City	Yes	Utility	Investment Tax Credit, Feed-In Tariff
Palmer et al. (2015)	Italy	No	Utility	Feed-In Tariff, PV Costs
National Renewable Energy Laboratory (2016)	California, Arizona, New Jersey, New York	Yes	Utility	Feed-in Tariff, Seeding, Leasing
Macal and Graziano (2014)	Southern California	No	Utility, Heuristics	None
Rai and Robinson (2015)	Austin, Texas	Yes	Theory of Planned Behavior	Rebates
Zhang and Vorobeychik (2014); Zhang (2016)	San Diego, California	No	Utility	Seeding, Subsidies
Alyousef et al. 2017	Germany	Yes	Utility	Feed-In Tariff, Electricity Prices, Battery Prices
Mohandes (2019)	Arabian Gulf Region	No	Logistic	Subsidies, PV Costs, Carbon Tax

This study develops an ABM, with Los Angeles County as a case study, that explores the impact of a broad range of scenarios on the adoption of residential rooftop solar panels by homeowners in the county, which is a population of approximately 1,607,200 (US Census: American Fact Finder 2017). Specifically, five different variations of the baseline are explored: adding incentives, increasing the cost of grid electricity, a falling cost of solar panels due to technological improvements, and two variations of the California Energy Commission building energy efficiency standards requiring residential homes to install a solar PV system in 2020. The first three scenarios were chosen to enable comparison with other models, as they have been evaluated in past literature (Zhao et al. 2011; Palmer et al. 2015; Alyousef et al. 2017;

Mohandes 2019). The last two scenarios explore the new California Energy Commission building policy that goes into effect in 2020 and has not been evaluated in previous literature, making it a particularly useful and interesting contribution to the current state of knowledge. Using data from a comprehensive survey of Los Angeles residents regarding decision-making around PV adoption, the model simulates the adoption of residential solar PV in LA County from 2018-2050. (Further detail about the survey may be found in the Appendix B).

4.3 Methods

In this section, an overview of the structure of the model is provided and shown in Figure 4-1. The approach used seeks to understand the factors affecting decisions to choose among adopting or not adopting solar photovoltaics (PV) by residents in Los Angeles (LA) County. Agents, defined as homeowners, are given the choice to decide between adopting one of two solar system options, a system that will replace 50% of the agent's annual electricity consumption or 100% of their annual electricity consumption, or choose to do nothing (i.e. not adopt solar and keep consuming 100% grid electricity) in each tick, or time step (representative of one year). All agents who have not yet adopted PV weigh their options annually, and decide if they will adopt solar, and if so at what level of current electricity offset.

According to a 2018 report from EnergySage, the average percentage of usage offset in California is 102%, meaning that the average rooftop system generates more electricity than is used by the homeowner (Energy Sage 2019). Which is why the 100% solar adoption option was chosen. In other parts of the United States, customers fall in the 50-90% range of electricity offsets (McLaren et al. 2015). Therefore, a second option of 50% solar adoption was chosen to act as a surrogate to account for all of the potential solar panel systems that offset a range of electricity levels between 50% and 100% annual electricity offset. This is a simplification in the model for the sake of computability, instead of selecting more offset bins. In addition, this makes the model applicable to other parts of the United States. Each time step is one year, and the model is run for 32 years, from 2018 to 2050, to enable comparison with other ABM and adoption models for residential solar adoption (Dong 2017).

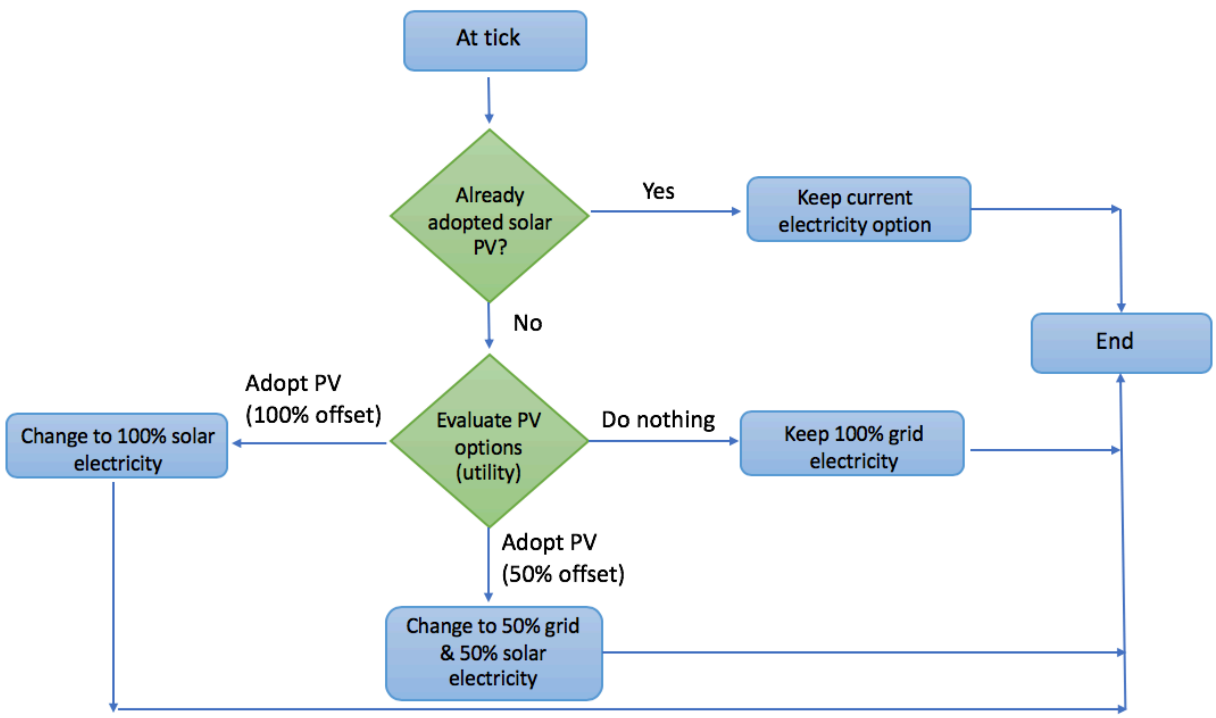


Figure 4-1 ABM Flowchart

At each tick, which is defined as one year, the agents that have not yet adopted solar, will evaluate three different electricity generation options. After evaluating the utility of the three options, they will decide to choose the option that offsets 100% of their electricity with solar, 50% of their electricity with solar, or choose to not adopt a solar panel system.

4.3.1 Decision Process

Agents select an electricity source (either grid purchased electricity or one of the two PV options) by evaluating the utility of the three options through a multi-attribute utility function and probabilistic decision making. Agents seek to maximize their utilities, with the utility function composed of values for characteristics of the solar PV system/bid as well as weights for the relative importance of the factor in the decision to adopt. The characteristics chosen were those that have been identified to be critical factors in adoption of residential solar PV systems in previous work, including lowering total electricity costs, adding to a home's market value, protection from rising electricity prices, ability to use renewable energy, ability to use new technology, reducing environmental impact, setting a positive example for others in the community, aesthetics, investment cost of system, payback period, influence of others, and lifespan of the system (National Renewable Energy Laboratory 2017; Zhang 2016; Sigrin 2015; Hoen 2013; DeShazo 2017; Faiers and Neame 2006; Wolske 2017; Macal et al. 2014; Rai and Reeves 2016; Palmer et al. 2015; Zhao et al. 2011).

Equation 5 presents the general form of this utility equation, which has been used to model solar PV adoption in the past (Zhao et al. 2011; Palmer et al. 2015; Macal et al. 2014; Zhang 2016; Rai and Reeves 2016). U_i is the utility of the technology, f_i is the normalized score of the factor of relative importance to the agent, such as system cost, and w_i is the weighting of the factor (informed from survey data as described in Section 4.3.2). The factors are normalized across the set of values for each individual factor, such as the initial cost of the three electricity generating options. The summation of the individual factors is 1 and normalized across the three utility functions (one for each option considered) using equation 2. An example of a factor would be purchased price of the system. This prevents the dominance of a single factor and follows standard practice. The weights are informed from the survey and are normalized to sum to one within each of the three utility functions. The summation of the individual factors is 1 and normalized across the three utility functions using equation 6.

$$U_i = \prod_i^n F_i * \ w_i \ (5)$$

$$Normalized\ factor = 1 - \frac{value - minumum\ value}{maximum\ value - minimum\ value} \ (6)$$

The utility of each option is used to determine the probability of the agent adopting each system according to:

$$P_A = \ \frac{e^{U_A}}{e^{U_A} + e^{U_B} \ + e^{U_C}} (7)$$

where the probability of the adoption of solar system A is the exponential raised to the utility of option A, divided by the summation of the exponential utilities. The overall probability of selection of one of the three options is equal to 1 and is generated through a summation of all three utilities (adopt solar and offset 50% electricity, adopt and offset 100% electricity, and don't adopt solar). The roulette wheel simulation is used to select the bid that is adopted. This selection technique is used to capture uncertainty within the model or that an agent might choose an option with lower utility, as human behavior is not entirely rational (Hicks et al. 2015).

4.3.2 Survey

A survey was conducted with the goal to understand the drivers and motivations for adoption of rooftop solar PV by residents of LA County. The online survey was deployed on

Qualtrics through their network of online pre-recruited panels to guarantee a pre-determined sample size that was representative of LA County. The survey respondents were screened for being a resident in Los Angeles County and owning a single-family home. Throughout the survey, the respondents were further separated into two classes: 1) those who have adopted a solar panel system ("adopters"), and 2) those who have considered adopting solar panel systems but decided not to or those who have not considered adopting solar panel systems ("non-adopters"). Each class was given a set of questions that were similar but worded for relevancy to their particular class. The survey was deployed from April 13, 2018 until May 11, 2018. All respondents were asked to provide their income and household size (square feet). Non-adopters were asked to rank the relative importance of 12 factors previously identified as important when adopting a solar PV system to better understand what would influence their decision to adopt solar PV, as described in Section 4.3.1.

Overall, the survey yielded 3,795 responses from residents across most zip codes in LA County. Responses were not received for 20 zip codes, including 90058, 90073, 90079, 90094, 90263, 90290, 90506, 90740, 90742, 90743, 90747, 90822, 90831, 91046, 91759, 92397, 92782, 93523, and 93563. To generate ranking of the 12 factors, the dataset was cleaned to removed residents that did not report their income or did not answer the ranking question. This resulted in 2,518 responses from non-adopters, and 1,206 responses from adopters. The percent of non-adopter respondents and their responses for whether the adoption factors would be important in their decision to adopt solar is found in Table 4-2 below. It is relevant to mention that several respondents did not rank all of the factors, with most choosing to rank only 2-3 factors. Further details about the survey can be found in the Appendix B.

Table 4-2 – Survey Responses for Factors Affecting Adoption

Adoption Factor	Percent of Non-Adopters
Lowering your total electricity costs	79%
Adding to your homes market value	26%
Protection from rising electricity prices in the future	36%
Being able to use renewable energy	31%
Being able to use a promising new technology	14%
Reducing your environmental impact	33%
Setting a positive example for others in your community	11%
Making your home more attractive	8%
Influence of others	15%
Overall cost of the system	14%
Length of time to payback upfront costs	14%
Lifespan of the solar system	19%

4.3.3 Model Design

The model is composed of an agent environment, defined as zip codes throughout LA County. To create the environment, a Geographic Information System (GIS) file from the LA County Open Data Platform, containing 302 zip codes in LA County, was integrated into the Netlogo agent-based modeling (ABM) software (Los Angeles County Enterprise GIS 2013; Wilensky 1999). The model is composed of 16,072 heterogenous agents. The model is scaled by 100, where each agent represents 100 homes to fit within the computing limits of the software. Agents are distributed randomly within each zip code and the number of agents assigned to each zip code is representative of the actual number of owner-occupied housing units in each zip code in the model using 2017 U.S. Census Bureau data and zipdatamaps.com (US Census: American Fact Finder 2017; Zipdatamaps 2017).

The initial agent attributes were assigned using both survey and regional data, including the University of California-Los Angeles (UCLA) Energy Atlas, United States (US) Census Bureau, and data from the DeepSolar database, and are found in Table 4-3 (UCLA Energy Atlas datasets 2015; Stanford University 2018; US Census: American Fact Finder 2017). Due to 2018 data not yet being available, 2017 data from the US Census Bureau on the income distribution for zip codes in LA County was used to assign an income level to agents in a particular zip code, ensuring it is representative of actual statistics for LA County. The income level was assigned probabilistically using the roulette wheel simulation method. This method probabilistically assigns the income level to each agent, based on the distribution of the incomes in LA County. It is generally used when the survey data is unrepresentative of the population or there is not a sufficient quantity of samples generated. Ten percent of survey respondents had an income level under $36474 compared to 31% in LA County, 10% had an income level between $36474 - $49375 compared to 12% in LA County, 17% had an income level between $49575 - $64375 compared to 16% in LA County, 18% had an income level between $64375 - $86622 compared to 12% in LA County and 45% had an income level over $86622, compared to 29% in LA County. Overall, the lowest income level (under $36474) is under-represented in the survey, while the highest income level (over $86622) is over-represented in the survey. Several zip codes, 127 in total, did not receive responses from one or more income levels. In addition, the number of responses from each income level within each zip code did not accurately reflect the actual income distribution in LA County from the US Census due to the survey being a general LA

County resident survey, and not sampling for particular zip code or incomes. Which is why it was necessary to use the probabilistic distribution method to generate the correct zip code income demographics for the agents.

After assigning an income, each agent was assigned an electricity consumption and weights for the utility function. These were again assigned using the roulette wheel simulation method (Hicks et al. 2015). In this case, the attributes and weights that were ultimately assigned to each agent in a particular zip code were assigned probabilistically by income level based on the survey data. The LA Energy Atlas was used to model the annual electricity consumption of agents because of known biases in self-reported values of household consumption (Pudney 2008). The LA Energy Atlas contains data on the electricity consumption by household size for all neighborhoods in LA County. The average area of houses was collected in the survey and used in combination with the LA Energy Atlas to assign the initial electricity consumption.

The model was also initialized with the degree of adoption in LA County in 2018 and the electricity offset level of current adopters. The DeepSolar database, built by Stanford University, was used to identify that adoption is currently around 6% of the 2018 owner-occupied housing population and that the average annual electricity offset of current adopters in LA County is 94%, which is why all initial adopters in the model have a PV system with 100% electricity offset (Stanford University 2018; US Census: American Fact Finder 2017). This was necessary due to the oversampling of adopters in the survey. Approximately 70% of survey respondents were adopters, while 30% were non-adopters. Each agent was assigned an initial social network, which was modeled based on the number of nearest neighbors who have adopted solar in relation to the 8 neighbors around the immediate location of the agent.

Table 4-3 – Agent Parameters

Agent parameters	**Definition**	**Source**
Electricity consumption (kWh)	Amount of electricity consumed by the agent in a year	Calculated using data on home size (survey) and median electricity consumption per ft^2 per zipcode (UCLA Energy Atlas)
Income ($)	Annual income of the agent	Randomly assigned to agents in a zipcode using an income distribution representative of each zipcode in LA County
Social network	Each agent is assigned a social network based on the total number of neighbors who have adopted solar in relation to the 8 neighbors around the immediate location of the agent	Agents are assumed to be have a stronger incentive to adopt PV as the number of communication links to PV adopters that are geographically close to an agent increases (Palmer at al. 2015; Zhang 2016).
Zip code	The zip code where an agent lives	Assigned to agents based on their GIS location
Solar?	Binary variable defining whether the agent has adopted or not adopted solar (0 if they haven't adopted, 1 if they have adopted)	Randomly assigned to agents with the total number of adopters equaling the level of adoption in LA County in 2018 (Stanford University 2018)
Electricity cost ($)	Annual cost for electricity for the agent	Calculated using electricity consumption of agents and assumed consumers are charged at an average rate of 0.16 cents/kWh in California (Rockzsfforde 2015)

Next, the bids were generated for the purchase of a solar PV system that offsets 50% or 100% of an agent's annual electricity consumption. According to the survey, 13% of current adopters leased a solar system, while 87% own a system. According to a report by GTM Research, solar leases peaked in 2014 at 72% of the market and has been on a downward trend since that time period (Greentech Media 2016). The shift to ownership of systems can be attributed to the cost of solar declining rapidly in recent years, making the upfront cost more affordable.

First, the system size to offset 50% or 100% of an adopter's electricity consumption is determined using the equation 7. It is assumed that all homes in LA County receive an average of 5.6 hours of sunlight per day in LA County according to the National Renewable Energy Lab (NREL) (National Renewable Energy Laboratory 2016; Aurora Solar 2016). It is also assumed that each home has a roof that is feasible for a solar PV system. A 2015 report from NREL estimates that 81% of residential buildings have suitable space for at least 1.5 kilowatts of solar on their rooftops, which reflects factors like rooftop area, shading, and rooftop orientation. After excluding renters and those who live in buildings too tall (37% of households), around 50% of households can install at least a 1.5 kW system (National Renewable Energy Laboratory 2015).

$$System\ size\ (kW) = \frac{Daily\ energy\ use\ (kWh)}{5.6\ hours/day} (8)$$

Next, the potential cost of each system is calculated to determine the financial feasibility (e.g. payback period and total electricity costs) over the system's lifetime using equations 8 and 9 (Energy Sage 2016). It assumes that the agent's electricity consumption does not change from year to year. The purchase price of a system is constant across all agents because potential adopters in the same area are assumed to have access to the same solar manufacturers and installers.

$$PC = System\ size\ (kW) * 1000\frac{Watts}{kW} * p * (1 - ITC) \quad (9)$$

$$PP = Purchase\ cost/(G * e) \quad (10)$$

Where PC is the purchase cost and PP is the payback period, e is the value of the electricity produced by the solar PV system ($0.16/kWh), p is the per unit price of the solar PV system ($3.45/kWh), ITC is the investment tax credit (0.3), G is the annual system electricity generation (kWh/year). The value of the electricity produced by the solar PV system, e, is $0.16/kWh, the average price of grid electricity in California (Rockzsfforde 2015). The average price of solar PV in California in 2018, as reported by Solar Reviews from an aggregation of many systems, was $3.45/Watt before any rebates or federal incentives were applied (Solar Reviews 2018).

The total electricity costs were calculated using the levelized cost of energy (LCOE) for solar PV to provide a comparison of lifetime costs to the cost of electricity from the grid. The following equation was used to calculate the simple LCOE, where O&M is the total operation and maintenance costs. According to NREL, the average operation and maintenance costs are $21/kW-year for residential systems and the inverter replacement price is 0.13/W (Fu 2017). The system lifetime is assumed to be 20 years, which is a common lifetime used in simple LCOE calculations for solar PV (National Renewable Energy Laboratory 2019). The solar potential is assumed to be 1642 kWh/kW-year (National Renewable Energy Laboratory 2016). The conversion efficiency and performance ratio of the panels is assumed to be 16% and 0.8, respectively (Hsu et al. 2012). Finally, according to a study by the Lawrence Berkeley National Lab on PV home premiums in California, approximately $5,911 is added for every 1 kW added to the home (Hoen 2013). As such, this assumption was used to calculate the characteristic values for home value increase on both bids.

$$LCOE = \frac{PC+O\&M}{System\ size\ (kW)*Solar\ potential\ \left(\frac{kWh}{kW-year}\right)*lifetime*efficiency\ (\%)*performance\ \ ratio} \quad (11)$$

4.3.4 Simulations

Multiple ABM simulations (100 runs) were performed to study the base case over the model period from 2018 to 2050. The base case is the solar PV market with no incentives or disincentives for adoption. Five scenarios were simulated 100 times each to explore changes to adoption from 2018-2050. The first scenario explores the effect of adding the federal tax credit to reduce the cost of a solar PV system by 30%. This scenario deducts 30% off the cost of the solar PV system over the time period of 2018-2050. Currently, 30% can be deducted from the cost of the solar PV system, however, the tax credit will be reduced to 26% in 2020 and 22% in 2021 and then phased out for residential systems in 2022 (Energy Sage 2016). The changes to the federal tax credit from 2018-2022 and the phase-out were not explored because, by 2022, adoption has already reached a critical mass in the model (Energy Sage 2016). The second scenario simulates a decrease in solar cost over time due to market developments and technological innovation. This was simulated using the NREL cost reduction roadmap modeling from 2017-2030 (Ardani 2018). NREL estimated that the installed cost of solar PV could be reduced to $1.21/watt by 2030. This 2030 target was used as a reference point and a linear decrease in solar panel cost was assumed each year until 2030. The third scenario explored was a change in electricity prices over time. Grid electricity prices in California have grown by nearly 3% per year for the last three years. Similar to Law et al. (2017) who also applied this scenario to an adoption model in LA County, a 3% increase until 2050 was used in this work. The fourth scenario simulates the California Energy Commission's building standards that go into effect in 2020 and require newly constructed residential homes to adopt solar PV. This scenario uses an approximation that 2000 new homes (1-unit) are built in LA annually according to 2017 housing statistics, which is approximately 0.1% of LA county owner-occupied homes (Los Angeles Housing Development Update 2018). In the model, it was assumed that 0.1% of agent homes are torn down each year, and new homes are built in their place due to the housing density of LA County. The California Energy Commission standards require all low-rise single-family homes to have a PV system with a minimum system size that offsets the homeowner's projected annual electricity use, or 100% of their annual electricity consumption to meet the minimum requirements (California Energy Commission 2018). A hypothetical scenario (fifth scenario) of the same standard with a minimum requirement of half of a homeowner's annual electricity use, or the 50% adoption option was also explored to understand how a change in the minimum system size requirement would impact adoption. The California Energy Commission has exceptions to the minimum size requirements based on location, and future work could explore this with a finer level of detail.

4.4 Results and Discussion

This section will describe the results of the ABM simulations broken up by baseline results and scenarios (Section 4.4.1) and comparison to other models (Section 4.4.2). The baseline and scenario results are shown in Figures 4-2, 4-3, 4-4, 4-5, 4-6 for the total adoption and Figures 4-7, 4-8, 4-9, 4-10, 4-11 for the total electricity consumption from solar and the grid.

4.4.1 Baseline and Scenarios

The baseline results demonstrate that 78% of the owner-occupied population in LA County will potentially adopt a solar PV system, which corresponds to about 8 billion kWh of solar electricity in 2050. Approximately 32% of homeowners will adopt a system that offsets 50% of their electricity consumption, while 45% will adopt a system that offsets 100% of their electricity consumption. Yet, 22% of the population will potentially not adopt solar by 2050.

The second scenario, adding the investment tax credit incentive, results in 97% of the owner-occupied population adopting a system by 2050, corresponding to 9 billion kWh of solar electricity. Compared to the base case scenario, adoption spikes in 2018-2019. This is due to the investment tax credit reducing the LCOE of adopting a solar PV system, making it less than the LCOE of grid purchased electricity. Therefore, homeowners who are solely interested in the costs of the electricity generating options and grid parity will adopt PV as a lower cost option under this scenario.

Similar results are demonstrated for the scenarios that decrease the cost of solar panels due to technological innovation and increase the cost of grid electricity. In both scenarios, 97% of the owner-occupied population potentially adopts a system by 2050, corresponding to 9.5 billion kWh of solar electricity. When the cost of solar is decreased each year per the NREL cost modeling roadmap, a spike in adoption occurs in 2022, which is when the LCOE of solar PV is less than the LCOE of grid purchased electricity. When the price of grid electricity is increased by 5% each year, a spike in adoption occurs in the year 2025 when the LCOE of grid purchased electricity is more than the LCOE of solar PV. This is due to 79% of homeowners in the survey indicating that the cost of their electricity generation technology is a critical factor in the decision to adopt solar PV, and therefore, will keep their current electricity generating option and only switch to solar PV when costs are more favorable.

The final scenario based on the new California Energy Commission standards has the strongest impact on future solar PV electricity generation potential in LA County. With the actual minimum system size requirement of 100% offset, 97% of the LA County owner-occupied population may potentially adopt a solar PV system, corresponding to 9.7 billion kWh of solar electricity. This is as expected because the new standards require homes to adopt a solar panel system regardless of their preferences on solar energy. With a hypothetical change in the minimum requirement to 50% electricity offset, 98% of the owner-occupied population of LA County may potentially adopt a solar PV system by 2050, corresponding to 8.5 billion kWh of solar electricity.

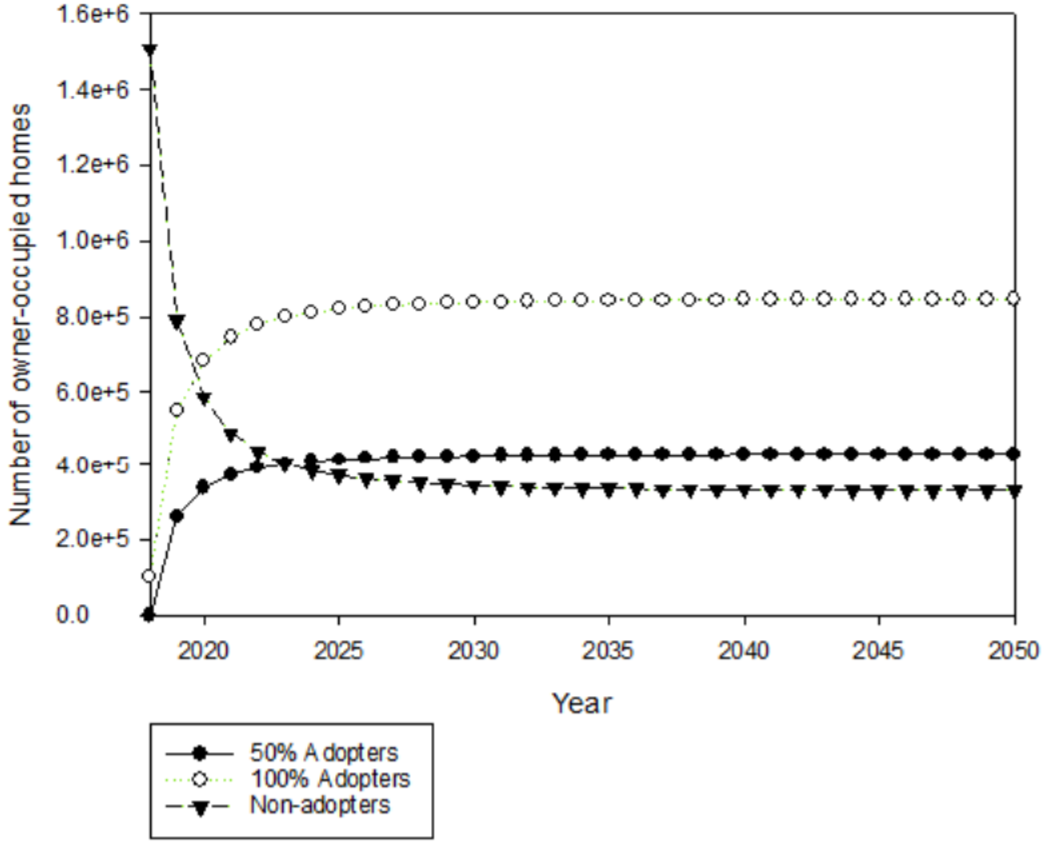


Figure 4-2 - Baseline adoption

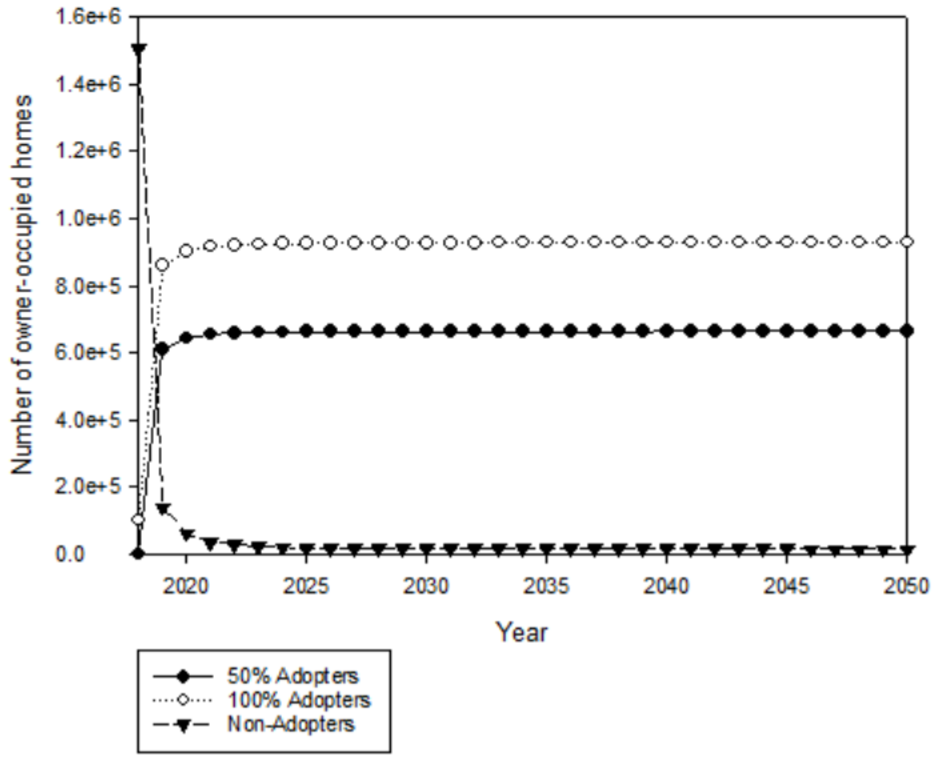


Figure 4-3 - Adoption due to adding investment tax credit

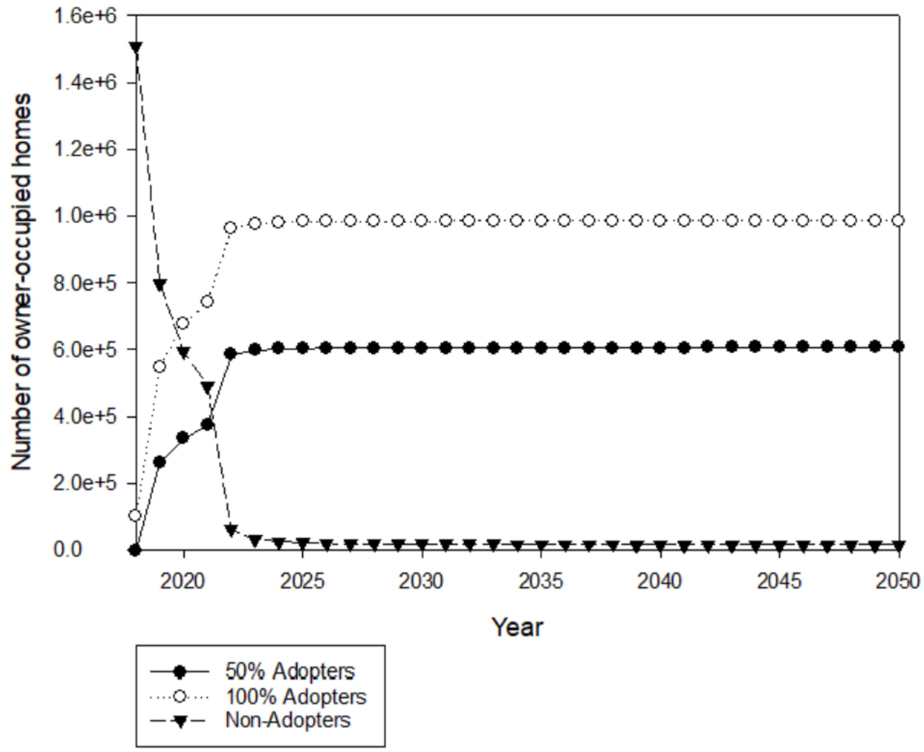


Figure 4-4 - Adoption due to decreases in solar panel cost

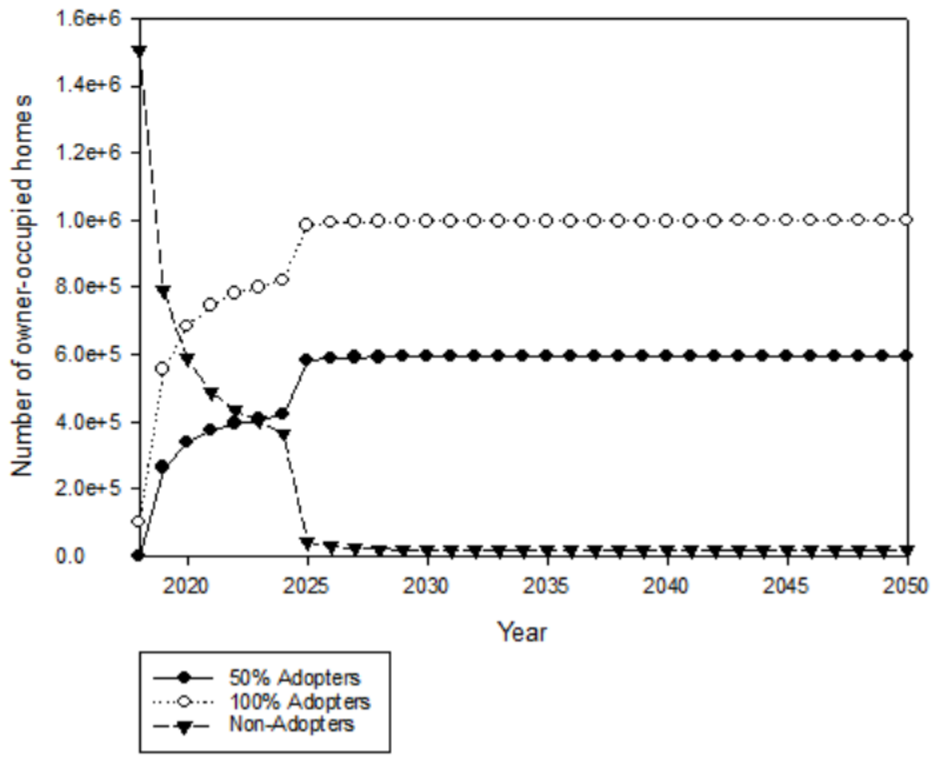


Figure 4-5 – Adoption due to increases in grid electricity cost

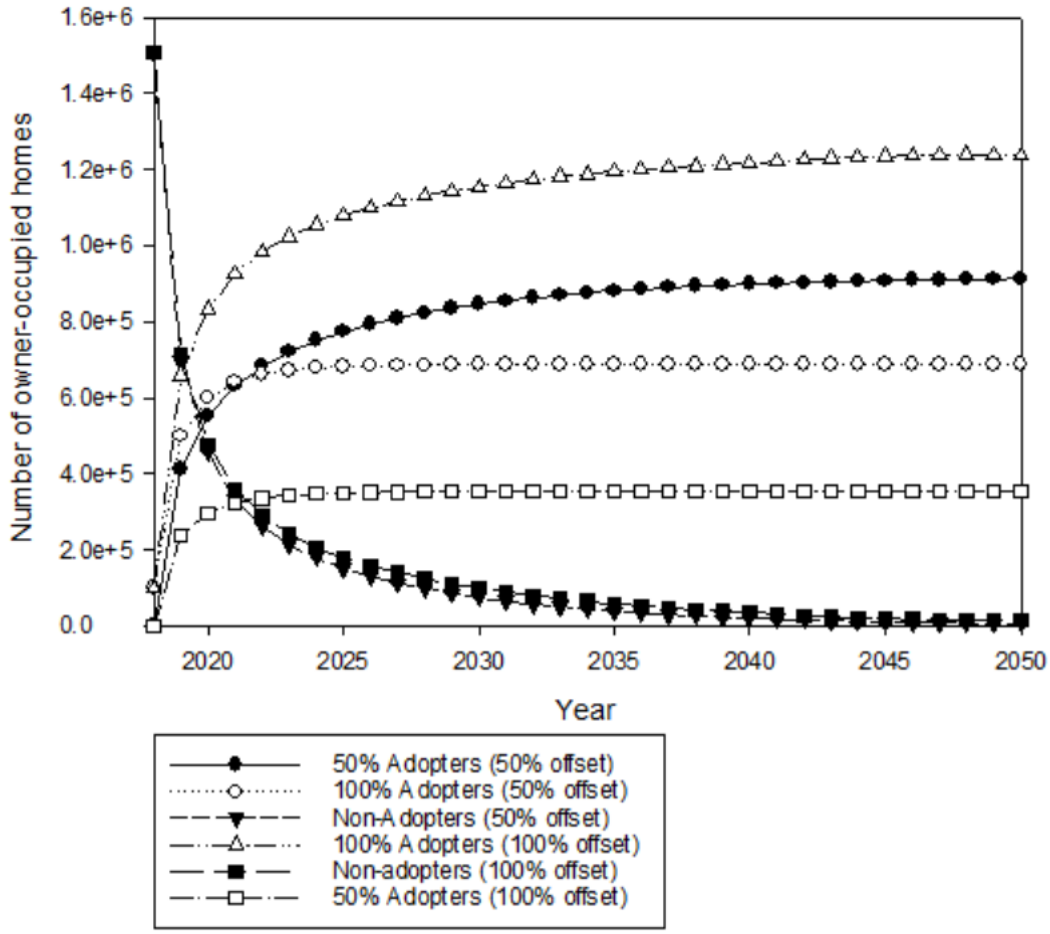


Figure 4-6 - Adoption due to new home standards

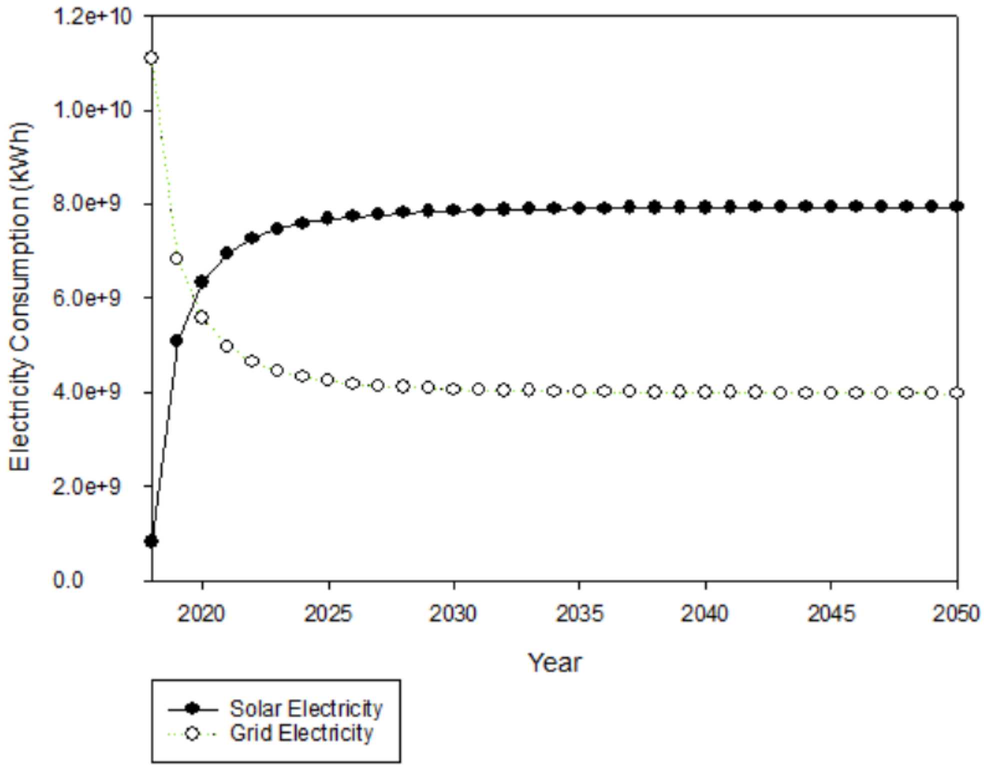


Figure 4-7 - Electricity consumption baseline

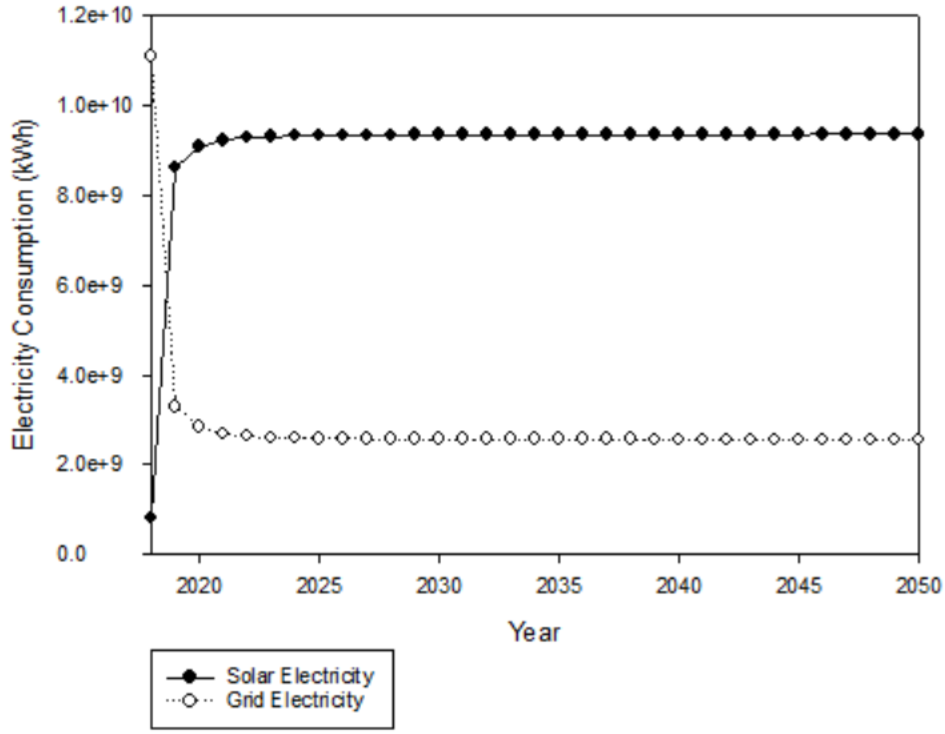


Figure 4-8 - Electricity consumption from adding investment tax credit

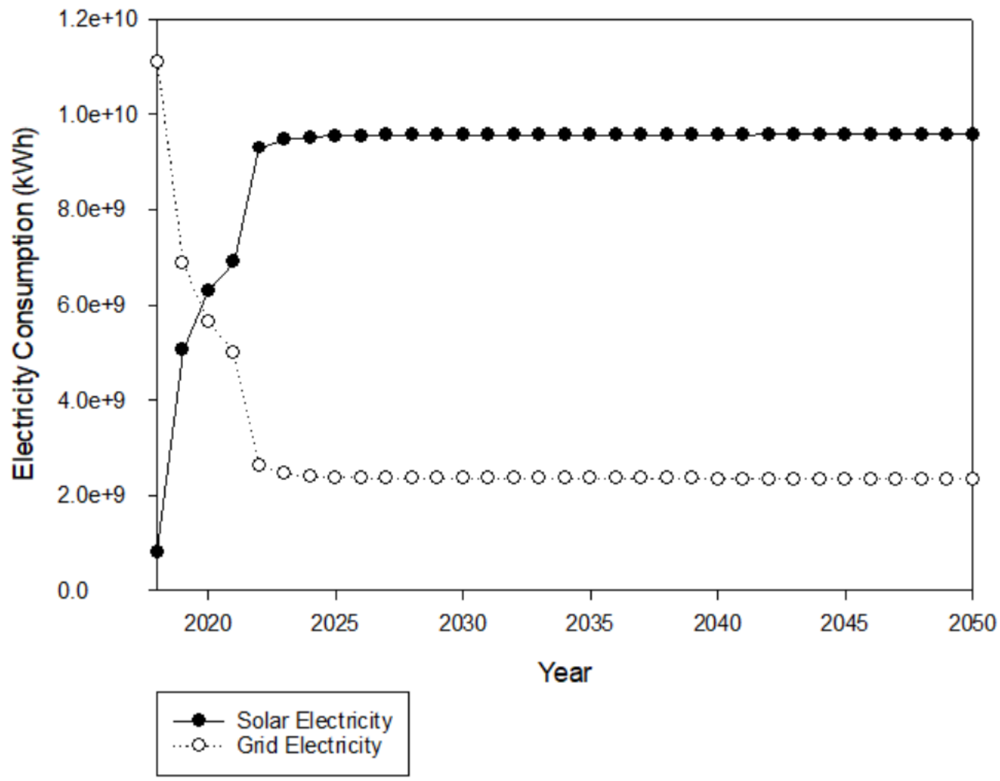


Figure 4-9 – Electricity consumption from decreases in solar panel cost

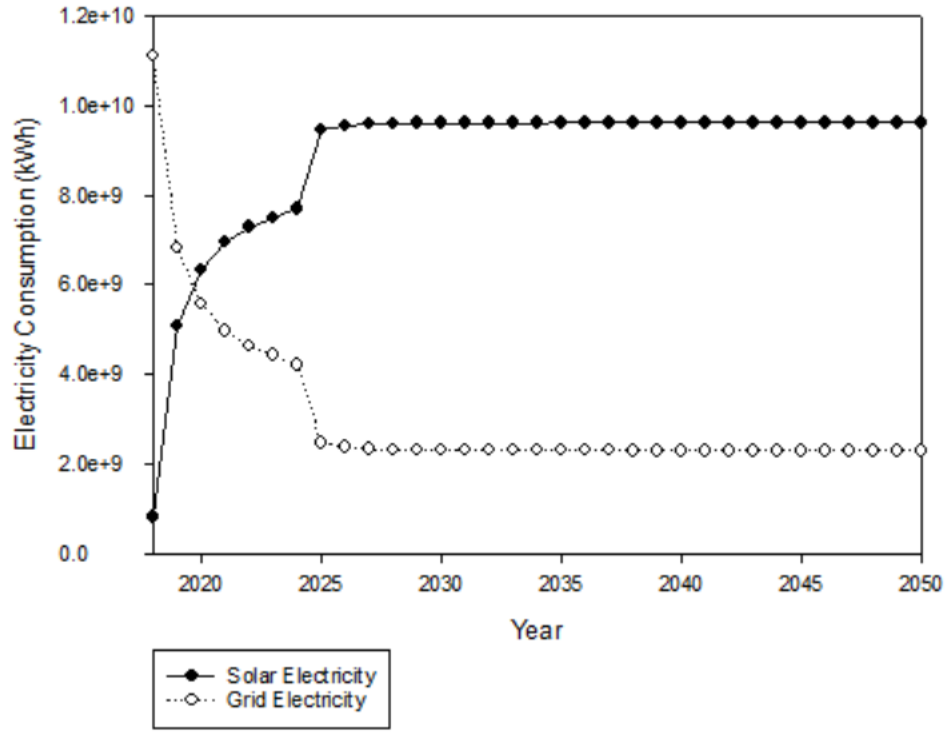


Figure 4-10 - Electricity consumption from increases in grid electricity

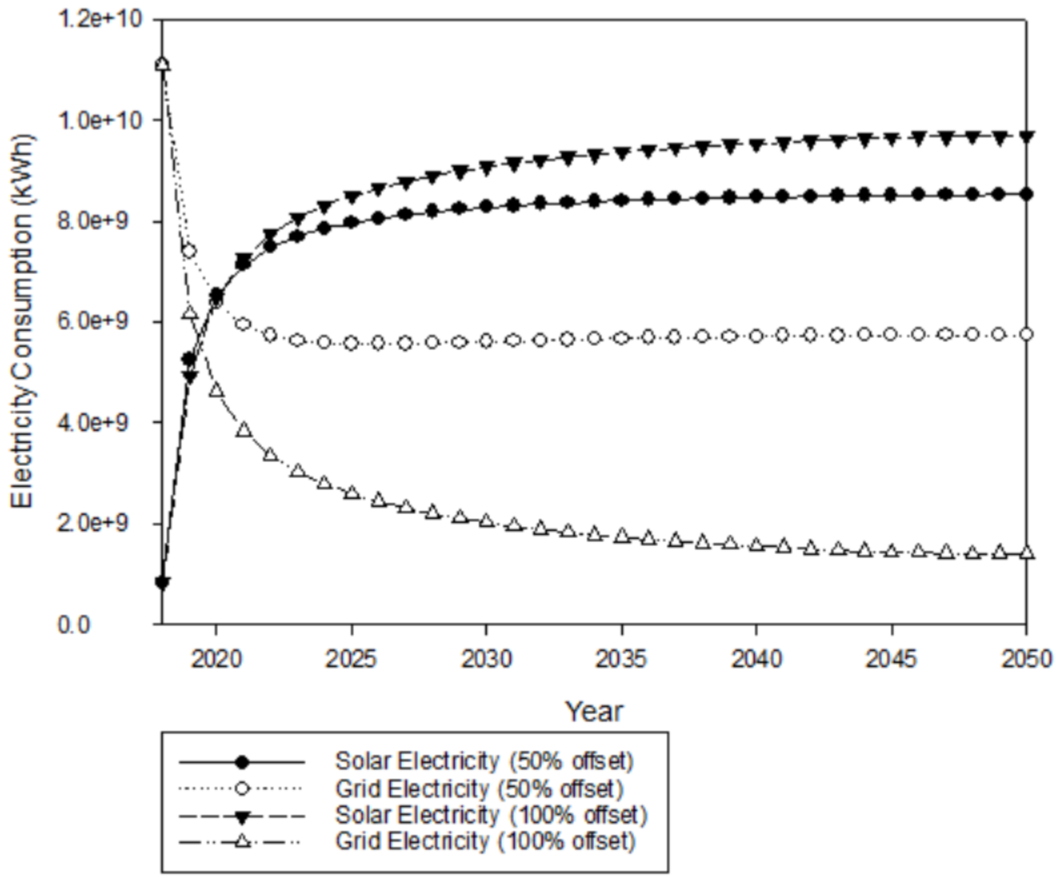


Figure 4-11 - Electricity consumption from new home requirements

4.4.2 Model Comparison

The baseline results for LA County were compared to a range of other models for residential solar adoption in California in Figure 4-12 (Dong 2017; E3 2015). The other models from the literature are not for LA County, the results for LA County from this work are shown with crosses for comparison, due to the lack of models that exist for LA county to present for comparison. Almost all models predict an S-shaped adoption curve until 2050 where adoption starts slowly, speeds up and then slows down over time. Similar to other models, adoption generally peaks around the year 2020 or 2022. One outlier is the TimeSeries model, which predicts a linear adoption curve over time. The TimeSeries model is based on an extrapolation of past adoption to predict future adoption, and therefore, does not consider the heterogeneity of the population. A second outlier is the E3 model, showing a general increase in adoption over time with the model stopping at the year 2024. Compared to other models, this work suggests that there is generally faster adoption of solar in the time interval of 2018-2019 in Los Angeles, largely due to it being an urban area with a high population density. Adoption of new technology is generally faster in urban areas compared to rural due to the social network effect (Hall 2002). This ABM also predicts a similar overall total percentage of adoption, at 78% in 2050, as other models.

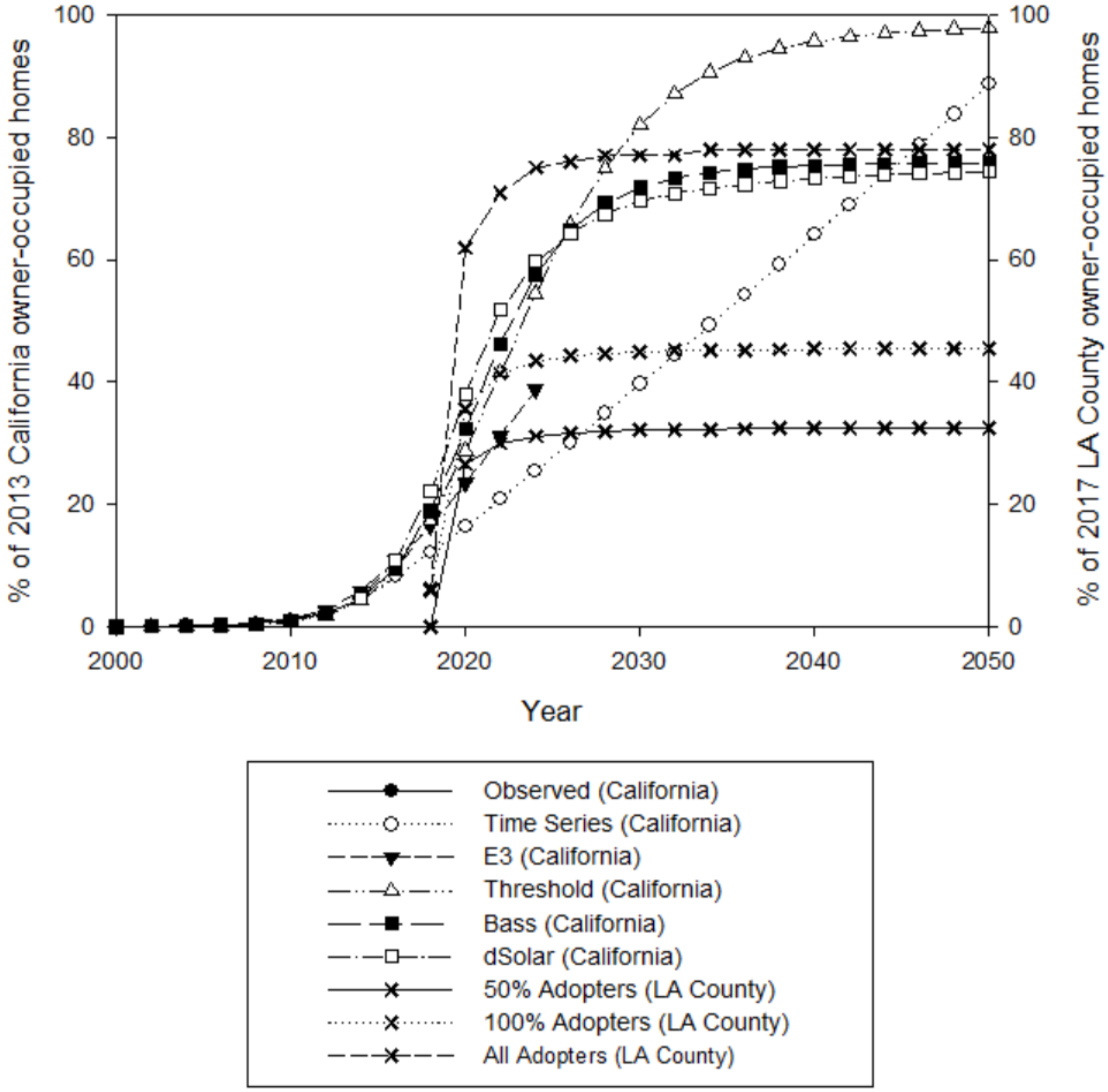


Figure 4 12 - Comparison to other adoption models (Dong 2017; E3 2015)

The shapes represent the % of adopters from various models in the literature and are graphed against the % of 2013 California owner-occupied homes. Crosses are used to graph the % of adopters in this work on LA County and are graphed against the % of 2017 LA County owner-occupied homes. 50% adopters and 100% adopters are the number of adopters that have adopted a solar panel system that offsets 50% of their electricity consumption, or 100% of their electricity consumption, respectively.

In this work, an ABM was created to model the adoption of rooftop solar from 2018 through 2050 as a case study of LA County homeowners. The goal was to understand the effect of different policies and technology evolutions (scenarios) on the overall adoption rate and electricity offset of the PV system adopted. The bottom-up modeling approach used to take into consideration the heterogeneity of the LA County population with respect to preferences and factors involved in the decision to adopt solar. The most common factor influencing the decision to adopt solar was lowering total electricity costs. However, 31% indicated that being able to use renewable energy would be an important factor and 33% indicated that reducing environmental impact would be an important factor in their decision.

The work has implications for understanding the potential adoption of solar energy technologies. The ensuing PV adoption rates would help facilitate the Sustainable LA Plan to increase local solar power and assist with meeting renewable energy targets in California. The LA Sustainable City Plan has established goals to increase solar power to at least 1500 MW by 2035 and eliminate reliance on coal-fired power plants completely by 2025 (UCLA 2015). Therefore, increasing adoption of solar energy has environmental implications with respect to the reduction of fossil-fuel electricity consumption.

It is also relevant for policy-makers to understand which policies have a significant impact on adoption. Across the scenarios that were evaluated, the investment tax credit policy and the two hypothetical scenarios of a falling cost of solar due to market developments and technological innovation, and an increasing price of grid electricity all significantly increased adoption to around 97% of owner-occupied homes. This indicates that more costly policies, such as the investment tax credit, may not be necessary to increase adoption over time. The new California Energy Commission policy that requires solar panel installations on newly built residential homes could potentially also increase adoption significantly to around 97% of owner-occupied homes. Compared to the other scenarios, this policy results in the highest amount of solar electricity due to the minimum system size requirement.

Although the solar tariff policy was not explored in this work, this policy may negatively impact the adoption of solar. The solar tariffs, that went into effect in 2018, will impose a 30% tax on imported solar panels over the next 4 years, which may increase the price per watt of solar panels (Swanson 2018). This may potentially result in fewer solar installations or slower growth trends.

4.5 Conclusion

This work developed an ABM on rooftop solar PV adoption for LA County as a case study. A large number of simulations were run to understand the likely patterns of solar PV adoption from 2018-2050 under various scenarios. Several policies and hypothetical scenarios were explored, including the investment tax credit, a falling cost of solar due to technological innovation, an increasing cost of grid electricity, and the California Energy Commission building standards. All scenarios had a significant impact on adoption trends, while the California Energy Commission standards had the strongest impact on future solar PV electricity generation potential in LA County.

The bottom-up ABM methodology used in this work could be expanded to residential installations in the whole state of California or other locations in the US with differing solar potentials or electricity prices. It could also be used to explore other financing options or policy interventions. For example, although leasing of solar PV systems was not explored in this work, leasing is available in California, and may be desirable for consumers whose primary concern is the upfront cost of solar panels. Also, the availability of more grid available renewable electricity options may also decrease the adoption of rooftop solar panels. Future work should also consider other technologies, such as batteries and roof integrated PV, may increase adoption further.

5. Environmental Impacts of Residential Electricity Consumption: Agent-Based Modeling of Rooftop Solar Adoption in Los Angeles County, California

5.1 Abstract

Solar photovoltaics (PV) is a renewable electricity technology with lower carbon dioxide equivalent (CO_2e) impacts compared to fossil electricity, making it a technology of interest with respect to combatting global climate change. This paper combines agent-based modeling (ABM) with life-cycle assessment (LCA) to simulate rooftop solar photovoltaic (PV) adoption in Los Angeles (LA) County from 2018-2050 and generate CO_2e impact data at the societal level to compare solar and grid electricity. With respect to solar PV panels, consumer adoption is the "pull" that moves the system and corresponding life-cycle CO_2e impacts forward. ABM is used to evaluate the impact of policies and evolutions in technology on the adoption of solar PV. LCA is used to quantify the life-cycle CO_2e impacts of solar PV (including raw materials, manufacturing, and use). The results show that scenarios that increase PV adoption also increase the CO_2e impacts from solar PV use in the short term, due to the raw materials and manufacturing portions of the life cycle. Yet, in the long term, adoption of solar PV may provide CO_2e impact savings from offsetting grid electricity. The CO_2e impacts of solar panels are dominated by the raw materials and manufacturing phases on a product level basis, but the use phase contributes to the majority of environmental impact savings from an adoption and societal-level perspective. Future work may apply the methodology to other locations in the United States to evaluate if solar panels are an advantageous electricity source compared to the environmental impacts of the electricity grid.

5.2 Introduction

The United States (US) consumes electricity from many different fossil and renewable sources. In 2018, 63% of US electricity consumption was from fossil fuel sources, such as petroleum, natural gas, and coal, while only 17% was from renewable sources (Energy Information Administration 2018). Fossil fuels generate divergent environmental impacts, such as global warming, per unit of electricity generated, and in general at a greater magnitude than renewables. Using renewable electricity sources, and solar photovoltaic (PV) panels, in particular represents an opportunity to reduce the global warming impacts from the US electricity sector.

The global warming impacts of solar PV panels is dependent on several factors, such as the type of solar panel, solar panel orientation and angle, installation type, lifetime of the panel, solar potential, efficiency of the technology, and electricity mix of the particular location (Sherwani et al. 2010). Life-cycle assessment (LCA) is a methodology that allows for an evaluation of the environmental impacts of products and processes throughout their life-cycle (Rebitzer et al. 2004). LCA has been used to study the global warming impacts of solar PV panels on a per unit of electricity generation basis previously (Kannan et al. 2006; Laleman et al. 2011; Celik et al. 2016); Hsu et al. 2012). Environmental impacts are analyzed by considering the inputs and outputs throughout the product's life-cycle stages, including raw material extraction, manufacturing, use and end-of-life (Suh and Huppes 2005). This includes all energy and material inputs and waste and emission outputs. Emissions of pollutants and waste contributes to impacts, measured or allocated to different impact categories such as global warming, acidification and eutrophication, among others (Saur 1997).

LCA is used to quantify the environmental impacts of a technology per a functional unit, such as per solar panel or kilowatt-hour (kWh) of electricity. LCA results can also be scaled up using hypothetical technology adoption scenarios. In the case of solar panels, a scaled-up approach may generate insight into the environmental impacts of solar panels at the societal-level to compare trade-offs between conventional electricity technologies and solar electricity generation (Grant and Hicks 2018). One drawback of LCA, however, is that it does not have the ability to model human behavior, and social or economic concerns. When LCA is combined with social science methods, technology adoption scenarios can be grounded in real human behavior (Gutowski 2018).

Agent-based modeling (ABM) is a simulation modeling technique, commonly used in the social and ecological sciences, that has been applied to a wide array of complex systems, such as the flow of metals through an economy (Bollinger et al. 2011), household electricity consumption (Hicks et al. 2015; Mashhadi and Behdad 2018), bioenergy use (Kempener et al. 2009), urban development (Baynes 2009), the hybrid car market (Andrews and DeVault 2009), air transport networks (DeLaurentis and Ayyaloasomayajula 2009), tourism (Soboll and Schmude 2009), piracy control strategies (Jeong and Khouja 2013), food consumption (Li 2018), and spreading of diseases (DePasse et al. 2017). An ABM consists of a system of autonomous decision-making entities, called agents (Bonabeau 2001). The goal of an ABM is to simulate the decisions and actions of individual agents and the relationships between them, which leads to macro scale impacts and trends.

ABM has been used in the past to model solar panel adoption patterns over time and for different locations, such as Italy, California, and Texas (Alyousef et al. 2017; Palmer et al. 2015; Rai and Robinson 2015; Zhang 2016; Zhao et al. 2011). With respect to solar PV panels, an agent is commonly defined as a household deciding to install solar panels on their roof. A utility function is commonly used to model the heterogenous agent’s decision to adopt solar panels

(Hicks et al. 2015). This function is comprised of characteristics of the product or technology, such as the cost of solar panels, and weights for how important that characteristic is in the agent's decision to adopt. Agents are heterogenous, and therefore, have unique preferences and weights in the ABM, which makes it an advantageous method to use over other top-down methods (e.g. equation-based modeling).

Several combined ABM and LCA models have been produced in the past for a variety of applications, such as car and bike sharing (Van de Veen et al. 2017), cropping systems (Sharp 2013; Van de Veen et al. 2017), water systems (Van de Veen et al. 2017), bio-electricity systems (Davis et al. 2009), household consumption (Bravo et al. 2013), transportation systems (Lu and Hsu 2017; Florent and Enrico 2015), green buildings (Ru et al. 2017), and smart homes (Walzberg et al. 2018). Davis et al. (2009) used LCA data within an ABM on bio-electricity infrastructures. Agents, defined as energy conversion facilities, made decisions to invest in a bio-based electricity feedstock (i.e. wood, palm oil, rapeseed oil, manure, etc.) using life-cycle performance data on each product. Bravo et al. (2013) used an ABM and a life-cycle environmental input output model to evaluate the effect of environmental policies on the greenhouse gas (GHG) emissions of household consumption of food, energy and transportation in Italy. Florent et al. (2015) simulated the environmental impacts of the evolving car market, including sales, use and dismantling of gasoline and diesel-powered cars and electric vehicles. The ABM and LCA developed by Florent et al. (2015) was used for scenario modeling and to assess the potential environmental impacts due to the variability in car characteristics and uses. Walzberg et al. (2018) used an ABM-LCA model to study user behavior in smart homes to assess the environmental benefits. Therefore, ABM and LCA methodology have been combined to study several different complex systems.

The studies reviewed above illustrate the novelty of coupling LCA with ABM to evaluate the environmental impacts of individual behaviors. One combined LCA and ABM model has been produced on solar panel adoption in the past (Indra Al Irsyad et al. 2019). The model was developed to estimate the effect of policies on the GHG emissions and other environmental impacts of PV investments in Indonesia. LCA data was used on the CO_2e impacts during the construction and operation of a PV power plant, and the use of steel, aluminum, concrete and energy during the construction of a PV power plant. Agents were defined as households and were characterized using data from a survey covering 200,000 households in Indonesia. The time step was yearly, and policy simulations were performed from 2010-2029. It was found that several policies (e.g. net metering) had an impact on adoption and the corresponding material use and GHG emissions of solar panels in Indonesia.

This work combines two models: an LCA to assess the life-cycle environmental impacts of solar PV panels, and an ABM to estimate the adoption of solar panels and household consumption of solar electricity versus electricity from the grid under different policy scenarios, in an integrated societal-level approach. The two models are both applied for a case study of Los Angeles (LA) County, California. Together, the models are used to assess the effect of policies on the CO_2e impacts of solar panel adoption and compare trade-offs between solar electricity and the electricity grid in LA County. The daily solar potential is high in LA County throughout the year and averages 4.5-6.5 kilowatt hours per square meter per day ($kWh/m^2/day$) (Hang et al. 2011), making LA County an ideal place for solar energy. The electricity mix in LA County has over one-third of their energy from renewable sources (UCLA Energy Atlas datasets 2015). Yet, only 11% is from solar energy. In 2017, the electricity mix was 11% solar, 30% natural gas, 18% coal, 11% wind energy, 2% hydroelectric, 2% geothermal, 5% biomass, 6% nuclear, 4% large hydroelectric, and 11% from unspecified sources (California Energy Commission 2017).

5.3 Methods

The methods section describes the two models in further detail. Section 5.3.1 describes the ABM design, survey design, and policies and scenarios considered. Section 5.3.2 describes the LCA data sources and assumptions. Section 5.3.3 discusses the combination of the ABM and LCA results.

5.3.1 ABM

An ABM was developed for LA County to evaluate the impact of policies and evolutions in technology on the adoption of residential solar panels by homeowners in the county from 2018-2050. A probabilistic utility function was used to model agents' adoption decisions. The factors in the utility function include lowering total electricity costs, adding to a home's market value, protection from rising electricity prices, ability to use renewable energy, ability to use new technology, reducing environmental impact, setting a positive example for others in the community, aesthetics, investment cost of system, payback period, influence of others, and lifespan of the system. The weights for the importance of these factors in agent's decisions is informed from survey data on the LA County homeowner population, including both adopters and non-adopters. Additional information about the survey can be found in Appendix B.

Agents, defined as 16,072 homeowners, evaluate the utility of three electricity consumption options on a yearly basis. The number of agents is representative of the LA County homeowner population in 2018, which was approximately 1,607,200. The model was built in Netlogo ABM software, and the population was scaled by 100 to fit within the Netlogo computing limits (Wilensky, 1999). The utility of each option determines the likelihood that an agent will adopt a solar panel system using probabilistic adoption. The options are to adopt a solar panel system that offsets 100% of an agent's annual electricity consumption, adopt a solar panel system that offsets 50% of the agent's annual electricity consumption, or not adopt a system and continue consuming electricity from the grid. The average percentage of usage offset in California is 102%, which is why the 100% solar adoption option was chosen (Energy Sage 2018). In other parts of the United States, customers offset 50-90% of electricity (McLaren et al. 2015). Therefore, a second option of 50% solar adoption was chosen to act as a surrogate to account for all of the potential solar panel systems that offset a range of electricity levels between 50% and 100% annual electricity offset. This is a simplification in the model for the sake of computability, instead of selecting more offset bins. In addition, it allows the model to be applicable to other locations. The output of the model includes the annual count of adopters of each solar PV panel offset option (50% and 100%), the annual solar panel capacity, the annual solar electricity consumption (kWh) and the annual grid electricity consumption (kWh) as a result of the individual solar panel adoption decisions.

Multiple policies were considered to evaluate changes to solar panel adoption and electricity consumption from 2018-2050. Specifically, five different variations of the baseline are explored: adding incentives to reduce the cost of solar panels, increasing the cost of grid electricity, a falling cost of solar panels due to technological improvements, and two variations of the new building standards that mandate all new residential homes to install solar panels starting in 2020. The last two scenarios represent the California Energy Commission building energy efficiency standards, which were newly adopted in 2018. New homes that are built under these standards in 2020 and beyond are expected to save $19,000 in energy costs over 30 years (Fortune 2018).

5.3.2 LCA

The solar panel LCA system boundary included the raw materials and manufacturing phases, transportation to LA County for installation, and the use phase. The functional unit is 1 m^2 of a multi-crystalline silicon (mc-Si) solar panel manufactured in China, Europe and the United States, solar panel transportation from manufacturing location to LA County, and use. The use phase is associated with the environmental impact savings from offsetting the environmental impacts of grid electricity with solar panels.

5.3.2.1 Raw Materials, Manufacturing and Transportation

SimaPro software and the The Tool for Reduction and Assessment of Chemical and other environmental impacts (TRACI) methodology (Bare 2011; SimaPro 2019) were used to perform the life-cycle impact assessment on solar panel raw materials, manufacturing and transportation. TRACI was chosen as it provides impacts in several different impact categories, including the impact category of global warming (GW) in units of g CO_2e. GW was chosen because is a critical impact category in the LCA of electricity generation (Turconi et al. 2013). Ecoinvent data was used for European solar panel manufacturing, which included life-cycle inventory data aggregated from several European manufacturing facilities (Ecoinvent database 2019). To represent US manufacturing, the Ecoinvent data was modified with a US electricity mix throughout all manufacturing processes due to unavailable data for US manufacturing. For Chinese manufacturing, literature data from Yao et al. (2014) was used. More details on this inventory dataset can be found in the Appendix A. For manufacturing in China and Europe, it was assumed that the panels were transported from the respective country to the LA port by boat, followed by rail (Union Pacific 2019; Sinovoltaics 2019). For US manufacturing, it was assumed that the panels were transported by rail and followed by truck to LA. A common manufacturing location of solar panels in China is Beijing, and a common location in Europe and the US, is Berlin, Germany, and Fremont, California, respectively (Energy Sage 2019). Therefore, the transportation distances were calculated from these locations using Google Maps.

5.3.2.2 Use Phase

It was assumed that the electricity from solar panels will displace traditional electricity from the LA County electricity grid. Therefore, the environmental impacts from the use of solar panels is calculated as the total weighted average of the environmental impacts of electricity technologies in the LA County electricity mix using the percentage of each electricity technology in the overall electricity mix. The US Life-Cycle Inventory (LCI) database was used to model the environmental impacts from electricity generation technologies due to its relevancy for a US context (National Renewable Energy Laboratory 2012). Due to unavailable data for the US, the European life cycle database (ELCD) was used for wind and hydroelectric electricity generation (European Commission 2012). Each life-cycle inventory database included, when applicable, processes associated with fuel provision, power plant operation, and plant infrastructure. More details can be found in the Appendix A.

5.3.2.3 Combined LCA and ABM

To generate CO_2e impact data at the societal level, the LCA results for raw materials, manufacturing and transportation (i.e. grams CO_2e/m^2 of panel) were converted to a kWh functional unit (i.e. grams CO_2e/kWh of electricity generated) to combine with the ABM outputs (i.e. annual kWh of solar electricity generation from 2018-2050). In addition, the use phase environmental benefits at the societal-level were calculated by multiplying the environmental impact of grid electricity (i.e. grams CO_2e/kWh of electricity generated) with the ABM output of annual kWh of grid electricity generation from 2018-2050.

5.4 Results and Discussion

The environmental impact results for the ABM scenarios are described in this section for the impact category of global warming (CO_2e). Results are displayed by raw materials through transportation to LA County in Figure 5-1 as a function of PV adoption, use of solar panels in LA County in Figures 5-2, and the combined total from raw materials through use in Figures 5-3.

5.4.1 Raw Materials and Manufacturing and Transportation

The potential CO_2e impacts of solar panel manufacturing shift over time with respect to adoption trends. In the baseline, shown in Fig 5-1a, the potential CO_2e impacts increase initially, in 2019, and then decrease over time until 2050 due to the leveling off of solar panel adoption over time. In the scenario of decreasing solar panel costs, a spike in CO_2e impacts occurs in the year 2022 in line with an increase in solar panel adoption in 2022 when solar panels become less costly than purchasing grid electricity with respect to the levelized cost of electricity (LCOE). Similarly, for a scenario of increased grid price, a spike in CO_2e impacts occurs in 2025 due to an increase in adoption in 2025 when the LCOE for grid electricity becomes higher than the LCOE for solar panel electricity.

It is also relevant to mention that the location of solar panel manufacturing affects the magnitude of environmental impacts in each scenario. A Chinese manufacturing scenario almost doubles the environmental impacts compared to a European or United States manufacturing scenario. The CO_2e impact results are 85 g CO_2e/kWh for China manufacturing, compared to 45 and 51 g CO_2e/kWh in Europe and the US, respectively. It was assumed that the entire solar panel was manufactured in one country, such as China. This allocation was consistent throughout the time frame and scenarios.

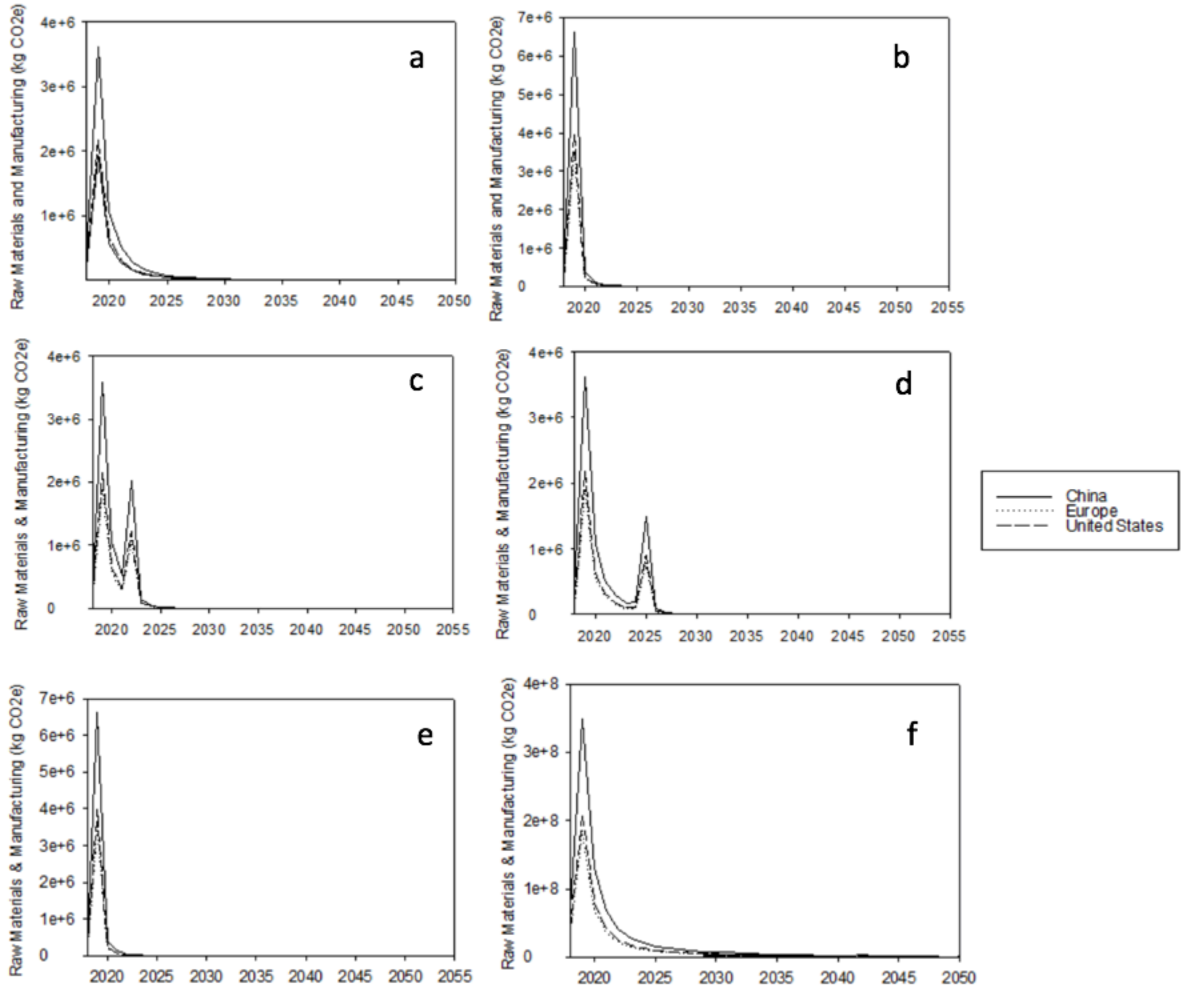


Figure 5-1 - Potential CO_2e impacts of solar panel raw materials and manufacturing

a) Baseline b) Adding incentives c) Decreasing cost of solar panels d) Increasing the grid electricity price e) Adding new homes (50% offset) f) Adding new homes (100% offset)

All of the policies above have the potential to increase the adoption of solar panels in LA County. However, there is also the potential to increase global warming impacts as a result due to the environmental impacts associated with the raw materials and manufacturing of PV. Currently, the majority of solar panels are manufactured in China (National Renewable Energy Laboratory 2018). However, the recent US tariff on the import of solar panels made in China may have the potential to shift this trend. The tariff went into effect in 2018 and imposes a 30%

tax on imported solar panels from China, thereby increasing the price of solar panels (Energy Sage 2019). The tariff will last for four years and will fall by 5% annually, dropping to a 15% tariff in 2021. Therefore, one recommendation is to increase the recycling and re-use of solar panels at the end-of-life. Solar panel recycling is advantageous from an environmental perspective due to raw materials (i.e. silicon) production of solar panels being an energy-intensive process. The energy needed to recover silicon from recycled solar panels is equivalent to one-third the energy needed from manufacturing silicon (Choi and Fthenakis 2010).

5.4.2 Use Phase

The use of solar panels has the potential to reduce the CO_2e impacts in LA County across various scenarios from 2018-2050 (Figure 5-2), due to a decrease in the usage of grid electricity. Figures 5-2 demonstrate the CO_2e impacts due to decreases in fossil fuel electricity use over time. A comparison to the CO_2e impacts from the current electricity mix in LA County is shown to illustrate the environmental benefits from solar panels during the use phase. The magnitude of environmental benefits varies significantly across the scenarios as compared to the baseline. In the baseline scenario, there is a 60% reduction in CO_2e impacts in 2050 compared to the CO_2e intensity of the grid. By adding incentives (and thus increasing adoption), a 73% reduction is demonstrated in Figure 5-2b. Decreasing the cost of solar panels and increasing the cost of grid electricity results in a 75% reduction. Requiring solar panels on new homes results in a 44% reduction compared to the CO_2e impacts from grid electricity. Overall, the total reduction in CO_2e emissions resulting from solar panel adoption depends on the electricity generation technologies that solar panels are offsetting over time. The LA County grid electricity mix that was modeled was annualized electricity data and did not capture any variances over time in the electricity market for simplicity, which is a limitation of the work.

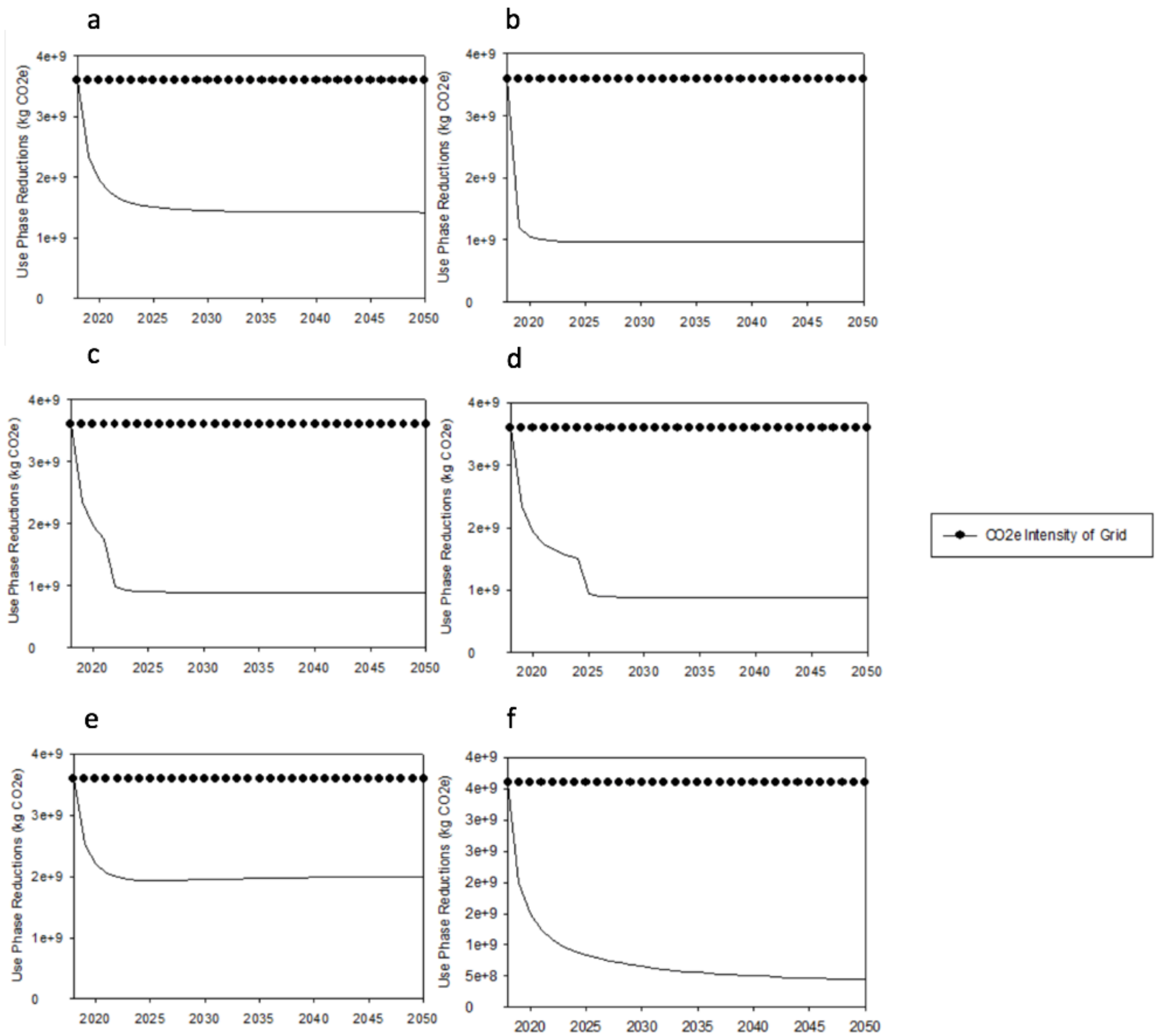


Figure 5-2 – Use Phase Environmental Benefits

a) Baseline b) Adding incentives c) Decreasing solar panel cost d) Increasing grid price) Adding new homes (50% offset) f) Adding new homes (100% offset) The bar plots depict the avoided CO_2 impacts from solar panel adoption. The scatter plot depicts the CO_2e impacts of the electricity grid without any solar adoption.

The use of solar panels can significantly reduce CO_2e emissions by offsetting grid electricity. In addition to the environmental benefits, using rooftop solar panels is critical with respect to energy resiliency. Energy resiliency is defined as the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions (US Department of Energy 2019). According to the LA Sustainability plan, a severe earthquake could cause LA to be without power for two or more weeks, making the adoption and use of solar PV critical by providing electricity when the grid is down (Sustainable City Plan, 2019). Solar farms (large decentralized solar panels) have been deployed for energy resiliency in several US states, such as North Carolina (Gearino 2018). Rooftop PV technology contributes to the resiliency of the electric grid when used with other components (e.g. batteries). For example, a neighborhood in San Diego, California, with 700 kW of rooftop solar, added community battery storage units, and communication and control technologies to function as a community microgrid (National Renewable Energy Laboratory 2014). A microgrid enables electricity from rooftop PV during grid outages due to its ability to operate both in a grid-connected fashion and as a standalone system. This suggests that, beyond the potential reduction in environmental impact, there are also other potential benefits due to the adoption of rooftop solar.

5.4.3 Combined Total Environmental Impacts

It is relevant to consider both the raw materials and manufacturing phases in addition to the use phase to get a comprehensive view of the environmental impacts and benefits of solar panel adoption from a societal-level perspective. Figure 5-3 demonstrate the combined CO_2e impacts from Figure 5-1 and Figure 5-2. Overall, the trends in the graphs are similar to the trends in Figures 5-2. This can be explained due to the environmental impacts from manufacturing of solar panels being several orders of magnitude less than the environmental impacts from fossil fuel electricity. This illustrates that, although the environmental impacts are dominated by the raw materials and manufacturing phases on a per m^2 of solar panel basis, the use phase contributes to the majority of environmental impact savings from an adoption and societal-level perspective. When combined, the manufacturing location of solar panels is not a significant factor. Throughout the time period of 2018-2050, the CO_2e impacts from raw materials and manufacturing of solar panels comprise at most 0.3% of the total environmental impacts.

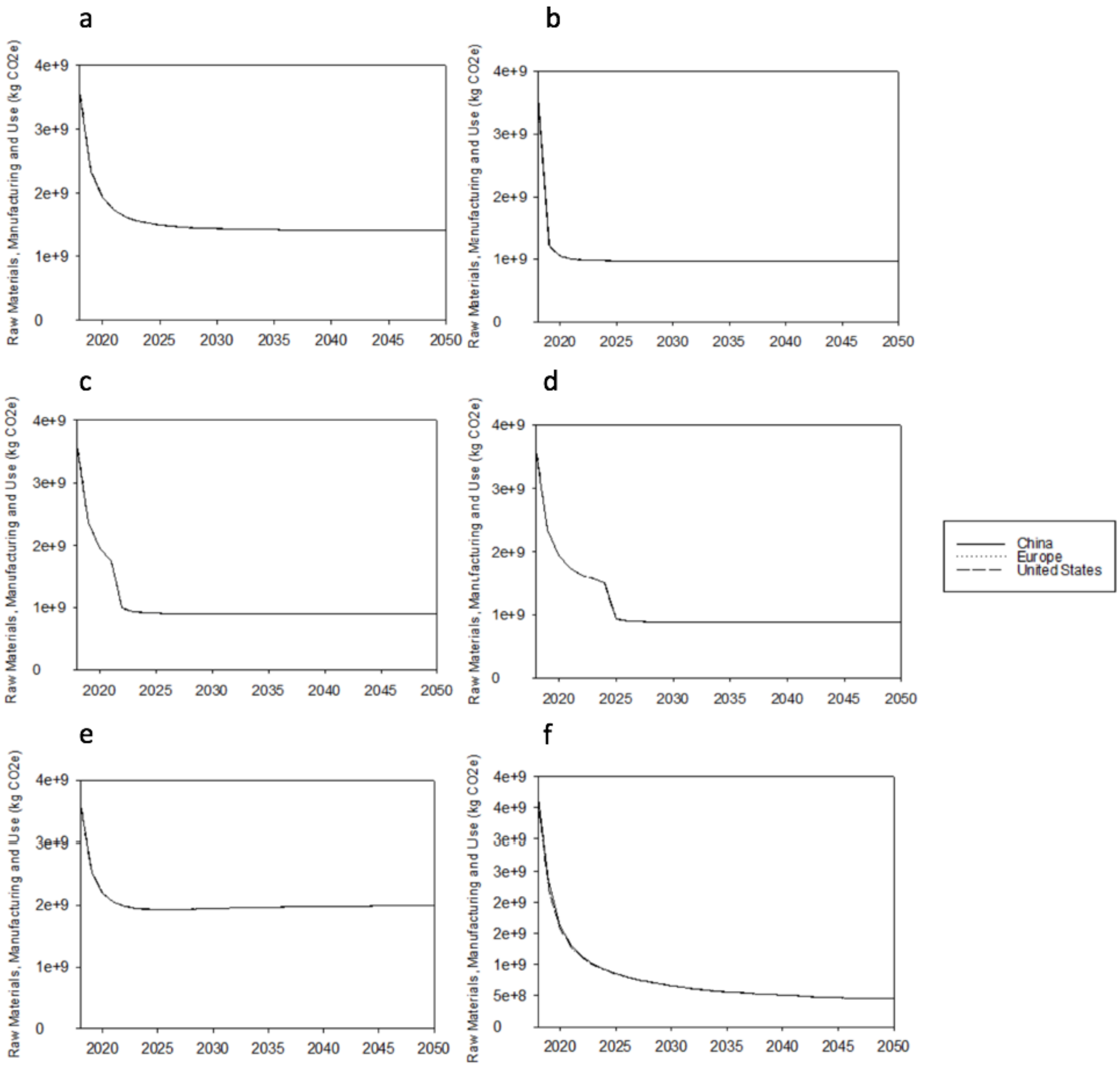


Figure 5-3 – Combined CO_2e Environmental Impacts

a) Baseline b) Adding incentives c) Decreasing cost of solar panels d) Increasing cost of grid electricity e) Adding new homes (50% offset) f) Adding new homes (100% offset).

This work provides an initial estimate of the environmental impacts and benefits of rooftop solar panel adoption in LA County from 2018-2050. Although expanding solar panel capacity in LA County results in additional environmental impacts, it also generates environmental benefits during the use phase. This work may be useful for policy makers and manufacturers to understand the environmental implications of PV technology adoption and electricity consumption and polices that aim to change adoption behavior.

Overall, ABM and LCA can be combined together to evaluate the environmental impacts and environmental impact savings from the use of solar panels. The varying population characteristics and decision-making attributes can impact the chosen electricity offset level of a PV technology and the resulting environmental impact savings compared to grid electricity. The methodology was applied to a case study of LA County, an ideal location for solar panels due to its high solar potential. However, the framework may also be applied to other locations with differing solar potential and electricity mixes to evaluate whether solar panels are as advantageous compared to the environmental impacts of the grid in other places. Future work could explore changes to the electricity mixes over time to explore a finer level of detail. Future work might also explore additional impact categories to evaluate trade-offs in environmental impacts, benefits, or potential constraints due to adoption of PV in LA County, California. For example, metal demand and material criticality (risk of disruptions to supply) may be a potential constraint for PV adoption (Goe and Gaustad 2014).

5.5 Conclusions

This study provides an assessment of the CO_2e impacts and benefits from the adoption of solar panels in LA County using a combined life-cycle assessment and agent-based modeling (ABM) approach. LCA was used to assess the CO_2e impacts from raw materials, manufacturing and use of solar panels, while ABM was used to evaluate the impact of a heterogenous population and various scenarios on adoption trends. The results demonstrate that the potential reductions in CO_2e impacts vary over time as a function of adoption scenario from

2018-2050. However, all scenarios show a potential CO_2e reduction of 44-87% in 2050 compared to the 2018 grid electricity mix in LA County. Future work might explore applying this methodology to other locations, additional impact categories, or exploring sensitivity and uncertainty analysis around environmental impacts.

6. Environmental payback periods of multi-crystalline silicon photovoltaics in the United States – how prioritizing based on environmental impact compares to solar intensity

6.1 Abstract

Electricity consumption is increasing due to global population expansion, which also intensifies the overall environmental impact. It is critical to shift towards more sustainable electricity production methods, which meet the increasing electricity demand without contributing significantly to the environmental footprint. Using photovoltaic (PV) systems as an alternative to conventional electricity is beneficial for the environment as it does not produce environmental impacts during use. However, there are still environmental impacts due to the raw materials and manufacturing of the PV. Life-cycle assessment (LCA) and environmental payback period (EPBP) were used to quantify the time it takes to recoup the environmental impacts due to production of solar PV compared to the environmental impacts of the current electricity grid. An EPBP analysis of all 50 states in the United States was performed to evaluate changes due to differences in solar potential, electricity mix, and impact category. The goal of this paper is to identify and prioritize states that could be used for solar panel deployment based on EPBP results, and how this prioritization would change compared to considering only solar intensity.

6.2 Introduction

The generation of electricity from solar photovoltaics (PV) is considered to be a renewable and clean energy. The rapid development of PV technologies over time has led to constant improvement in the cost-effectiveness and efficiency of PV products (Energy Sage 2019). The manufacturing processes for PV systems have been advancing and machines in the production-line have become more energy-efficient, thus reducing the environmental impacts of production.

Using PV as an alternative to fossil fuel-based electricity is beneficial for the environment as it does not create environmental impacts during operation and use. However, carbon dioxide

(CO_2) emissions and other environmentally harmful gases are emitted during the process of manufacturing and disposing or recycling of the solar PV panel (Lu and Yang 2010). Utilizing life cycle assessment (LCA) enables the consideration of the energy and materials and emissions into the environment that occur throughout the entire life cycle of the PV technology (International Organization for Standardization 2006). The life-cycle includes, for example, the mining or production of raw materials, manufacturing of solar PV panels and balance of system components, installation, operation, and end of life.

The majority of manufacturers of solar panels are using silicon as a major raw material (US Department of Energy 2013). Silicon is one of the most common elements on earth and it is non-toxic, but new technologies and materials are in the development stage and have the potential to be more efficient than silicon-based solar panels (Ludin et al. 2018). The most widely used technologies on the market are mono-crystalline and multi-crystalline, and together, represented 91% of the global market in 2013 (Fraunhofer Institute for solar energy systems 2013). Thin-film technologies represent about 9% of the global market, including cadmium telluride and copper indium gallium diselenide technologies. Although there are other emerging PV technologies, such as dye-sensitized solar cells (using solar inks and dyes as raw materials), these technologies are not used commercially (National Renewable Energy Laboratory 2019).

Previous studies have identified that the quantity of electricity and environmental impacts generated from a solar panel depends on several factors, such as the type of PV technology, the efficiency of the solar panel, the lifetime, and the solar irradiation present at the solar panel installation location (Ludin et al. 2018). Multiple studies have addressed the environmental impacts of silicon-based PV systems (Sherwani et al. 2010; Bhandari et al. 2015).

In addition, more recently, other forms of PV have been a focus of LCA studies, such as building-integrated photovoltaics (BIPV) (PV systems that replace conventional building materials) (Carvalho et al. 2019).

A popular LCA indicator, used in various LCA studies, is environmental payback period (EPBP) and is used to measure the sustainability of a solar PV system (Bhandari et al. 2015; Chen et al. 2016). EPBP, using CO_2 as an example, is a measure of the embedded CO_2 impacts of solar PV systems divided by the CO_2 impacts from the electricity mix where PV is installed. Table 6-1 summarizes the CO_2 payback periods from previous studies. Previous literature has found EPBP to range from 0.39 - 7.8 years, across all PV technologies. Several factors affect the EPBP results. In addition to the multiple factors previously studied (technology type, efficiency, solar potential), the electricity mix (or the portion of materials used in electricity production) can also affect the EPBP results. As the electricity mix is not consistent across the US, more analysis is needed to explore sensitivity around these factors in order to prioritize and choose the locations for PV installations.

Table 6-1 – Summary of previously found environmental payback periods of solar PV with respect to CO_2 impacts

Study	PV Technology	CO_2 payback period (years)	Mounting System
Kim et al. (2014)	multi-crystalline Si	1.53-1.91	Ground-mounted

Kim et al. (2014)	mono-crystalline Si	2.53	Ground-mounted
Tripanagnostopoulos et al. (2005)	multi-crystalline Si	2.7	Rooftop
Garcia-Valverde et al. (2009)	mono-crystalline Si	7.77	Rooftop (Stand-alone)
Marimuthu and Kirubakaran (2013)	multi-crystalline Si	0.39	Rooftop
Lu and Yang (2010)	Building-integrated	5.2	Rooftop

In this work, each state in the United States (US), with differing solar potentials and electricity mixes, will be taken into consideration to determine the order of prioritization for PV installations (National Renewable Energy Laboratory 2012). The metric used for prioritization is environmental payback period, which will be estimated for each state, across multiple LCA impact categories, and then compared to solar potential prioritization. The environmental payback period will measure the time in years, that it takes to recoup the environmental impacts from raw materials and manufacturing of PV compared to the environmental impact of the electricity mix. For this study, the multi-crystalline silicon PV technology will be assumed, as crystalline silicon technology is one of the most established technologies on the commercial market (Energy Information Administration 2009). Each state has different factors that influence the environmental payback period, such as the current electricity grid mix (from both renewable and nonrenewable sources), solar potential, and the total environmental impacts due to the raw materials and manufacturing of the PV system.

6.3 Methods

6.3.1. Electricity Grid

First, the electricity mix for each state in the US was calculated using data from the Energy Information Administration database (US Energy Information Administration 2019). The amount of electricity produced, in kilowatts per hour, was collected for the following electricity types: coal, hydroelectricity, natural gas, nuclear, petroleum, solar, wind, wood, geothermal, pumped storage, other biomass[1], other gases[2], and other[3] (US Energy Information Administration 2019). Then, the total amount of electricity generated from each type was divided by the state's total electricity produced, which resulted in the state's electricity mix (i.e. percentages by electricity type). This process was repeated for all states in the U.S.

6.3.2 Environmental Impact Caused by Electricity Grid

Next, the environmental impacts from the production of the electricity mixes were calculated. The impact categories, from the Tool for the Reduction and Assessment of chemicals and other Environmental Impacts (TRACI), that were considered are listed, followed by their unit of measure: ozone depletion (kg CFC-11 eq), global warming (kg CO2 eq), smog (kg O3 eq), acidification (kg SO2 eq), eutrophication (kg N eq), carcinogenic (CTUh), non-carcinogenic (CTUh), respiratory effects (kg PM2.5 eq), ecotoxicity (CTUe), and fossil fuel depletion (MJ surplus) (Bare,

[1] Other biomass includes agricultural byproducts, landfill gas, biogenic municipal solid waste, other biomass (solid, liquid and gas) and sludge waste.
[2] Other gases include blast furnace gas, and other manufactured and waste gases derived from fossil fuels.
[3] Other includes non-biogenic municipal solid waste, batteries, chemicals, hydrogen, pitch, purchased steam, sulfur, tire-derived fuels, waste heat and miscellaneous technologies.

2011). The environmental impacts for each electricity type was calculated based on the environmental impact due to the production of one kilowatt-hour of each state's electricity mix using SimaPro version 8.0.1 and several databases (Ecoinvent 3, U.S. Life-Cycle Inventory and the European Life-Cycle Databases). Additional information can be found in the SI. The generated impact data from SimaPro for each electricity type was multiplied by the corresponding percentage of the electricity type in the state's electricity mix. Then, the total impacts for each impact category were summed together to represent the total impact per kilowatt-hour of the electricity mix for each impact category on a state by state basis.

6.3.3 Electricity Generated Over the Lifetime of a PV System

Equation 11 was used to calculate the electricity generated by a PV system over its lifetime, in kilowatt-hours (kWh). This equation was used by Gazbour (2018) in order to dissect 30 published crystalline LCA PV studies and ultimately proposed a combination of parameters to take into consideration when doing LCA research. Equation 11 consists of multiplying these factors: I - average annual solar irradiation (kWh/m^2/year), A - total surface area of a PV module (m^2), η - the efficiency of the module in converting the solar irradiation energy into electrical energy (unitless), T - the lifetime of the PV system (years), PR - the initial performance ratio, which represent the electrical energy being generated by the panel if it consistently converted sunlight to electricity as expected (unitless), and DR - the degradation rate, which is the panel's productivity and decreases over time (unitless).

$$Epv = I \times A \times \eta \times T \times PR \times \sum_{y=1}^{T} (1-(y \times DR)) \qquad (13)$$

The average annual irradiation was calculated using data from the National Renewable Energy Laboratory (2012) which provided a solar map of the U.S. from the year 1996 – 2009 with average daily total solar irradiation information. The minimum, maximum, and average daily solar irradiation was visually estimated for all 50 states and the values were multiplied by 365 days to calculate annual solar irradiation. The total surface area of a solar panel was set to be 1m x 1m. According to the Gazbour (2018), $1m^2$ is considered a functional unit (FU), along with two other functional units being kWh and kWp, that were proposed to be essential units of analysis for LCA studies. The average module efficiency of PV systems has been increasing over the years and industry data shows the efficiency for mono-crystalline silicon material of 17% and 16% for multi-crystalline silicon (Gazbour 2018). There are two different formulas to calculate the initial performance ratio: a traditional formula or weather-corrected formula (Dierauf et al. 2003). Since the cells in the panel are affected by a variety of weather patterns, the weather-corrected method is expected to have higher accuracy. However, methods result in the same annual average performance ratio of 84%. Older studies relating crystalline modules had a lifetime of 20 or 25 years, but recent studies recommend using a value of 25-30 years (Gazbour 2018). In this work, the value of 30 years will be used for the lifetime of the PV systems. The degradation rate is based on the issue that the PV modules and its system will lose performance each year, and a recommended factor of 0.91% per year was assumed for crystalline PV systems (Dierauf et al. 2003). An average lifetime degradation rate of 0.86 was calculated, which represent about 14% of performance lost over the lifetime of a solar panel.

The lifetime electricity generated by the PV system will vary on a state basis due to the range of solar irradiations found in the US. Additionally, a minimum, maximum, and average electricity generation was calculated for each state using the minimum, maximum, and average solar irradiation data that was estimated. These values were then divided by 30 years (PV lifetime expectancy) to calculate the annual electricity outputs anticipated. The minimum and maximum EPBP results can be found in the Appendix A.

6.3.4 Calculating Environmental Impact Saved Annually by Using PV Systems

Using the environmental impact data of the electricity grid (impact unit / kilowatt-hour) and the electricity generated over the lifetime of a PV system (kilowatt-hour), the environmental impact savings were calculated. The minimum, maximum, and average electricity generated (as a function of the range in solar irradiation across the state) from PV system in each state were multiplied with the electricity grid impacts, which resulted in minimum, maximum, and average environmental impact savings for all 10 impact categories used in this paper. These values represent the impact savings if solar panels are used instead of the electricity grid. This data will be further used in equation 12 to calculate the environmental payback periods.

6.3.5 Solar Panel LCA

LCA studies define a system boundary, which indicates the stages of the life cycle included in the analysis. This paper includes raw materials, the manufacturing stage, the installation of the system using the balance of system (BOS), and transportation from manufacturing location to installation location, in order to determine the environmental impact of the PV system. Section 6.3.5.1 and 6.3.5.2 describe the data sources used to calculate life-cycle assessment impacts of the solar PV systems.

6.3.5.1 Environmental Impact due to Raw Materials and Manufacturing

Life-cycle inventory data from the literature and the Ecoinvent database was used to calculate the environmental impact caused by manufacturing and BOS per $1m^2$ of solar panel (Yao et al. 2014; Fu et al. 2015; Ecoinvent database 2019). This data assumes that the manufacturing is completed in China, due to their significant share of the global market. The type of solar panels being manufactured are multi-crystalline silicon PV systems. The installation is assumed to be done in the U.S. states on a slanted residential roof.

6.3.5.2 Environmental Impact from Transportation

The environmental impact caused by the transportation of the PV systems was calculated, assuming that the solar panels were transported from Beijing, China to the capital of each U.S. state, utilizing the U.S. LCI database. The PV systems are traveling from Beijing, to the port of Shanghai, China. Then, they will be shipped by sea to the port of Los Angeles (L.A.), California, then to each state's capital, which is assumed to be the final destination. If the distance traveled on land, from the port of L.A. to the state's capital, is larger than 1,000 miles (about 1,609 km) then it assumed that rail transportation was used for the majority of the trip and the last 200 miles (about 322 km) were transported by a semi-truck. For example, Concord, New Hampshire is 2,977 miles (about 4791 km) from the port of L.A., so 2,777 miles (about 4469 km) are assumed to be traveled on train and the remaining 200 miles on a semi-truck. If the distance traveled on land, from the port of L.A. to the state's capital, is less than 1,000 miles, then it is assumed to be transported by a semi-truck. The distances traveled by transportation type (by sea, train, or truck) were calculated using the ShipTraffic mapping tool and were multiplied by the mass (in tons) of the PV system and the impact per tonne-kilometer traveled (ShipTraffic 2019). Lastly, the total impacts from all transportation types were summed together for each PV system.

6.3.6 Calculating Solar Panel's Environmental Capital Cost

The solar panel's capital cost will be considered as the total amount of environmental impact created as a consequence of producing all components necessary to allow the solar panels to function. To calculate the capital cost, the impacts caused by the extraction of the raw materials, manufacture, installation, and transportation of these system was added together. This results in values for the capital cost for each state and impact category, which will be used in equation 12 to calculate the environmental payback period.

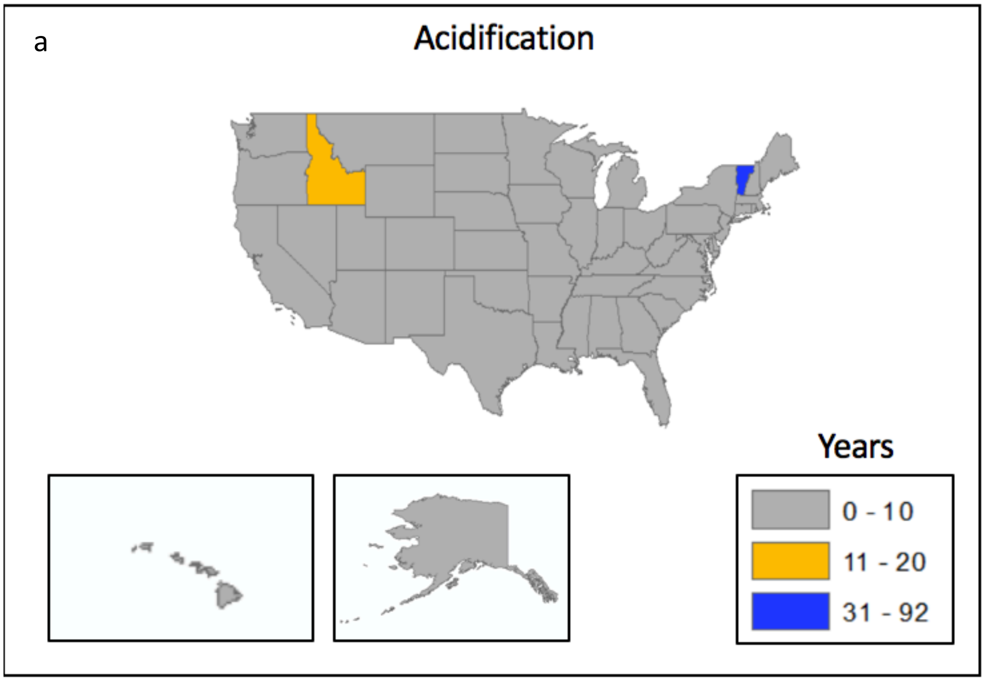
6.3.7 Calculating Environmental Payback Period

The minimum, maximum and average environmental payback period was calculated for each state using equation 12 below. To visually present results by state and impact category, the results for average EPBP for each state were plotted into ArcMap, a geographical information system (GIS) program. The minimum and maximum EPBP results can be found in the Appendix A.

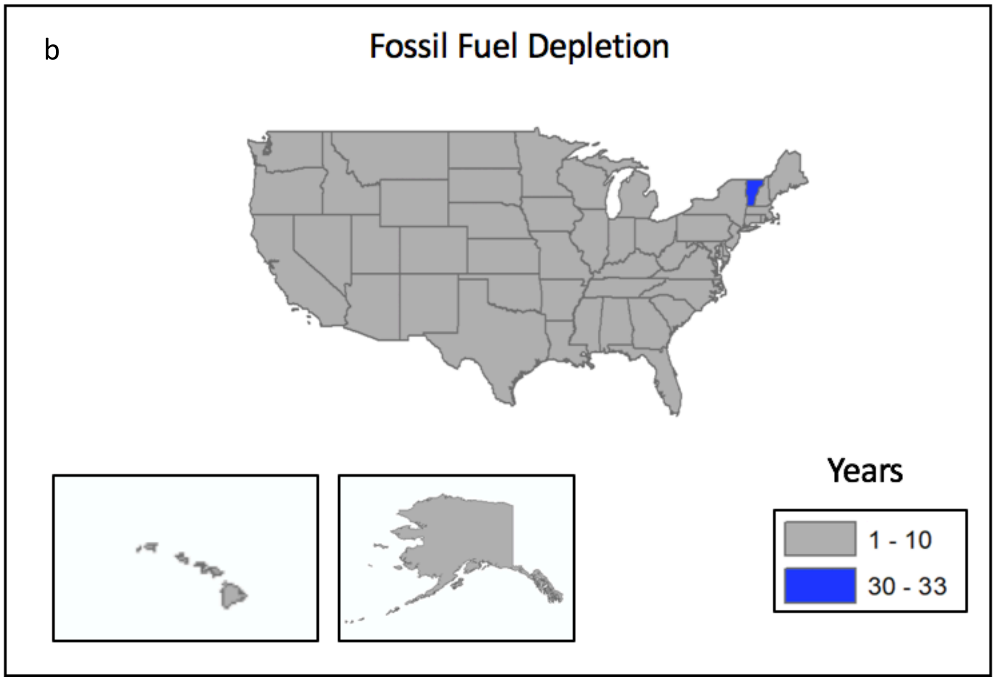
$$\text{Capital Cost / Savings} = \text{Environmental Payback Period (EPBP)} \tag{14}$$

6.4 Results

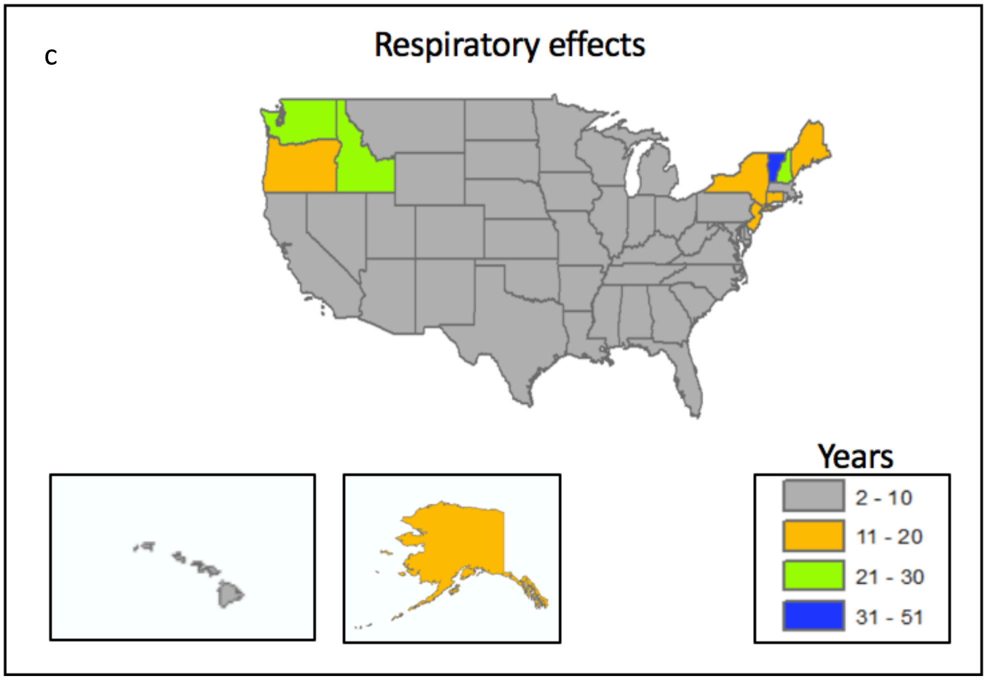
The results for EPBP for each impact category are shown in Figure 6-1. Overall, the prioritization of solar PV deployment by state varies as a function of the impact category considered. For the global warming impact category, the lowest EPBP is around 2 years, which is the time it takes to recoup the impact of the electricity grid by using PV systems. The highest value for the global warming impact is 113 years (for the state of Vermont) due to its current electricity grid having low global warming impacts. Vermont has a high level of renewables in its grid, with 60% hydroelectricity 20% wood and 20% other renewables. For the eutrophication impact category, the lowest EPBP was Missouri with a value of 11 years, and the highest value is Washington with 244 years.



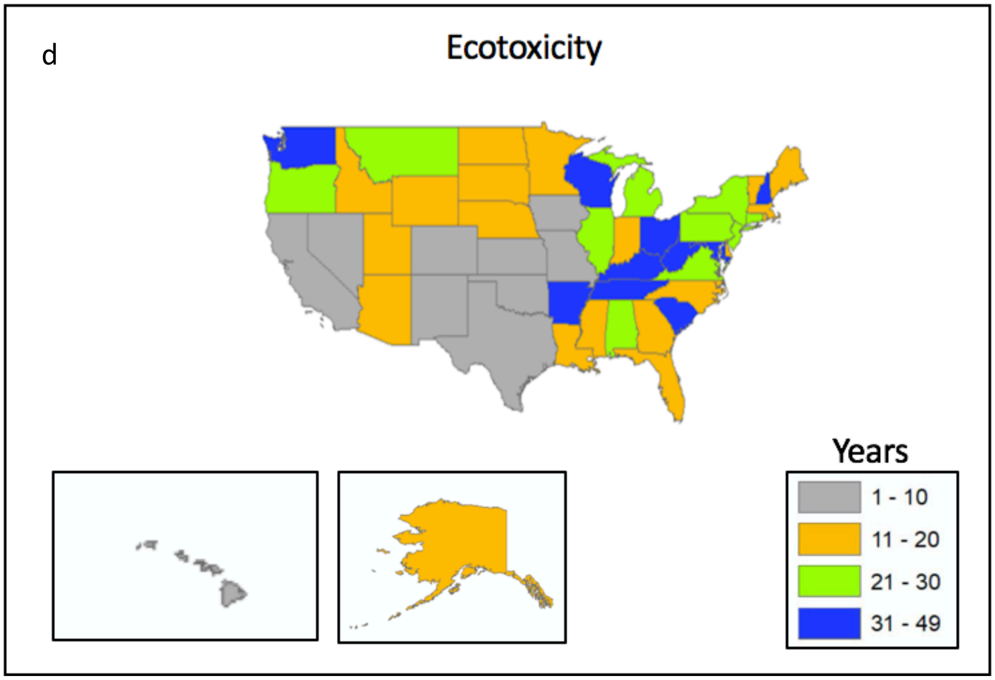
All states, except Idaho and Vermont, have an acidification EPBP < 10 years, which means that it takes at most 10 years to recoup the acidification impacts from raw materials and manufacturing of PV. The acidification impacts of Vermont's grid are the lowest in the US at 1.83E-04 kg SO_2e/kWh, particularly due to the hydropower part of the electricity mix (60% of mix). Hydropower has the lowest acidification impacts out of the electricity mix sources. Idaho's electricity mix also has 60% hydropower, but the natural gas part of the grid causes it to have higher acidification impacts than Vermont.



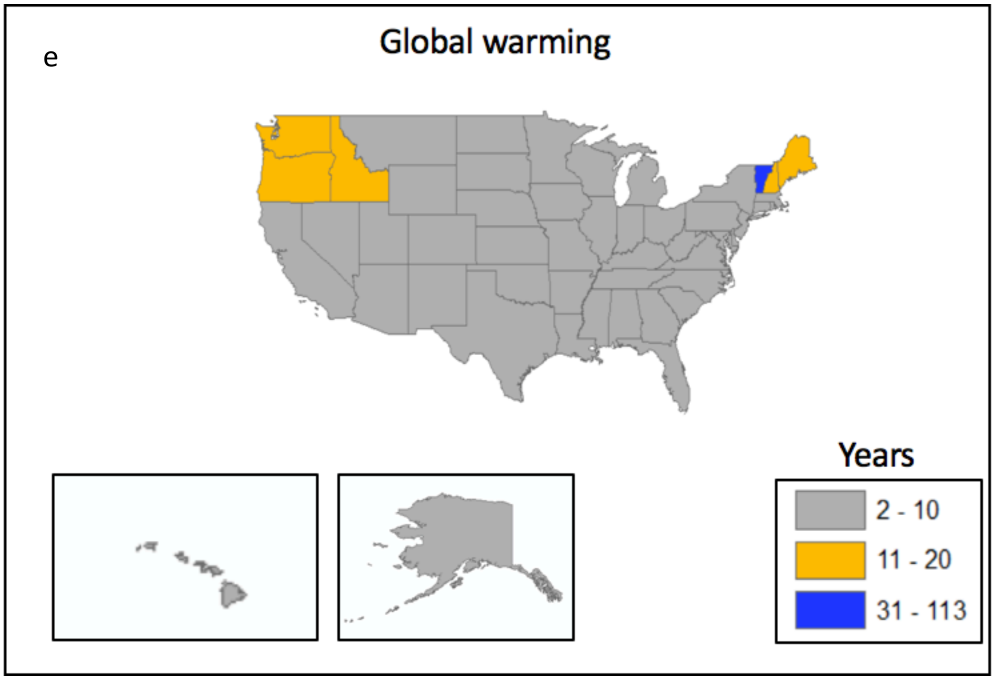
All states, except Vermont, have a fossil fuel depletion EPBP result < 10 years, which means that it takes at most 10 years to recoup the fossil fuel depletion impacts from raw materials and manufacturing of PV. The result is over 30 years for the state of Vermont, meaning it is longer than the average lifespan of a solar panel. The fossil fuel depletion impacts of Vermont's electricity grid are the lowest out of all states at 4.07E-02 MJ/kWh of electricity generated. This is due to the hydropower part of the electricity mix, which constitutes 60% of the mix, and has the lowest fossil fuel depletion impacts out of the electricity mix sources in Vermont.



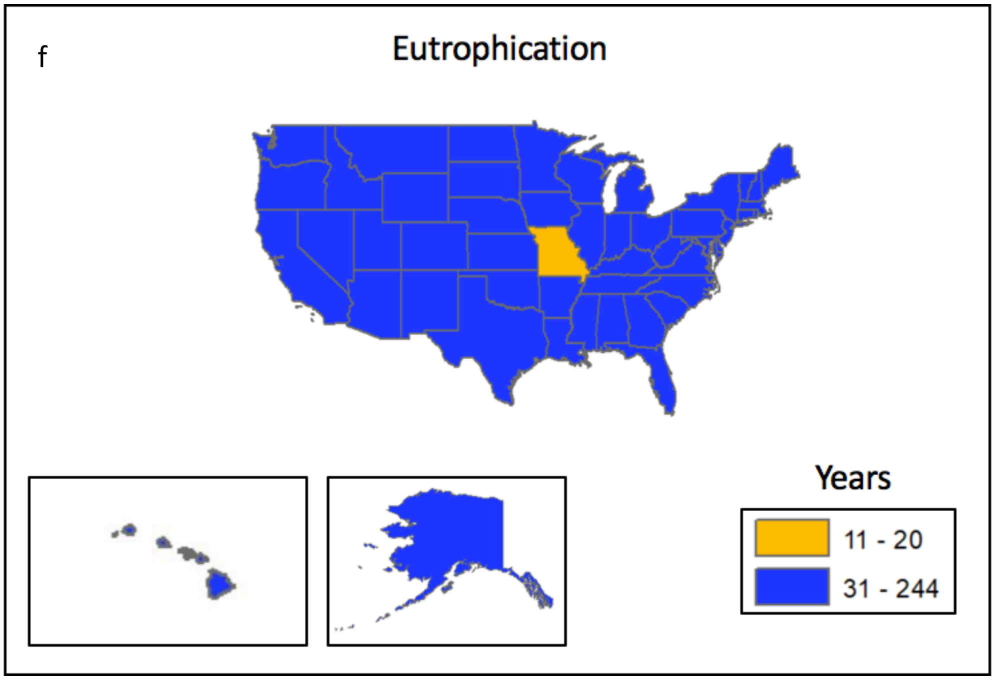
Vermont has a result longer than 30 years in respiratory effects EPBP. The respiratory effects of Vermont's electricity grid are the lowest out of all states at 4.83E-05 kg PM 2.5 eq/kWh of electricity, due the hydropower part of the electricity grid. Idaho, Washington and New Hampshire also have longer respiratory effects than other states (between 21 and 30 years). While Idaho, Vermont and New Hampshire also have hydropower as part of the electricity mix, the natural gas part of their mixes creates higher respiratory effects than Vermont, and a shorter payback period.



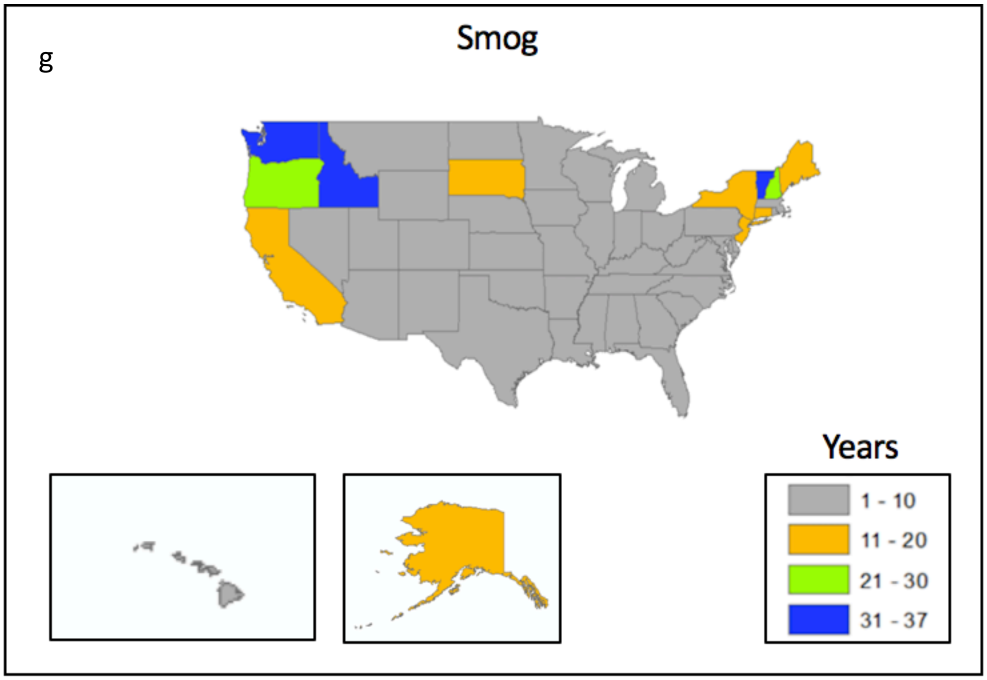
The results for ecotoxicity EPBP are between 5 and 49 years. Washington, Wisconsin, Ohio, Kentucky, Tennessee, Arkansas, South Carolina, Maryland and New Hampshire, District of Columbia, Missouri have a result greater than 30 years, meaning it is longer than the average solar panel lifespan. Solar, wind and pumped storage cause the ecotoxicity impacts of the electricity grid to be higher. Therefore, states with higher percentages of one or a combination of these electricity sources in their grid (such as California) will have a shorter ecotoxicity EPBP.



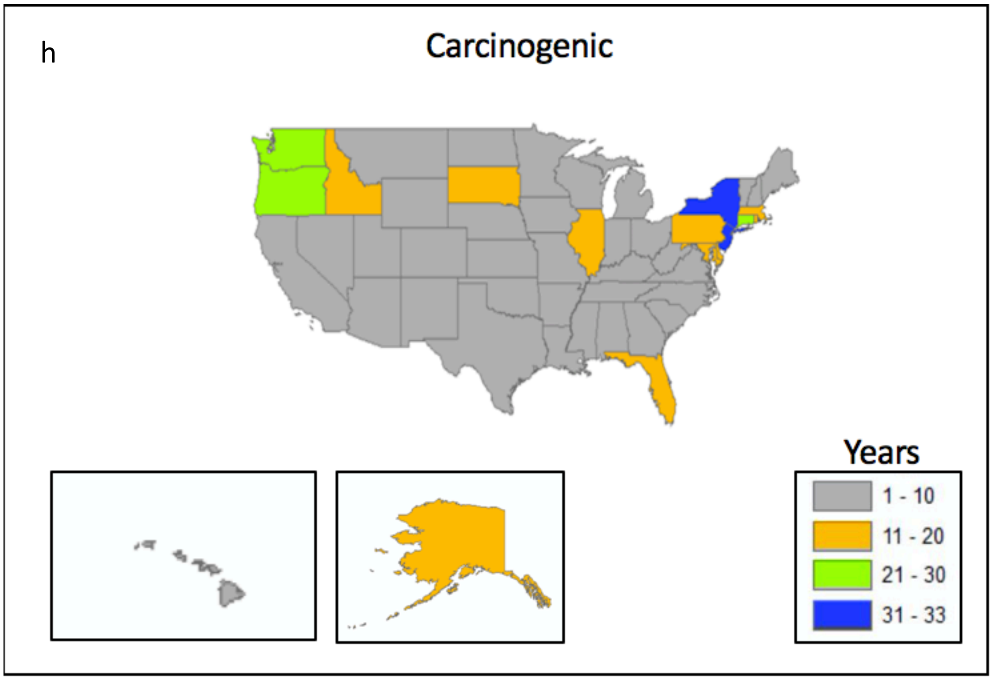
For all states states, except Vermont, the global warming EPBP is less than 20 years, meaning that it takes at most 20 years to pay back the initial investment in global warming impacts from raw materials and manufacturing of PV. Vermont has a result greater than 30 years, which is longer than the average lifespan of a solar panel. The global warming impacts of Vermont's electricity grid are the lowest in the US with 2.59E-02 kg CO_2e/kWh of electricity generated. This is due to the hydroelectric part of Vermont's electricity mix, resulting in a lower global warming impact grid, and longer payback period. Hydroelectric makes up 60% of Vermont's electricity mix and has the lowest global warming impacts per killowatt-hour out of all electricity mix sources.



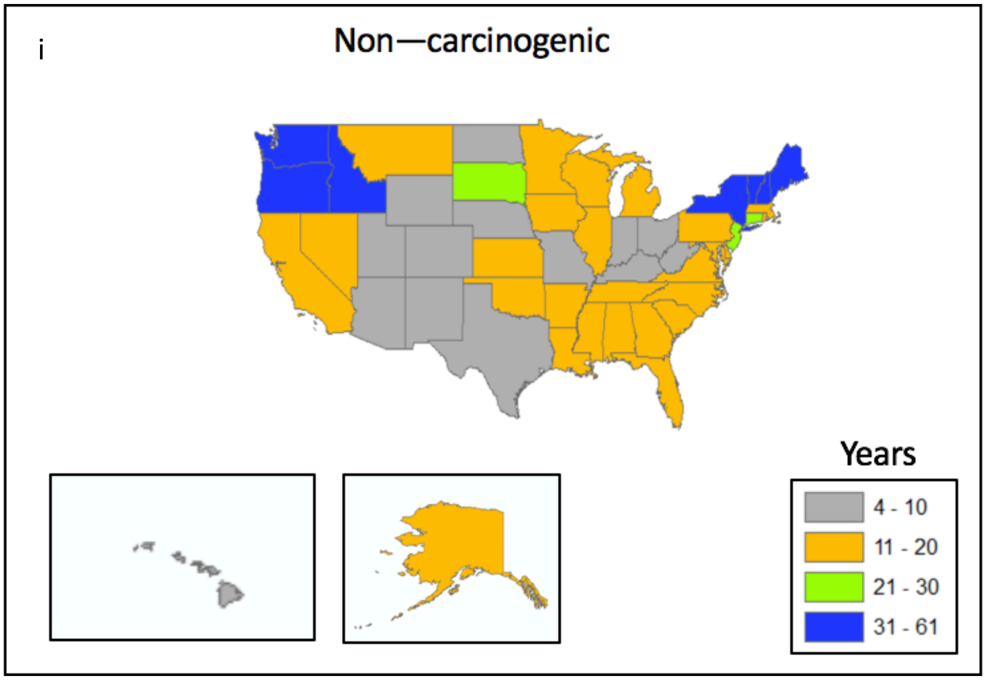
The results for eutrophication EPBP are all greater than 30 years, which means that the eutrophication impacts of raw materials and manufacturing of PV will not be offset by the use of PV over its lifetime. The average US electricity grid has 7.95E-05 kg N eq/kWh of electricty generated, which does not exceed the eutrophication impacts from raw materials and manufacturing of PV.



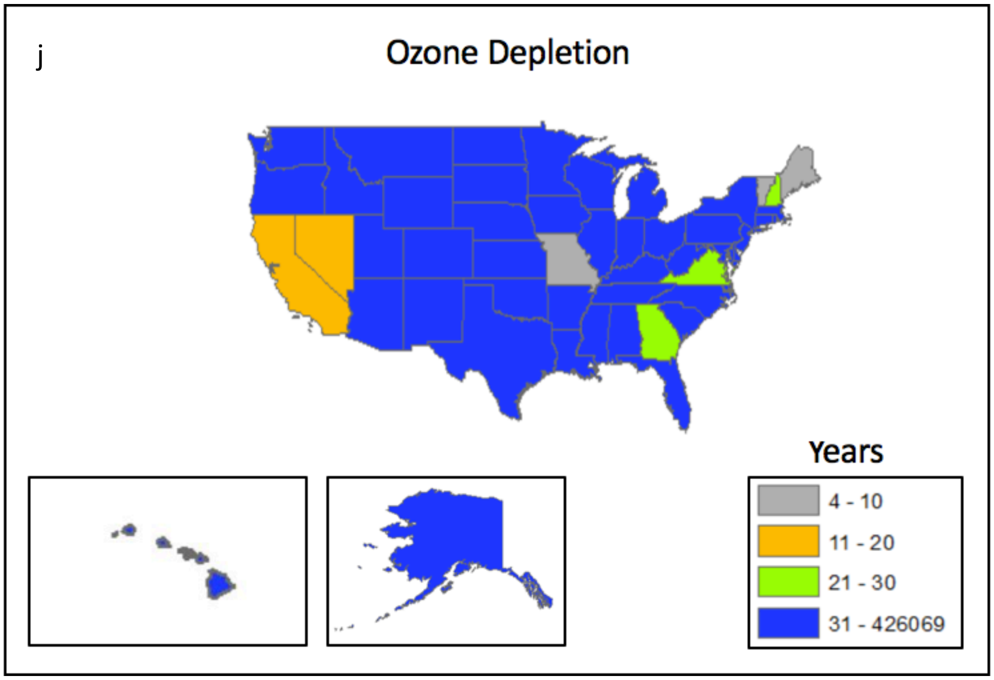
As can be seen in Figure 1g, Vermont, Washington, and Idaho have a smog EPBP result that is greater than the average solar panel lifespan of 30 years. This is due to the low smog impacts from the electricity grids in these states (i.e. the three lowest states for smog impacts). The wood and biomass parts of Vermont's electricity grid create smog impacts. The coal and natural gas parts of Washington's electricity grid create smog impacts, making up 15% of Washington's electricity grid. In Idaho, the natural gas part of Idaho's grid creates smog impacts, and it represents 18% of Idaho's electricity grid.



As can be seen in Figure 1h, New York, New Jersey and District of Columbia have a carcinognic EPBP result that is greater than 30 years, meaning it is greater than the average solar panel lifespan. New York and New Jersey's carcinogenic impacts from the electricity are both from the natural gas part of the grid. Natural gas makes up 38% of New York's grid and 51% of New Jersey's grid. Both states have the lowest carcinogenic impacts from the grid compared to other states. Therefore, it takes longer to payback the initial investment from the raw materials and manufacturing of PV.



As can be seen in Figure 1i, the states of Washington, Oregon, Idaho, New York, Vermont, New Hampshire, District of Columbia and Maine have a result longer than 30 years, meaning that the environmental payback period is longer than the average solar panel lifespan. The higher quantities of coal and petroleum in the grid contribute to higher non-carcinogenic impacts, and therefore, create shorter non-carcinogenic EPBT results.



The results for ozone depletion EPBP are between 4 and 426,069 years. All states have an environmental payback period longer than the average solar panel lifespan, except California and Nevada (11-20 years), Georgia, Virginia, and New Hampshire (21-30 years), and Missouri, Vermont and Maine (4-10 years). Ozone depletion category has longer payback periods compared to other impact categories. Although electricity grid impacts vary by state, the US average electricity grid has 1.99E-09 kg CFC-11/kWh of electricty generated, which does not exceed the raw materials and manufacturing ozone depletion impacts of PV.

Figure 6-1 Average Environmental Payback Periods

a) acidification b) fossil fuel depletion c) respiratory effects d) ecotoxicity e) global warming f) eutrophication g) smog h) carcinogenics i) non-carcinogenics j) ozone depletion. The average environmental payback period results are presented as rounded to nearest whole number.

6.5 Discussion

Table 6-2 provides the average EPBP results and average solar potential data that was used for each US state. The minimum and maximum EPBP results can be found in Appendix A. The analysis confirms that the ranking is different by solar potential compared to ranking by EPBP. The state of Arizona can be considered as an example. Arizona is ranked number 1 by solar potential prioritization. The average solar potential in the US is 5 kWh/m^2/day, while Arizona receives more than the average solar potential at 6.5 kWh/m^2/day, which is highest out of all US states. However, at the same time, the global warming impacts of Arizona's current electricity grid (having equal proportions of natural gas, coal and nuclear) are not as high as other US states that are more coal-dominant (e.g. West Virginia, Wyoming, Utah). Which results in Arizona having a lower ranking by EPBP prioritization compared to other states.

The ranking results suggest the locations where policy could be used to provide environmental benefits. For example, choosing solar PV locations with shorter EPBPs will result in more pronounced environmental benefits compared to purchasing electricity from the grid. In the case of global warming EPBP, the average EPBP is 8 years across all states with a range of 0.3 – 113 years. This means that most states will see a net environmental benefit, in reducing greenhouse gas emissions, within the average operating lifetime of the panel. Other states, such as Vermont, will not see net environmental benefits within the panel lifetime. This is due to the high level of renewables already within the current electricity mix. Essentially, the larger the current portion of renewable electricity is in the electricity grid, the less benefit a state will see from the adoption and usage of PV for an environmental impact perspective.

Table 6-2 – Average Environmental Payback Period Results for US States

US State	Ozone Depletion EPBP (years)	Global Warming EPBP (years)	Smog EPBP (years)	Acidification EPBP (years)	Eutrophication EPBP (years)	Carcinogenics EPBP (years)	Non-carcinogenics EPBP (years)	Respiratory effects EPBP (years)	Ecotoxicity EPBP (years)	Fossil Fuel Depletion EPBP (years)	Solar Potential (kWh/m^2/Day)
Alabama	62	4	8	1	80	9	14	5	27	1	5
Alaska	3723	6	11	3	106	17	15	11	18	1	4
Arizona	94	3	6	1	46	9	10	4	16	2	7
Arkansas	70	3	5	1	65	7	11	4	32	2	5
California	15	6	11	4	31	10	15	9	7	1	6
Colorado	66	2	4	1	34	5	7	3	9	2	6
Connecticut	258	7	13	5	134	29	26	12	26	1	5
Delaware	1101	3	7	2	67	14	12	5	14	1	5
District of Colombia	426069	11	1	6	100	32	47	20	45	2	5
Florida	147	3	7	1	66	11	12	5	16	1	5
Georgia	26	4	7	1	45	7	12	5	20	1	5
Hawaii	54	3	3	2	34	4	4	10	5	1	5
Idaho	48	18	31	12	99	16	42	27	13	3	5
Illinois	1041	6	8	1	100	12	17	6	29	5	5
Indiana	845	2	3	0	45	5	7	3	20	2	5
Iowa	204	4	6	1	53	7	12	5	8	5	5
Kansas	185	4	6	1	53	7	12	5	7	7	5
Kentucky	316	2	4	0	51	5	7	3	41	3	5
Louisiana	55	4	8	2	66	9	11	5	15	1	5
Maine	8	14	16	9	63	3	31	17	13	3	4
Maryland	290	5	8	1	99	14	17	7	33	3	5
Massachusetts	47	4	8	3	47	16	15	7	14	1	5
Michigan	72	4	7	1	65	9	13	5	25	2	4
Minnesota	64	5	7	1	67	8	14	6	14	4	4
Mississippi	61	4	9	2	69	10	13	5	15	1	5
Missouri	4	6	4	3	11	3	10	10	7	2	5
Montana	645	4	6	1	75	8	12	4	26	7	5
Nebraska	459	3	4	1	54	6	9	3	16	7	5
Nevada	15	4	9	2	31	10	11	5	8	1	6
New Hampshire	22	15	22	8	142	9	45	21	40	3	4
New Jersey	242	7	13	4	99	32	23	11	22	1	5
New Mexico	111	2	4	1	34	5	7	3	9	2	6
New York	155	10	18	6	132	33	35	16	27	2	4
North Carolina	59	4	7	1	59	9	13	5	20	2	5
North Dakota	299	3	5	1	53	6	10	4	11	8	4
Ohio	694	3	5	1	67	8	10	4	32	2	4
Oklahoma	114	4	7	1	49	8	12	5	7	1	5
Oregon	119	13	25	6	154	23	41	19	21	3	5
Pennsylvania	225	5	9	2	94	15	18	7	30	2	4
Rhode Island	1923	4	8	3	75	20	14	6	13	1	5
South Carolina	34	6	9	2	62	10	19	7	39	3	5
South Dekota	277	9	14	2	93	12	23	10	11	8	5
Tennessee	61	5	7	1	65	10	15	5	49	4	5
Texas	230	3	6	1	54	8	10	4	10	1	5
Utah	57	2	3	0	31	5	6	2	14	2	6
Vermont	9	113	37	92	66	4	57	51	17	33	4
Virginia	28	5	9	2	51	10	16	7	21	1	5
Washington	118	20	33	6	244	25	61	27	38	6	5
West Virginia	3379	2	3	0	50	5	7	3	44	6	5
Wisconsin	132	3	5	1	69	7	11	4	33	3	4
Wyoming	745	2	3	0	43	5	7	2	20	5	5

The average environmental payback period results and average solar potential data used is presented as rounded to nearest whole number. Gray shaded boxes = 0-10 years, orange shaded boxes = 11-20 years, green shaded boxes = 21-30 years, blue shaded boxes = 31+ years.

Currently, solar adoption is shaped by many factors, such as state policy and incentives and how much residents value solar (Vivent Solar 2018). California, for example, has the largest solar capacity and has a strong Renewable Portfolio Standard (RPS), which requires utilities in the state to source 100% of its electricity production from renewable sources (e.g. solar panels) by 2045 (Solar Power Rocks 2019). Various California utilities also offer net metering incentives for residents, where a homeowner receives bill credits for their extra solar power at the retail rate from their utility (Energy Sage 2019). Net metering and other incentives create a quicker return on investment, or economic payback period, for solar PV (Solar Power Rocks 2019). For example, the economic payback period ranges from 5-18 years for all US states and depends on the price of electricity and solar PV system, incentives available in each state as well as the energy production of the system (based on available sunlight).

While traditionally the focus has been on economic payback period from a policy perspective, environmental payback period provides a life-cycle approach with respect to quantifying the time it takes to recoup the embedded environmental impacts of solar PV in each state. It has value in assisting with improved policy discussions, and ultimately decisions, by helping to identify aspects of the PV systems which are important for the results. For example, the electricity mix varies within the United States, which can change the environmental impacts and benefits of PV.

However, further work is needed to understand how to best apply the results from this work from a policy perspective. Commonly, the LCA metric used in reports targeting policy makers on alternative energy products is greenhouse gas emission savings (Chum et al. 2011; Fulton et al. 2009; Bird et al. 2011). As such, the global warming payback period results from this work can be useful for policy to illustrate the benefits of solar energy in mitigating climate change and how the global warming savings vary geographically. Although the other environmental impact categories evaluated in this work are not commonly targeted from a policy perspective, they are beneficial to add to the body of knowledge surrounding the life-cycle benefits of solar panels compared to fossil fuels. For example, not only do fossil fuels (coal, natural gas, petroleum) exceed PV in global warming impacts, but they also exceed PV in four other impact categories: ozone depletion, smog, acidification, and fossil fuel depletion. Therefore, including these four impact categories, in addition to global warming, have the potential to illustrate the additional benefits of PV over fossil fuels from a policy perspective.

Several limitations exist for this work. The solar potential for each state was visually estimated using National Renewable Energy Lab (NREL) solar potential maps from 2012. In addition, a transportation calculator was used to estimate average distances to market in each state. If more accurate and current data becomes available for these data sources, it may improve data quality. In addition, the analysis in this paper represents the current state of PV technology for multi-crystalline PV systems. As PV technologies are continually improving, the results should be monitored over time with respect to changes to PV parameters, such as efficiency. Also, the analysis considers the current electricity mixes using the latest data from the Energy Information Administration, and future work might update the analysis when new data becomes available. Future work should consider additional impact assessment methods and possibly applying weights to the impact categories, once weighting data becomes available, to reflect the importance of each impact category to stakeholders.

6.6 Conclusions

LCA and the EPBP indicator can be used to measure the sustainability and prioritization of solar panel installations compared to prioritizing using solar potential alone. EPBP quantifies the time it takes to recoup the environmental impact from the production of solar PV compared to the environmental impacts of the electricity grid. Compared to previous work, an EPBP analysis was completed for all 50 states in the US and the District of Columbia, with differing solar potentials and electricity mixes, and all 10 LCA impact categories from TRACI. The results indicate that the ranking of states is different using EPBP compared to considering solar potential only. Future work might consider additional impact assessment methods, and updating the analysis when data becomes available and with respect to improvements to PV technologies or electricity mixes.

7. Conclusions and Future Work

7.1 Summary and Contributions

The introduction paper (Chapter 2) presented ABM as a methodology to further investigate PV adoption and the environmental impacts and benefits of solar PV. Through a survey of the literature, previous ABM research was discussed and opportunities for integration with LCA were identified.

The first environmental payback period paper (Chapter 3) was focused on five urban cities (Los Angeles, Miami, Seattle, Phoenix, Indianapolis) with different solar potentials and electricity mixes. It established an initial analysis on the environmental payback period of rooftop PV in the United States and laid the foundation for future work by finding that the larger the current portion of renewable electricity is in the electricity grid, the less benefit a state will see from the adoption and usage of PV for an environmental impact perspective. It also estimated the environmental impacts of c-Si PV systems in various manufacturing locations using LCA.

The ABM paper (Chapter 4) developed a model to investigate the adoption of rooftop PV in Los Angeles County, California and analyze how polices and evolutions in technology impact adoption. Agents, representative of households, select between one of two solar PV systems (offsetting 50% vs. 100% electricity consumption) or choose to continue consuming electricity from the grid using a probabilistic utility. The model was informed by survey data of LA County homeowners. The adoption of solar PV systems was compared under five scenarios: an investment tax credit, a falling cost of solar due to technological improvements, an increase in grid electricity prices, and two variations of the California Energy Efficiency Standards (which mandates that new homes be built with PV). It was found that all five scenarios increased adoption by the year 2050 compared to 2018 levels. It also found that, by the year 2022, adoption will reach a critical mass in the model (97%) under all scenarios, after which adoption levels off. From a policy perspective, the model suggests that both policies and evolutions in technology result in similar adoption rates. Therefore, more costly policies, such as the investment tax credit, may not be necessary to increase adoption if rooftop solar prices are expected to fall on their own.

The ABM-LCA paper (Chapter 5) investigated the potential environmental impacts of solar panel adoption, as at the societal-level, to compare trade-offs between conventional electricity generation and solar electricity generation. The LCA on the life-cycle impacts of solar PV and the ABM on adoption of solar PV in LA County are combined for a case study of LA County. The ABM-LCA model suggests that PV adoption will increase CO_2e impacts in the short term, due to the raw materials and manufacturing portions of the life cycle. Yet, in the long term, adoption of solar PV may provide CO_2e impact savings from offsetting grid electricity. It also suggests the value in an integrated approach, in this case coupling ABM and LCA, in order to evaluate the impact of policy on the environmental impacts and benefits of PV.

The second environmental payback period paper (Chapter 6) furthered the research of the first environmental payback period paper by increasing the scope to all US states. More detailed data on the electricity mixes of each state and a range of solar potential data (minimum, maximum, average) was included in this paper to determine the order of prioritization for PV installations in the US and how this prioritization would change compared to considering only solar intensity of states. The paper confirms that the ranking of states is different by solar potential compared to environmental payback period. Compared to previous work, it also introduced impact assessment methodologies as a way to rank states from an environmental payback period perspective.

Overall, this work provides a comprehensive assessment of solar PV technology adoption and use as a substitute for conventional electricity generation technologies. It includes the impact of policies, and geographical and temporal variations on the overall life-cycle environmental impacts and benefits of PV use.

7.2 Future Work

Further research into several areas would contribute to this body of research. The ABM model suggests that adoption in LA County could benefit from PV economic improvements, among other policies until 2022, at which point the model reaches a critical mass. Future work should explore additional scenarios or policies and the impact on the ABM results. The model could also be applied to other locations with different electricity prices and available incentives and policies to compare adoption results.

Increased adoption of solar PV will also increase the volume of end-of-life PV systems. End-of-life PV panels are projected to reach 78 million tonnes by 2050 (International Renewable Energy Agency 2016). Future work should focus on quantifying the environmental impacts and benefits achieved from implementing end-of-life processes to determine a more complete picture of the solar PV life-cycle and how end-of-life impacts the raw materials and manufacturing portions of the life-cycle.

Limitations exist with this work, as with all work. Such as the intermittency of PV electricity generation was not considered. Future studies should include this, and other complimentary technologies (i.e. battery storage), to compare the environmental impact of PV generation with other electricity sources.

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Appendix A

A1. Solar Panel Life-Cycle Inventory Data

The tables below present the life-cycle inventory data from Fu et al (2014) used to model the environmental impacts of Chinese solar panel manufacturing.

China metallurgical silicon smelting

Functional unit = 6.08 kg metallurgical grade silicon (99%)

Input/output	Quantity	SimaPro Database
Quartz sand	20.48 kg	Sand, quartz
Standard coal	45.50 kg	Coal, 29.3 MJ per kg
Carbon dioxide (emissions to air)	132.91 kg	Carbon dioxide
Carbon monoxide (emissions to air)	1.7 kg	Carbon monoxide
Nitrogen oxide (emissions to air))	279.55 kg	Nitrogen oxide
Silicon dioxide (emissions to air)	1.7 kg	Silicon dioxide
Sulfur dioxide (emissions to air)	0.79 kg	Sulfur dioxide
Slag for disposal	4.38 kg	Slags

Table S2- China solar grade multi-Si purification life-cycle inventory

Functional unit = 5.52 kg solar grade silicon

Input/output	Quantity	SimaPro Database
Metallurgical silicon	6.08 kg	See Table S2
Calcium oxide	6.52 kg	Quicklime, at plant/US (US LCI)
Hydrochloric acid (30%)	2.93 kg	Hydrochloric acid, Mannheim process (30% HCL), at plant/RER Economic (Agri-footprint)
Hydrofluoric acid (20%)	0.06 kg	Hydrogen fluoride {GLO} production, alloc def u (Ecoinvent 3)
Hydrogen (>99.8%)	0.50 kg	Hydrogen, liquid, chlor-alkali electrolysis, at plant/RNA (US LCI)

Nitric acid (35%)	0.22 kg	Nitric acid, without water, in 50% solution state {GLO} market for, alloc def u (Ecoinvent 3)
Nitrogen gaseous	71.16 kg	Nitrogen, via cryogenic air separation, production mix, at plant, gaseous EU-27 S (ELCD)
Silicon tetrachloride (>99%)	8.29 kg	Silicon tetrachloride {GLO} production, alloc def u (Ecoinvent 3)
Sodium hydroxide (20%)	4.81 kg	Sodium hydroxide, production mix, at plant/RNA (US LCI)
Water	10,397 kg	Tap water {ROW} market for, alloc def u (Ecoinvent 3)
Electricity	635 kWh	Electricity, high voltage {CN} market group for, alloc rec, u (Ecoinvent 3)
Steam	385 kg	Steam, in chemical industry {ROW} production, alloc def u (Ecoinvent 3)

The table below presents the life-cycle inventory data from Yao et al (2014) used to model the environmental impacts of Chinese solar panel manufacturing.

China solar panel manufacturing life-cycle inventory

Functional unit = 2 m^2 of panel
72 cells per panel
1.02 wafers per cell

Input	Quantity	SimaPro database
Poly-silicon	41 g/wafer	See Table S3
Silicon carbide	32 g/wafer	Silicon carbide {ROW} production, alloc def u (Ecoinvent 3)
Polyethylene glycol	36 g/wafer	Epoxy resin, liquid {ROW} production, alloc def u (Ecoinvent 3)
Hydrogen fluoride	0.4 g/wafer	Hydrogen fluoride {GLO} production, alloc def u (Ecoinvent 3)
Hydrogen chloride	0.4 g/wafer	Hydrogen chloride gas, production mix for PVC production, at plant RER (ELCD)

Sodium hydroxide	0.04 g/wafer	Sodium hydroxide, production mix, at plant/RNA (US LCI)
Potassium hydroxide	0.02 g/wafer	Potassium hydroxide {ROW} production, alloc def u (Ecoinvent 3)
Nitric acid	0.2 g/wafer	Nitric acid, without water, in 50% solution state {ROW} nitric acid production, product in 50% solution state, alloc def u (Ecoinvent 3)
Nitrogen	3.6 g/wafer	Nitrogen, via cryogenic air separation, production mix, at plant, gaseous EU-27 S (ELCD)
Argon	13 g/wafer	Argon, liquid {ROW} production, alloc def u (Ecoinvent 3)
Water	1310 g/wafer	Tap water {ROW} production, alloc def u (Ecoinvent 3)
Electricity	2.9 kWh/wafer	Electricity, high voltage {CN} alloc rec u (Ecoinvent 3)
Silane	0.8 g/cell	Silicon tetrahydride {GLO} silicon hydrochloration, alloc def u (Ecoinvent 3)
Phosphoryl chloride	0.02 g/cell	Phosphoryl chloride {ROW} production, alloc def u (Ecoinvent 3)
Hydrogen fluoride	4.0 g/cell	Hydrogen fluoride {GLO} production alloc def u (Ecoinvent 3)
Hydrogen chloride	1.1 g/cell	Hydrogen chloride gas, production mix for PVC production, at plant RER (ELCD)
Oxygen	0.5 g/cell	Oxygen, liquid, at plant/RNA (US LCI)
Nitrogen	76 g/cell	Nitrogen, via cryogenic air separation, production mix, at plant, gaseous EU-27 S (ELCD)
Nitric acid	2.8 g/cell	Nitric acid, without water, in 50% solution state {ROW} nitric acid production, product in 50% solution state, alloc def u (Ecoinvent 3)
Ammonia	2.3 g/cell	Ammonia, liquid {ROW} market for, alloc def u (Ecoinvent 3)
Silver	0.6 g/cell	Silver {GLO} market for, alloc def u (Ecoinvent 3)
Aluminum	1.5 g/cell	Aluminum alloy, AlLi {ROW} production, alloc def u (Ecoinvent 3)
Water	3350 g/cell	Tap water, {ROW} market for, alloc def u (Ecoinvent 3)
Electricity	0.7 g/cell	Electricity, high voltage {CN} market group for, alloc rec u (Ecoinvent 3)

Copper wire	36 g/module	Copper wire, technology mix, consumption mix, at plant, cross section 1 mm^2 EU-15S (ELCD)
Aluminum frame	3400 g/module	Aluminum alloy, AlLi {ROW} production, alloc def u (Ecoinvent 3)
Glass	2 g/module	Solar glass, low iron {ROW} production, alloc def u (Ecoinvent 3)
Back foil	2 g/module	Polyvinylfluoride, film {ROW} production, alloc def u (Ecoinvent 3)
Ethylene vinyl acetate	1850 g/module	Ethylvinylacetate, foil {ROW} production, alloc def u (Ecoinvent 3)
Silicone	110 g/module	Silicon product, {GLO} market for, alloc def u (Ecoinvent 3)
Water	41800 g/module	Tap water {ROW} market for, alloc def u (Ecoinvent 3)
Electricity	18 kWh/module	Electricity, high voltage {CN] market group for, alloc rec u (Ecoinvent 3)

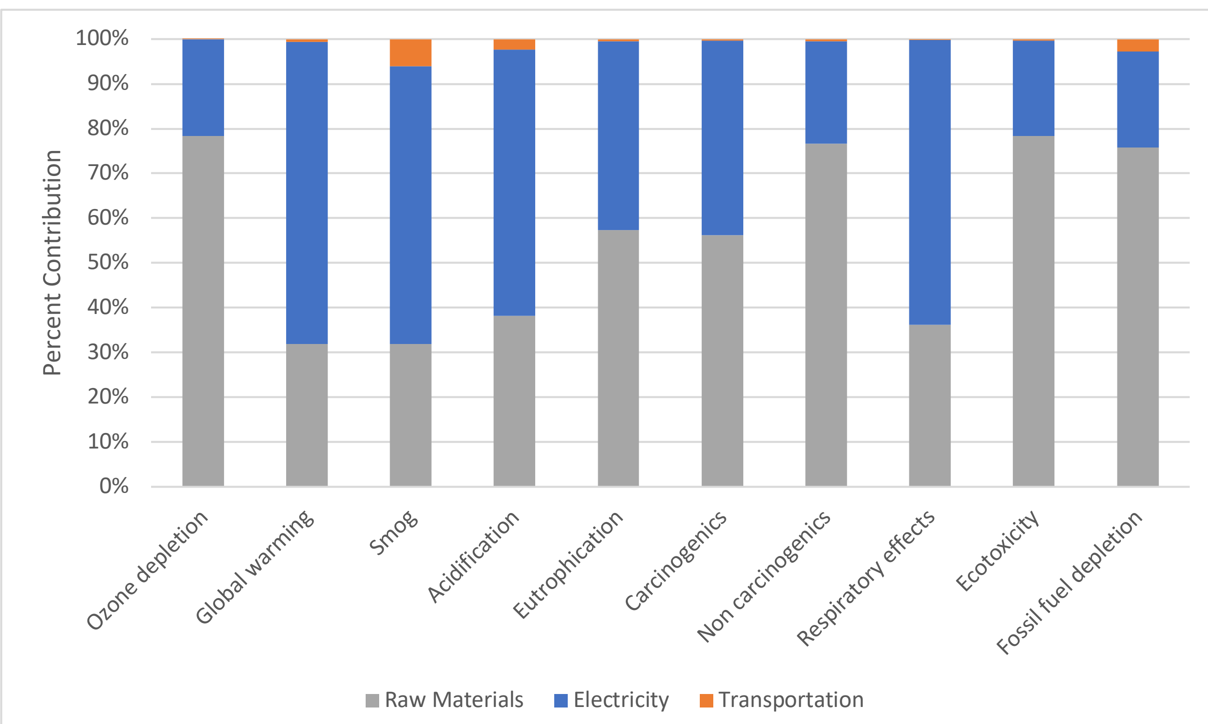
- SimaPro database used for European solar panel manufacturing
    - *Photovoltaic cell, multi-Si wafer {US} production, alloc def u (Ecoinvent 3)*
    - To produce a United States solar panel manufacturing scenario, the following electricity mix was substituted for the European mix: *Electricity, medium voltage {US}| market group for | Alloc Def, U*
- SimaPro database used for Inverter and Mounting System for all manufacturing locations
    - Inverter: *0.5kW {RER}| production | Alloc Def, U (of project Ecoinvent 3 - allocation at point of substitution - unit)*
    - Mounting System: *Photovoltaic mounting system, for slanted-roof installation {RER}| production | Alloc Def, U (of project Ecoinvent 3 - allocation at point of substitution - unit)*
- SimaPro databases used for transportation modeling
    - Ocean: *Transport, ocean freighter, residual fuel oil powered/US LCI*
    - Rail: *Transport, train, diesel powered/US LCI*
    - Truck: *Transport, single unit truck, diesel powered/US LCI*

A2. Solar Panel Life-Cycle Assessment Results

The tables below show the LCA results and the additional LCA figures show the contributions to the impacts.

Impact Assessment Results (per m^2 of panel manufactured in China)

Impact category	Unit	Total
Ozone depletion	kg CFC-11 eq	1.8692E-05
Global warming	kg CO2 eq	518.586856
Smog	kg O3 eq	31.8612621
Acidification	kg SO2 eq	2.97240865
Eutrophication	kg N eq	0.91746618
Carcinogenics	CTUh	1.2524E-05
Non carcinogenics	CTUh	0.00010929
Respiratory effects	kg PM2.5 eq	0.4364792
Ecotoxicity	CTUe	2609.5348
Fossil fuel depletion	MJ surplus	235.390901

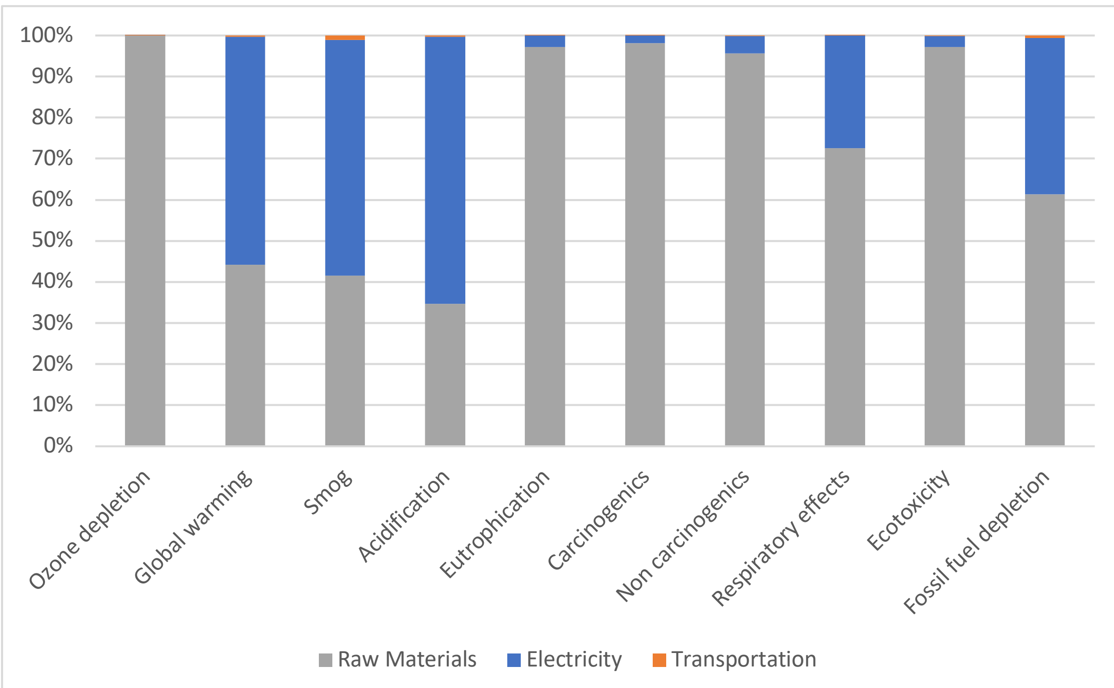


Contribution analysis of China mc-Si panel manufacturing

Impact Assessment Results (per m^2 of panel manufactured in United States)

Impact category	Unit	Total

Ozone depletion	kg CFC-11 eq	4.3634E-05
Global warming	kg CO2 eq	255.39879
Smog	kg O3 eq	16.4607578
Acidification	kg SO2 eq	1.1170794
Eutrophication	kg N eq	1.79
Carcinogenics	CTUh	1.4562E-05
Non carcinogenics	CTUh	0.00010478
Respiratory effects	kg PM2.5 eq	0.21723954
Ecotoxicity	CTUe	2084.02367
Fossil fuel depletion	MJ surplus	233.486654

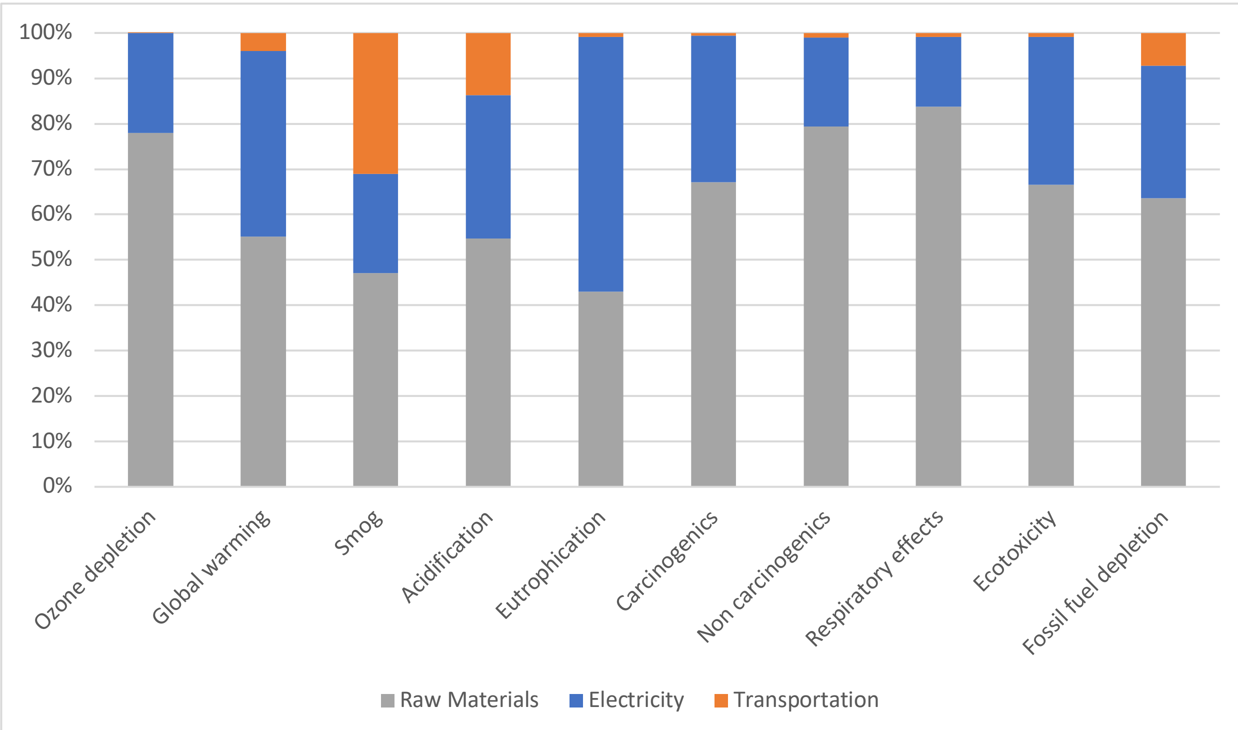


Contribution analysis of US mc-Si panel manufacturing

Impact Assessment Results (per m^2 of panel manufactured in Europe)

Ozone depletion	kg CFC-11 eq	5.0358E-05
Global warming	kg CO2 eq	201.009184
Smog	kg O3 eq	10.9791927
Acidification	kg SO2 eq	1.07078333
Eutrophication	kg N eq	1.0037875
Carcinogenics	CTUh	1.7787E-05
Non carcinogenics	CTUh	0.0001121
Respiratory effects	kg PM2.5 eq	0.30465782
Ecotoxicity	CTUe	2445.45946

Fossil fuel depletion	MJ surplus	199.231783



Contribution analysis of US mc-Si panel manufacturing

A3. Electricity Mixes

The table below presents electricity mix data used for the states analyzed in Chapter 6.

State	Coal %	Hydroelectric %	Natural gas %	Nuclear %	Petroleum %	Solar %	Wood %	Wind %	Geothermal %	Pumped Storage %	Other Biomass %	Other Gas %	Other %
Alabama	22.5	6.6	37.9	30.5	0.0	0.1	2.4	0.0	0.0	0.0	0.0	0.0	0.0
Alaska	8.6	25.3	49.8	0.0	13.6	0.0	0.0	2.2	0.0	0.0	0.7	0.0	0.0
Arizona	29.7	6.5	28.0	30.6	0.1	4.7	0.1	0.5	0.0	0.0	0.0	0.0	0.0
Arkansas	43.3	4.8	28.5	20.9	0.1	0.1	2.2	0.0	0.0	0.0	0.2	0.0	0.0
California	0.2	22.3	46.5	0.9	0.0	12.8	1.6	6.7	6.1	0.2	1.5	0.7	0.4
Colorado	54.3	3.5	23.3	0.0	0.0	1.8	0.2	17.3	0.0	-0.6	0.1	0.0	0.1
Connecticut	0.6	1.0	46.2	47.7	0.5	0.1	0.6	0.0	0.0	0.0	1.7	0.0	1.6
Delaware	11.2	0.0	81.7	0.0	2.4	0.6	0.0	0.1	0.0	0.0	1.0	2.9	0.0
District of Columbia	0.0	0.0	29.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	70.5	0.0	0.0
Florida	15.7	0.1	67.6	12.2	0.6	0.4	0.9	0.0	0.0	0.0	1.2	0.0	1.3
Georgia	25.5	1.9	41.4	26.4	0.2	1.6	3.7	0.0	0.0	-1.0	0.3	0.0	0.1
Hawaii	14.0	0.7	0.0	0.0	67.6	1.8	0.0	5.4	3.3	0.0	3.0	0.5	3.7
Idaho	0.1	61.3	17.7	0.0	0.0	2.6	2.0	14.6	0.5	0.0	0.7	0.0	0.4
Illinois	31.6	0.1	8.2	52.9	0.0	0.0	0.0	6.7	0.0	0.0	0.3	0.1	0.1
Indiana	73.2	0.3	18.2	0.0	0.1	0.3	0.0	5.1	0.0	0.0	0.5	2.0	0.3
Iowa	43.8	1.8	7.9	9.0	0.3	0.0	0.0	36.9	0.0	0.0	0.4	0.0	0.0
Kansas	38.1	0.1	4.2	20.9	0.1	0.0	0.0	36.5	0.0	0.0	0.1	0.0	0.0
Kentucky	78.2	6.2	14.2	0.0	0.7	0.0	0.5	0.0	0.0	0.0	0.2	0.0	0.1
Louisiana	12.6	0.9	60.3	15.8	4.7	0.0	2.7	0.0	0.0	0.0	0.1	2.2	0.6
Maine	0.6	30.1	19.9	0.0	1.2	0.0	22.5	20.7	0.0	0.0	1.6	0.0	3.5
Maryland	25.0	5.8	19.7	44.3	0.3	0.8	0.4	1.6	0.0	0.0	1.2	0.0	0.9
Massachusetts	3.5	3.2	68.8	15.7	0.8	2.4	0.4	0.7	0.0	-1.4	3.2	0.0	2.6
Michigan	37.4	1.5	23.3	28.8	1.0	0.1	1.3	4.6	0.0	-0.6	0.9	1.5	0.2
Minnesota	38.8	2.1	11.4	23.7	0.1	1.0	2.2	19.0	0.0	0.0	1.1	0.0	0.7
Mississippi	7.7	0.0	77.3	12.3	0.0	0.1	2.4	0.0	0.0	0.0	0.0	0.0	0.0
Missouri	79.8	1.4	6.2	9.8	0.1	0.1	0.1	2.4	0.0	0.1	0.1	0.0	0.0
Montana	49.1	38.8	1.5	0.0	1.6	0.0	0.1	7.6	0.0	0.0	0.0	0.0	1.2
Nebraska	59.8	4.2	1.8	19.5	0.0	0.0	0.0	14.4	0.0	0.0	0.3	0.0	0.0
Navada	4.9	4.7	69.7	0.0	0.0	10.9	0.0	0.9	8.6	0.0	0.2	0.0	0.1
New Hampshire	1.6	8.1	20.5	57.3	0.6	0.0	8.4	2.4	0.0	0.0	0.8	0.0	0.3
New Jersey	1.6	0.0	49.8	45.0	0.2	1.2	0.0	0.0	0.0	-0.2	1.2	0.3	0.8

New Mexico	54.8	0.6	27.2	0.0	0.1	3.5	0.0	13.7	0.0	0.0	0.1	0.0	0.0
New York	0.6	23.5	36.9	32.9	0.5	0.1	0.5	3.2	0.0	-0.3	1.3	0.0	0.7
North Carolina	26.8	3.0	30.0	33.0	0.2	4.0	1.6	0.4	0.0	0.0	0.5	0.0	0.4
North Dakota	64.5	6.2	1.6	0.0	0.1	0.0	0.0	27.4	0.0	0.0	0.0	0.1	0.1
Ohio	57.2	0.2	24.1	14.8	1.0	0.1	0.2	1.3	0.0	0.0	0.4	0.7	0.0
Oklahoma	23.6	2.8	41.3	0.0	0.0	0.0	0.3	32.0	0.0	-0.2	0.1	0.0	0.1
Oregon	2.8	61.1	24.0	0.0	0.0	0.3	1.0	9.9	0.3	0.0	0.6	0.0	0.1
Pennsylvania	22.3	1.5	33.9	38.9	0.2	0.0	0.2	1.7	0.0	-0.3	0.9	0.2	0.4
Rhode Island	0.0	0.0	94.4	0.0	0.8	0.2	0.0	2.0	0.0	0.0	2.7	0.0	0.0
South Caroline	19.5	2.0	18.4	58.4	0.1	0.1	2.4	0.0	0.0	-1.1	0.2	0.0	0.0
South Dakota	18.9	48.1	6.0	0.0	0.0	0.0	0.0	27.1	0.0	0.0	0.0	0.0	0.0
Tennessee	35.1	11.0	13.0	40.3	0.2	0.1	1.1	0.1	0.0	-0.9	0.1	0.0	0.0
Texas	29.7	0.2	45.2	8.5	0.0	0.5	0.2	14.8	0.0	0.0	0.1	0.5	0.1
Utah	70.5	3.5	15.7	0.0	0.1	5.9	0.0	2.3	1.3	0.0	0.2	0.0	0.5
Vermont	0.0	59.8	0.1	0.0	0.3	4.6	20.4	14.3	0.0	0.0	0.6	0.0	0.0
Virginia	11.9	1.2	49.2	33.8	0.5	0.3	3.2	0.0	0.0	-1.4	1.0	0.0	0.2
Washington	4.7	70.9	9.4	7.0	0.0	0.0	1.4	6.0	0.0	0.0	0.3	0.3	0.0
West Virginia	93.2	2.3	2.1	0.0	0.2	0.0	0.0	2.3	0.0	0.0	0.0	0.0	0.0
Wisconsin	55.1	4.1	21.0	14.8	0.2	0.0	1.3	2.5	0.0	0.0	0.9	0.0	0.0
Wyoming	85.7	2.4	1.7	0.0	0.1	0.0	0.0	9.2	0.0	0.0	0.0	0.8	0.1

The tables below present the life-cycle impact assessment data utilized to calculate the environmental impacts of each state's electricity mix.

Environmental impacts of biomass electricity

1 kWh Electricity, biomass, at power plant/US (of project USLCI)		
Impact category	Unit	Impact/ kwh
Ozone depletion	kg CFC-11 eq	9.59E-14
Global warming	kg CO2 eq	0.04576586
Smog	kg O3 eq	0.24150305
Acidification	kg SO2 eq	0.00083965
Eutrophication	kg N eq	4.03E-05
Carcinogenics	CTUh	1.48E-09
Non carcinogenics	CTUh	3.32E-10
Respiratory effects	kg PM2.5 eq	7.44E-06
Ecotoxicity	CTUe	0.00641623
Fossil fuel depletion	MJ surplus	0.00481708

Environmental impacts of natural gas electricity

1 kWh Electricity, natural gas, at power plant/US (of project USLCI)		
Impact category	Unit	Impact/ kwh
Ozone depletion	kg CFC-11 eq	5.15E-13
Global warming	kg CO2 eq	0.72024043
Smog	kg O3 eq	0.015253495
Acidification	kg SO2 eq	0.0061274
Eutrophication	kg N eq	5.97E-05
Carcinogenics	CTUh	3.01E-09
Non carcinogenics	CTUh	3.91E-08
Respiratory effects	kg PM2.5 eq	0.000361902
Ecotoxicity	CTUe	0.96075016
Fossil fuel depletion	MJ surplus	1.8793098

Environmental impacts of hydroelectricity

1 kWh Electricity from hydro power, AC, production mix, at power plant, 230V RER S (of project ELCD)		
Impact category	Unit	Impact/ kwh
Ozone depletion	kg CFC-11 eq	4.14E-12
Global warming	kg CO2 eq	0.00594657
Smog	kg O3 eq	0.00013731
Acidification	kg SO2 eq	9.17E-06

Eutrophication	kg N eq	5.00E-07
Carcinogenics	CTUh	1.28E-11
Non carcinogenics	CTUh	3.36E-10
Respiratory effects	kg PM2.5 eq	8.18E-07
Ecotoxicity	CTUe	0.00039118
Fossil fuel depletion	MJ surplus	0.00184882

Environmental impacts of nuclear electricity

1 kWh Electricity, nuclear, at power plant/US (of project USLCI)		
Impact category	Unit	Impact/ kwh
Ozone depletion	kg CFC-11 eq	6.75E-12
Global warming	kg CO2 eq	0.01150785
Smog	kg O3 eq	0.00174204
Acidification	kg SO2 eq	0.00027845
Eutrophication	kg N eq	3.81E-06
Carcinogenics	CTUh	3.14E-11
Non carcinogenics	CTUh	1.53E-09
Respiratory effects	kg PM2.5 eq	1.44E-05
Ecotoxicity	CTUe	0.0494312
Fossil fuel depletion	MJ surplus	0.01006092

Environmental impacts of diesel electricity

1 kWh Electricity, diesel, at power plant/US U (of project USLCI)		
Impact category	Unit	Impact/ kwh
Ozone depletion	kg CFC-11 eq	4.32E-11
Global warming	kg CO2 eq	1.1302118
Smog	kg O3 eq	0.04856127
Acidification	kg SO2 eq	0.00296327
Eutrophication	kg N eq	0.00013489
Carcinogenics	CTUh	1.59E-08
Non carcinogenics	CTUh	1.56E-07
Respiratory effects	kg PM2.5 eq	6.21E-05
Ecotoxicity	CTUe	2.9152256
Fossil fuel depletion	MJ surplus	2.1714583

Environmental impacts of wood electricity

1 kWh Electricity, onsite boiler, softwood mill average, NE-NC/kWh/RNA (of project USLCI)		
Impact category	Unit	Impact/ kwhr
Ozone depletion	kg CFC-11 eq	5.60E-08
Global warming	kg CO2 eq	0.06440002
Smog	kg O3 eq	0.01558483

Acidification	kg SO2 eq	0.00062581
Eutrophication	kg N eq	0.0001953
Carcinogenics	CTUh	8.37E-08
Non carcinogenics	CTUh	2.08E-08
Respiratory effects	kg PM2.5 eq	0.00020404
Ecotoxicity	CTUe	0.16176364
Fossil fuel depletion	MJ surplus	0.1278379

Environmental impacts of wind electricity

1 kWh Electricity, high voltage {WECC, US only}| electricity production, wind, <1MW turbine, onshore | Alloc Def, U (of project Ecoinvent 3 - allocation, default - unit)		
Impact category	Unit	Impact/ kwhr
Ozone depletion	kg CFC-11 eq	1.23E-09
Global warming	kg CO2 eq	0.01389342
Smog	kg O3 eq	0.00084459
Acidification	kg SO2 eq	7.84E-05
Eutrophication	kg N eq	9.81E-05
Carcinogenics	CTUh	8.67E-09
Non carcinogenics	CTUh	1.75E-08
Respiratory effects	kg PM2.5 eq	2.00E-05
Ecotoxicity	CTUe	4.1908359
Fossil fuel depletion	MJ surplus	0.0139868

Table S9– Environmental impacts of geothermal electricity

1 kWh Electricity, high voltage {WECC, US only}| electricity production, geothermal | Alloc Def, U (of project Ecoinvent 3 - allocation, default - unit)		
Impact category	Unit	Impact/ kwhr
Ozone depletion	kg CFC-11 eq	3.97E-08
Global warming	kg CO2 eq	0.06265697
Smog	kg O3 eq	0.01146877
Acidification	kg SO2 eq	0.00048817
Eutrophication	kg N eq	0.00019804
Carcinogenics	CTUh	1.33E-08
Non carcinogenics	CTUh	2.12E-08
Respiratory effects	kg PM2.5 eq	9.01E-05
Ecotoxicity	CTUe	0.87580071
Fossil fuel depletion	MJ surplus	0.10228785

Environmental impacts of pumped storage

1 kWh Electricity, high voltage {WECC, US only}| electricity production, hydro, pumped storage | Alloc Def, U (of project Ecoinvent 3 - allocation, default - unit)		
Impact category	Unit	Impact/ khwr
Ozone depletion	kg CFC-11 eq	1.06E-07
Global warming	kg CO2 eq	0.90715123
Smog	kg O3 eq	0.042964151
Acidification	kg SO2 eq	0.003799237
Eutrophication	kg N eq	0.002598018
Carcinogenics	CTUh	3.66E-08
Non carcinogenics	CTUh	1.23E-07
Respiratory effects	kg PM2.5 eq	0.000225963
Ecotoxicity	CTUe	3.856189
Fossil fuel depletion	MJ surplus	1.0834942

Environmental impacts of solar electricity

1 kWh Electricity, low voltage {WECC, US only}| electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, panel, mounted | Alloc Def, U (of project Ecoinvent 3 - allocation, default - unit)		
Impact category	Unit	Impact/ kwh
Ozone depletion	kg CFC-11 eq	1.28E-08
Global warming	kg CO2 eq	0.05589377
Smog	kg O3 eq	0.00361095
Acidification	kg SO2 eq	0.00042462
Eutrophication	kg N eq	0.00050267
Carcinogenics	CTUh	7.51E-09
Non carcinogenics	CTUh	6.94E-08
Respiratory effects	kg PM2.5 eq	6.17E-05
Ecotoxicity	CTUe	5.187027
Fossil fuel depletion	MJ surplus	0.05845251

A4. Additional Environmental Payback Period Results

The table below displays the maximum and minimum EPBP results for carcinogenics, non-carcinogenics, respiratory effects, ecotoxicity, and fossil fuel depletion impact categories

	Carcinogenics EPBP		Non carcinogenics EPBP		Respiratory Effects EPBP		Ecotoxicity EPBP		Fossil Fuel Depletion EPBP	
US State	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Alabama	11	9	17	14	6	5	32	26	2	1
Alaska	20	15	18	13	13	10	21	16	2	1
Arizona	10	9	12	10	5	4	18	16	2	2
Arkansas	8	6	12	10	4	4	36	30	2	2

California	13	9	19	13	12	8	9	6	1	1
Colorado	7	5	11	7	4	3	13	8	3	2
Connecticut	35	28	31	25	14	11	31	24	2	1
Delaware	15	13	12	11	6	5	15	13	1	1
District of Colombia	34	31	49	44	21	19	48	43	2	2
Florida	12	10	12	10	5	4	17	14	1	1
Georgia	8	7	14	11	6	5	23	19	1	1
Hawaii	7	3	7	3	17	8	9	4	1	1
Idaho	20	13	53	35	34	23	17	11	4	3
Illinois	15	12	20	16	7	6	34	27	6	5
Indiana	7	5	9	7	3	3	27	21	3	2
Iowa	8	6	14	11	6	4	9	7	6	5
Kansas	8	6	14	10	6	4	8	6	8	6
Kentucky	6	5	8	7	3	3	43	39	3	3
Louisiana	10	8	13	11	6	5	18	14	1	1
Maine	4	3	37	26	21	15	15	11	3	2
Maryland	15	12	18	15	7	6	35	29	3	2
Massachusetts	19	15	18	14	9	7	17	13	1	1
Michigan	11	8	16	11	6	4	30	21	3	2
Minnesota	9	6	17	12	7	5	17	12	5	4
Mississippi	12	10	15	13	6	5	18	15	1	1
Missouri	3	3	10	9	11	9	7	6	2	2
Montana	12	7	17	10	6	4	38	23	10	6
Nebraska	7	5	11	8	4	3	18	14	9	6
Nevada	14	10	14	10	7	5	10	7	1	1
New Hampshire	10	7	55	38	25	18	49	34	4	3
New Jersey	37	30	28	22	12	10	26	21	1	1
New Mexico	6	5	8	6	3	3	11	8	2	1
New York	35	28	37	29	17	14	28	23	2	2
North Carolina	11	9	15	12	6	5	23	19	2	2
North Dakota	7	5	11	9	4	3	12	10	9	7
Ohio	8	7	11	9	4	3	34	27	2	2
Oklahoma	9	7	14	10	6	4	8	6	2	1
Oregon	30	17	53	31	25	15	26	15	4	2
Pennsylvania	16	13	19	15	7	6	32	26	2	2
Rhode Island	21	19	15	13	7	6	14	12	1	1

South Carolina	11	10	19	18	8	7	41	38	3	3
South Dakota	15	10	28	19	12	8	13	8	9	6
Tennessee	10	9	16	13	6	5	52	43	4	3
Texas	10	7	12	9	5	3	12	8	1	1
Utah	6	4	8	6	3	2	19	13	3	2
Vermont	5	4	70	54	61	48	20	16	40	31
Virginia	10	8	17	14	7	6	23	19	1	1
Washington	35	21	84	50	37	22	53	31	9	5
West Virginia	6	5	8	6	3	2	50	40	7	5
Wisconsin	8	6	12	9	4	3	35	28	3	2
Wyoming	7	4	11	6	4	2	32	18	8	5

The table below displays the maximum and minimum EPBP results for ozone depletion, global warming, smog, acidification, and eutrophication impact categories

	Ozone Depletion EPBP		Global Warming EPBP		Smog EPBP		Acidification EPBP		Eutrophication EPBP	
US State	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Alabama	72	59	5	4	9	7	1	1	94	77
Alaska	4344	3258	7	5	13	10	4	3	123	92
Arizona	111	94	4	3	7	6	1	1	54	46
Arkansas	78	63	4	3	6	5	1	1	72	59
California	19	13	8	5	14	10	5	4	40	28
Colorado	94	58	4	2	6	3	1	0	49	30
Connecticut	307	245	9	7	15	12	5	4	160	128
Delaware	1163	1046	4	3	8	7	2	2	71	64
District of Colombia	449740	404766	11	10	1	1	7	6	106	95
Florida	155	129	4	3	7	6	1	1	70	58
Georgia	30	25	4	4	8	6	1	1	53	43
Hawaii	91	44	4	2	5	3	3	1	56	27
Idaho	60	40	22	15	39	26	15	10	124	83
Illinois	1236	989	7	5	10	8	1	1	119	95
Indiana	1109	887	3	2	4	3	1	0	59	47
Iowa	242	194	5	4	7	6	1	1	63	51
Kansas	218	157	5	4	8	5	1	1	62	45
Kentucky	333	300	3	2	4	3	1	0	54	49
Louisiana	64	52	4	3	9	7	2	1	77	63
Maine	10	7	17	12	19	13	11	8	77	54
Maryland	306	251	6	5	8	7	1	1	105	86

Massachusetts	55	44	5	4	9	7	3	2	55	44
Michigan	87	61	5	4	8	6	1	1	79	56
Minnesota	79	55	6	4	8	6	1	1	82	58
Mississippi	71	58	4	3	10	9	2	2	81	66
Missouri	4	4	6	5	4	3	3	2	12	10
Montana	942	557	6	3	8	5	1	1	109	65
Nebraska	535	402	4	3	5	4	1	1	63	47
Nevada	20	14	5	3	12	8	3	2	41	28
New Hampshire	27	19	19	13	26	18	10	7	172	121
New Jersey	287	229	8	6	16	13	5	4	118	95
New Mexico	139	107	3	2	4	3	1	0	42	33
New York	164	131	11	8	19	15	7	5	141	112
North Carolina	68	56	5	4	8	7	1	1	69	56
North Dakota	329	263	4	3	5	4	1	1	59	47
Ohio	737	590	3	3	5	4	1	1	71	57
Oklahoma	133	99	5	3	9	6	1	1	57	43
Oregon	153	89	17	10	32	19	8	5	198	116
Pennsylvania	239	191	6	5	9	8	2	1	100	80
Rhode Island	2030	1827	4	4	8	7	3	2	79	71
South Carolina	35	32	6	6	10	9	2	1	65	59
South Dakota	329	219	11	7	17	11	2	2	110	73
Tennessee	64	52	5	4	8	6	1	1	69	56
Texas	276	191	4	3	7	5	1	1	65	45
Utah	76	53	3	2	4	3	1	0	42	29
Vermont	10	8	137	106	45	35	112	87	80	62
Virginia	30	24	5	4	9	8	2	2	55	45
Washington	163	96	28	16	45	27	9	5	337	199
West Virginia	3802	3041	3	2	4	3	1	0	56	45
Wisconsin	140	112	4	3	5	4	1	1	73	58
Wyoming	1192	646	3	2	5	3	1	0	69	37

Appendix B

B1. Survey Demographic Data

The survey data was collected from April 13, 2018 until May 11, 2018 in the Los Angeles County area. 3,795 responses across all zip codes of Los Angeles County were collected. The gender distribution is 58% female, 41% male, and 1% other/declined to answer.

Race identity of survey population

Race	% of Survey Respondents
Caucasian/White	59%
African American/Black	8%
Asian, Hispanic, Native Hawaiian, Pacific Islander, American Indian, Alaska Native	21%
Other	8%
Prefer not to answer	4%

Survey population age distribution

Range	% of Survey Respondents
18 to 19	3%
20 to 24	9%
25 to 34	23%
35 to 44	18%
45 to 54	13%
55 to 59	8%
60 to 64	8%
65 to 74	13%
75 to 80	3%
80+	2%

Average annual household income of survey population

Income Range	% of Survey Respondents
$0 to $24,999	8%
$25k to $49,999	9%

$50k to $99,999	22%
$100k to $149,999	11%
$150k +	10%
Prefer not to answer	40%

Political orientation of survey population

Political Orientation	% of Survey Respondents
Conservative	23%
Liberal	30%
Moderate	37%
Other	9%
Not reported	1%

Electricity provider of survey population

Electricity provider	% of Survey Respondents
Southern California Edison	50%
Burbank Water and Power	1%
Los Angeles Department of Water and Power	40%
Azusa Light and Power	1%
City of Cerritos	0%
City of Industry	0%
City of Vernon	0%
Glendale Water and Power	3%
Pasadena Water and Power	2%
Don't know or other	2%

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