Solar Photovoltaic Power: Short Term Volatility and Its Future Under Climate Change

ABSTRACT

Solar power is becoming increasingly important as a source of energy in the United States. While solar represents a low-emission source of energy, integrating it into the electrical grid is challenging. The power output of solar is not controlled by operators, but is instead determined by the weather. Since solar power is not able to be controlled as a typical power station would be, analyzing its behavior is essential. This paper looks at three main points: the significance of short term variability in solar power output, mitigation techniques for short term variability, and how solar resources could change over the 21st century.

New England is the geographical focus of the analysis of short term variability as well as the geographical focus of the mitigation analysis. This region was chosen because its climate makes it especially susceptible to short term variability. Additionally, its solar industry is already being affected by policy decisions where short term variability plays a role. This study found that short term variability of solar photovoltaic arrays was significant in both magnitude and frequency. Over the course of a year, panels could be expected to fluctuate over 95% of their rated power output in a 5 minute time interval. Additionally, a strong seasonal correlation was found with short term variability. Variability reached a minimum in the winter, while peaking in the late spring and early autumn.

The mitigation analysis found that the addition of a storage system could effectively moderate the effects of short term variability produced by solar panels. The driving factor of the effectiveness of the storage system in mitigating variability was its maximum power output.

The Southwestern United States is the focus for the analysis on how solar resources may change in the 21st century. This region was chosen because it currently has the best solar resources in the US, which may lead to expensive and long-lasting infrastructure being installed in the area. Thus, the projected climate of the region becomes important. This study finds that solar resources in the Southwestern United States are projected to remain relatively steady over the coming century. The quality of the solar resources in the Southwest is expected to be maintained even under a medium or high carbon dioxide emissions scenario. Interestingly, the average cloudiness of the region is expected to increase with no effect on the amount of solar radiation the region receives.

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INTRODUCTION

Background of Solar Photovoltaic Power

Solar photovoltaic panels harvest solar radiation and transform that energy into electricity. They represent a clean and renewable source of energy. In years past, these panels provided a negligible source of electricity in the United States; however, in recent years, their use has exploded. Roofs of residential and commercial buildings are being outfitted with panels and firms are building utility-scale photovoltaic systems on the scale of megawatts. This no-fuel, no-emissions source of electricity is a relatively new addition to the electrical grid and behaves differently than previous methods of generating power. One major difference is that it is non-dispatchable. This means that it is not turned 'on' or 'off' by an operator. This major drawback of solar photovoltaic power makes its installation on the electrical grid complicated. As solar PV becomes a more important source of power, research into how to add it to the grid in a safe and reliable manner becomes essential.

Solar power offers a significant opportunity for a low-emission, yet substantial, source of energy. Compared to other renewable sources, solar is energy dense in terms of power output per unit of land exploited. On average, it produces between 10-20 W/m^2. This compares to other renewables favorably, with biofuels producing around 1W/m^2 and wind less than 1 W/m^2.[1] This energy density shows that solar is

[1] Keith, David. 2015.

a viable option to produce large amounts of energy in the future. On average, each square meter of the United States receives roughly 5 kWh of solar radiation per day. In the Southwest these values can be over 6.5 kWh/m^2; in the Pacific Northwest and Northeast they can be as low as 3.75 kWh/m^2 per day.[2] To put this in perspective, the average US home used 30 kWh of electricity per day in 2014. [3] Using the US average of 5 kWh/m^2 of solar energy received per unit land area and a hypothetical solar photovoltaic efficiency of 15%, it would only take 40,000 km^2 of land (1/2 of the size of South Carolina) to provide the entirety of the United States' energy over the course of a year. Thus, solar energy has the potential to power the country in the future.

Solar photovoltaic technology is experiencing explosive growth in the United States. In 2010, 850 MW of solar photovoltaic capacity was installed in the United States. In 2014, this increased by 650% to 6212 MW of capacity being installed.[4] The newly installed capacity of over 6 GW was split between residential, commercial, and utility systems. The majority of installed capacity came from utility-scale solar PV systems. One reason for this explosive growth is dramatically falling prices for PV systems. Since 1998, prices have fallen 6-8% per year for solar photovoltaic modules. This translates into a drop from $12/Watt installed in 1998 to under $4/W installed today.[5] Solar is beginning to make a significant impact on the electricity landscape of the United States.

[2] United States Photovoltaic Solar Resource: Flat Plate Tilted at Latitude
[3] How Much Electricity Does an American Home Use?
[4] SEIA Market Insight Report 2015
[5] Feldman *et al.* 2014

Solar photovoltaic power generation represents a departure from the typical way electricity is generated. Historically, power is produced in a few large power plants and distributed throughout the electrical grid. These power plants can be turned on and off and have their power output controlled. In contrast, solar power can be distributed, or spread out in small systems throughout the grid. More importantly, it cannot be controlled by human operators. Electricity produced by solar is “must-take”, meaning that whatever is produced must be used. This poses a significant and major change from the historical generation of electricity. Since solar is becoming a larger factor in US electricity supply, the importance of investigating these differences between solar and other power sources, as well as putting an effective plan in place for its use, has significantly increased.

Although solar photovoltaic power is a promising energy source, it has two major problems: 1) it only works during the daytime and 2) its power output during the day can be variable. There is notable concern over the solar ‘duck curve’. The ‘duck curve’ is the name for the hypothetical electrical load profile that would occur with a high level of solar penetration (seen in figure I below). Large amounts of power produced during the day from solar panels would cause a large dip in power required from conventional generation. Then, as the sun went down, a massive ramp up of conventional generation would be required to meet demand. This problem is currently being studied to a great extent. Variation in solar power output during the day is also important. Power output can vary on short timescales and this can pose problems for grid operators as this source of electricity is not steady. However, not as much research has gone into daytime volatility and very little has gone into short-term volatility. This important problem requires more research, especially as the amount of solar photovoltaic capacity increases on the grid.

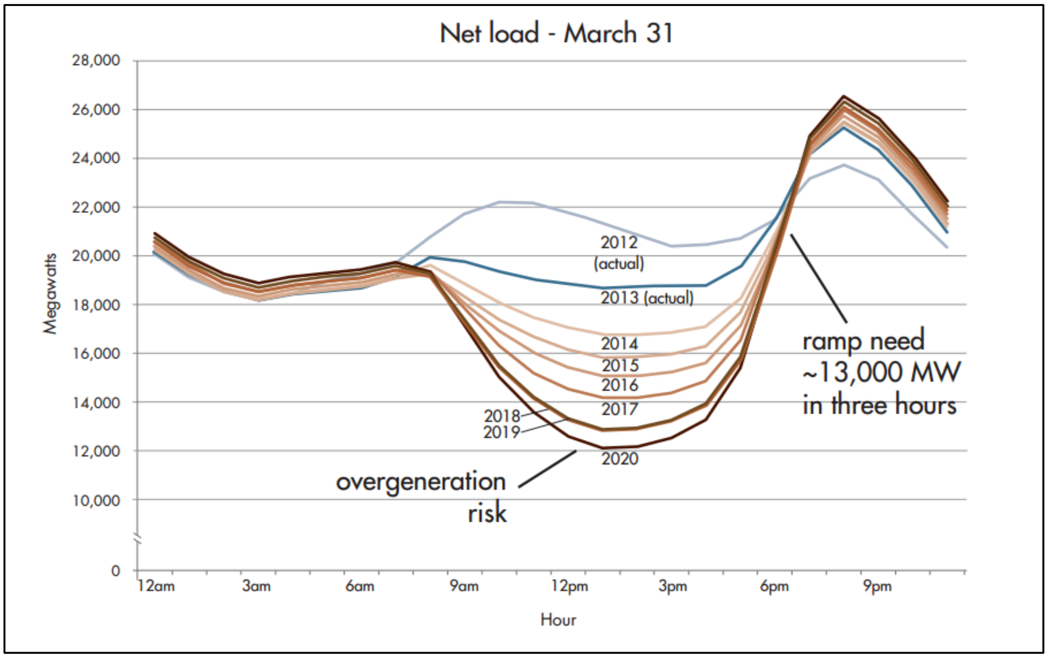

Figure I | Hypothetical 'Duck Curve' projected by California ISO[6]
This figure shows the projected load on a typical day in March for the California electrical grid over various years. The large dip occurring in the middle is due to solar power production, which reaches its peak just after noon. This graph is emphasizing the steep 'ramp up' period that utilities may have to deal with if a large amount of solar is added to the grid. This 'ramp up' period occurs because the sun is setting so solar power is dropping at the same time people are arriving home from work and using large amounts of electricity.

Short Term Volatility of Solar Power

Short term solar power volatility is the fluctuation of power output over short timescales. These short timescales range from being measured as an hour in length to as short as being measured in seconds; the discrepancy usually occurs due

[6] California ISO, 2013.

to the data resolution available. It is important to note that short term volatility does not have to do with day-night cycles. In other words, it is not the variation that occurs as the sun rises and sets. Short term volatility is unpredictable and the major factor in its creation is clouds. Clouds have their greatest effect during partly cloudy days when the clouds are cumulus in nature. These large, puffy clouds tend to cause deep shadows and are sporadically placed in an otherwise sunny sky. Figure II shows a partly cloudy day in May 2015 that is a prime example of how drastic the fluctuations in incoming solar radiation can be.

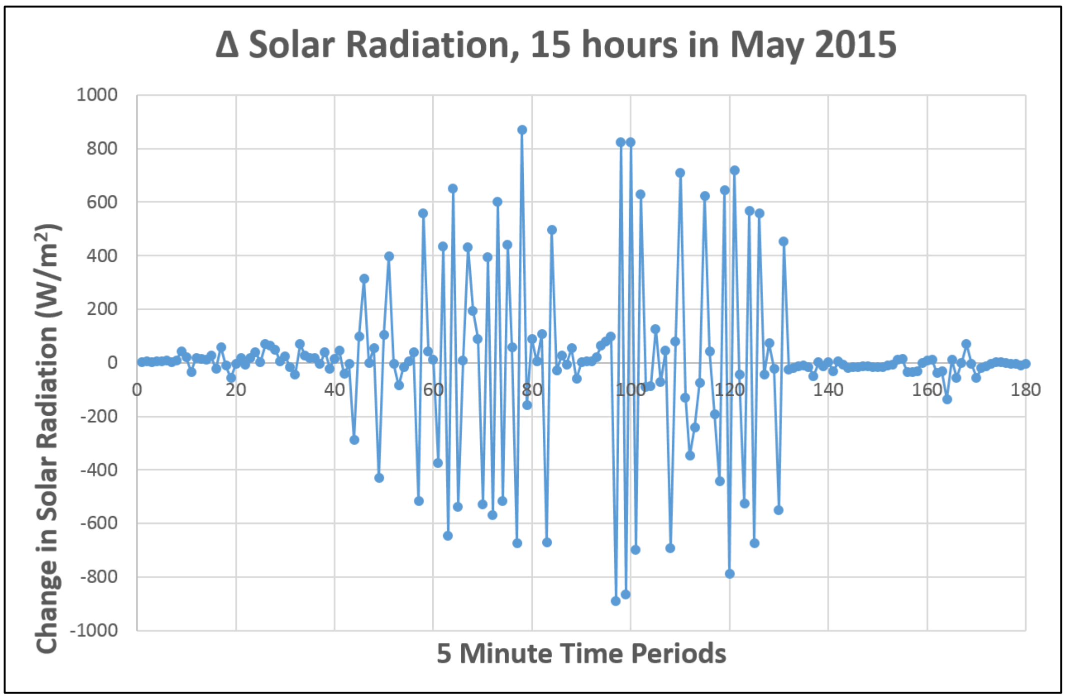

Figure II | Solar radiation fluctuations during one day in May 2015
This figure shows the change in solar radiation reaching the ground in Cambridge in May 2015. The large magnitude, as well as high frequency, of the fluctuations demonstrates the ability of solar radiation to be variable.

Currently, there is not much research that has been done in short term solar power volatility. However, there are a few papers that explore this topic using short term timescales. In one study, Tomson and Tamm used 1-minute timescale solar radiation data in Estonia. They concluded that radiation variability is especially important in global regions that are prone to cyclonic activity. They found that there was a small amount of variability from high clouds and very little variability from low rain clouds. After statistical analysis, they determined that a one-minute change of < 50 W/m^2 during sunny days and < 150 W/m^2 during cloudy days could be considered stable.[7] Another paper by Tomson used one second sampling to see how clouds affected solar radiation. This was again conducted in Estonia. This research was focused more heavily on clouds rather than solar radiation and found that visual recognition of cloud types can be used to estimate variability.[8]

Another study by Mohrail and Kukarni analyzed short-term variability in India. However, this study used a timescale of one hour and models to study variability rather than using real data from sub-hour timescales.[9] An interesting paper by Tarroja, Mueller, and Samuelsen looked at how special distribution of solar photovoltaic arrays can affect short-term variability. They utilized 5 minute data from the Pacific Northwest to investigate their question. They concluded that geographic variation can help with short term variability significantly. In other words, more solar PV sites spread out over a larger area had less total volatility than one large system.[10]

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[7] Tomson and Tamm, 2005.
[8] Tomson, 2009.
[9] Moharil and Kulkarni, 2010.

[10] Tarroja, Mueller, and Samuelsen, 2012.

Overall, short term volatility in solar photovoltaic power is an important topic that has received some research attention but not as much as it should have received. As solar capacity increases, short term variability of solar power will only become more important. More research is required to fully understand how much solar power can vary on short timescales and what effect, if any, this would have on the operation of the electrical grid.

Why Short Term Variability of Solar Power Matters

Research into short term volatility is important because of the way the electrical grid operates. Supply must meet demand on the grid. This is difficult enough with dispatchable energy sources and gets more complicated as more non-dispatchable sources are added. Short term solar volatility is especially important because of how the system currently manages volatility. Utility operators manage variability with a system of reserve generation capacity. Generation capacity known as 'spinning reserves' are synchronized to the system and can respond quickly to changes in electrical demand.[11] However, spinning reserves are expensive both economically and environmentally. They are turbines that are running and utilizing energy but producing nothing useful in return. Put another way, spinning reserves are power plants (or single turbines) that are operating but not producing power. This makes them expensive to operate and they also produce atmospheric emissions of greenhouse gasses and other pollutants. Spinning

[11] Milligan *et al*. 2010

reserves are the piece of the electrical grid that would be most affected by short term volatility in power generated by solar photovoltaics.

Short term volatility research is also important from an energy policy perspective. Small scale solar installations can use what is called net-metering. Net metering allows for electricity consumers to produce their own electricity to offset their overall electricity usage. A net meter will spin forward when a customer is using electricity from the grid and spin backwards when their method of generating electricity is producing excess electricity. Thus, the customer would only be charged for their 'net' electrical usage from the grid.[12] Net metering is important for solar photovoltaics because many residential and commercial users of PV arrays use this method to maintain a constant, quality supply of electricity. However, many states have capped the amount of net metering that is allowed within the grid system. Half of states that allow net metering also have caps, including Massachusetts. Explosive growth in PV capacity could cause several states to reach their capacity by 2018. [13] One reason for the cap is the volatility that panels introduce into the system. Thus, further research into this volatility will provide better information on how to manage net metering in the future.

[12] CMR 220, 2014.
[13] Heeter, Gelman, and Bird, 2014.

Exploring Changing Solar Resources due to Climate Change

Another important factor in the future of solar power is how climate change will affect solar resources over the coming century. Solar energy resources are inherently susceptible to being affected by weather patterns. The more sunny a location is, the better suited it is for a solar photovoltaic system. An example of a prime location for solar photovoltaic arrays is the Southwestern United States. The Southwest has a dry climate and is drenched in sunlight. However, climate change will change weather patterns over the next century. Since solar photovoltaic arrays cannot be easily moved after being built and full exploitation of this resource will require a tremendous investment in long-term infrastructure, it is important to see how solar resources will change over the coming decades.

Solar radiation can come in two main forms, direct or indirect. The first, direct solar radiation, is light that is coming in a 'beam' from the sun. The second form, diffuse radiation, is light that is scattered by particles in the atmosphere and does not come from the direction of the sun. Solar photovoltaic panels accept both direct and diffuse radiation to produce electricity.[14] The only measure that matters for a photovoltaic panel is the total energy of the radiation reaching the surface of the panel. While a panel does not discriminate between direct and indirect radiation, the placement of the panel can have an effect on how much diffuse radiation is reaching the surface. The amount of diffuse radiation reaching the surface depends on how much of the sky the panel is exposed to. For example, a flat panel will see

[14] Bhatia, 2014.

all of the sky and will receive the full amount of indirect radiation. Tilting the panel by 45 degrees reduces the amount of the sky the panel sees by half, which reduces the amount of indirect radiation reaching the panel by half. [15] However, direct radiation is more valuable to photovoltaic panels than indirect radiation because it is typically much stronger. Tilting panels to receive more direct radiation from the sun will generally outweigh the loss of indirect radiation from seeing less of the sky. While both forms of radiation matter to the power production of solar photovoltaic panels, direct radiation is more important.

As mentioned earlier, clouds have a significant impact on how well an area is suited for solar PV systems. Clouds block sunlight that would otherwise reach the ground. Additionally, reflected or diffused radiation is not as valuable to solar photovoltaics as is radiation from a clear sky. Related to clouds' effect on radiation are aerosols. Aerosols are tiny particles that are suspended in the air of the atmosphere.[16] They can scatter radiation directly or influence the formation of clouds. Clouds and aerosols stand to be affected by climate change and there is research available into this topic that will be reviewed.

One tool that can be used to analyze changing solar resources is a global climate model (GCM). Global climate models utilize numerical methods to represent physical processes in the climate system.[17] GCMs can be run with different greenhouse gas emission scenarios which allows for studying multiple situations in an uncertain future. These models use a grid across the Earth to depict

[15] Masters, 2004.
[16] Allen, 1996.
[17] IPCC, 2013.

what will happen in each individual area. This allows for the effects of climate change to be analyzed on a more local level. Global climate models are not perfect and carry uncertainty but are a useful tool for examining how the future of Earth's climate might behave. In particular, GCM data can be used to see how solar resources can change over the next century.

Project Overview

My project focuses on analyzing solar photovoltaic technology. It has three main parts:

1. Determine the significance of short term volatility.
2. Explore mitigation techniques for short term volatility.
3. Examine how climate change can possibly affect solar resources over the coming century.

Determining the significance of short term volatility means analyzing whether or not solar photovoltaic power can fluctuate enough in short time scales to effect power generation quality. This part will focus on how much hypothetical arrays can change on short time scales, specifically in the Northeastern United States. After determining its significance, mitigation methods for short term volatility and their effectiveness will be examined. A hypothetical system in the form of a mathematical model will be created to minimize the amount of volatility that occurs within the power production of the photovoltaic system. Finally, there will be a literature review of how clouds and aerosols are expected to change throughout the century. In addition to the literature review, global climate model data will be analyzed to better answer the question of how solar resources in the United States will be affected by climate change.

CHAPTER 1 – Significance of Short Term Volatility of Solar Power

The goal of this chapter is to determine if short term variability from solar photovoltaic power is large enough in magnitude and frequency to be considered significant. To determine whether or not short term solar power variability is significant, a year's worth of data from a weather station was collected and analyzed. Using a model, weather station data could be translated into power output data and the difference in power output between each five-minute timestep could be calculated. The difference in power output at these timescales is the short term variability in the system. The larger and more frequent the fluctuations, the more variability there is in the system.

For a narrower focus on how short term solar power variability could affect a microgrid, the second part of the significance analysis adds in electrical demand data from a microgrid on Harvard's campus. By adding in demand, two goals are accomplished: 1) solar variability could be placed in the context of a real microgrid and 2) it could be determined whether or not demand variability would help to mitigate or exacerbate solar power fluctuations.

1.1 Methods

1.1.1 Data Collection

To answer the question of whether or not short term variability of solar power is significant, weather and electrical demand data was acquired, cleaned, prepared and analyzed.

The first dataset analyzed consisted of weather data collected on five minute timescales. The weather data was collected from the top of Gund Hall, a building in the Harvard Graduate School of Design in Cambridge, Massachusetts. To collect this data, a HOBO U30 Weather Station[18] with Wifi link was used. The HOBO U30 measured temperature data by itself. However, for solar radiation intensity, a solar pyranometer (model S-LIB-M003) was used in conjunction with the HOBO U30 station. Using this station, weather data was collected from June 2014 – December 2014 (this experiment known as 'Experiment 2') and from February 2015 – July 2015 (this dataset known as 'Experiment 4'). Solar radiation intensity was measured in watts per meter squared. Temperature was recorded in degrees Celsius.

The second dataset utilized in the study was electrical demand data from Harvard's campus. In conjunction with the weather station data from Harvard's campus, the electrical demand data would provide the necessary components to study how a solar array's power volatility could affect the Harvard microgrid. The electrical demand data was provided by Robert Manning, Director of Energy and Utilities for Harvard. The demand data was collected at the six substations serving

[18] HOBO U30-NRC Weather Station Starter Kit

Harvard. Each substation connects to a different microgrid. The stations that data were collected from were CUP, Gutman, Hilles, Holyoke, McCollum, and Northwest. Demand data is given in the total amount of kilowatts that the substation is drawing from the overall electrical grid at the given time. The timescale of the data provided is 5 minutes. Data was provided for the period July 2014 – July 2015.

1.1.2 Data Organization and Cleaning

For more precise resolution when analyzing the significance of variability, each dataset was split into parts by being separated by month. This data was stored and organized using Microsoft Excel. It is also important to note that the datasets were not perfect. For some timestamps, there was an error in one of the various sensors collecting the data. To remedy this situation and allow for the effective use of modeling, the missing piece of data was filled in by averaging the values of 5 minutes pre- and post-error. This small amount of data cleaning was insignificant when compared to the amount of data points that were analyzed and were only used to allow for more effective and efficient modeling.

1.1.3 Solar Variability Model

In order to effectively study the power production of solar panels without any solar power production data, a model was required to convert solar radiation and temperature data into hypothetical power output. The PVWatts[19] Module Model was used for this study. Its parameters are given below:

$$P(t)\begin{cases}\dfrac{I(t)}{1000}\times A_{std}\times\left[1+\gamma\left(T_{panel}-T_{std}\right)\right], & I(t)\geq 80\\ \dfrac{0.008\times I(t)^2}{1000}\times A_{std}\times\left[1+\gamma\left(T_{panel}-T_{std}\right)\right], & I(t)<80\end{cases}$$

Overall, this model converts temperature and insolation data into power output from a given solar array. Power, *P(t)* , is the electrical power being produced at time *t*. *I(t)* is the insolation at time *t,* which is given by the dataset. A_{std} refers to the solar panel array size, or the rated maximum power output of the array (ie 100kW). γ is a constant value known as the temperature coefficient, which is fixed at -0.5 % per degree Celsius.[20] T_{panel} and T_{std} refer to different temperatures that are associated with the model and will be discussed further in the following paragraph. Depending on the overall insolation, one of two equations will be used. This discrepancy comes from the way solar photovoltaic modules behave at low levels of insolation. Overall, this model represents a way to convert weather station data to hypothetical power output in an accurate manner.

The temperature variables in the PVWatts model are integral to the accuracy of the model. T_{std} refers to the Standard Test Condition (STC) of temperature for solar panels. This standard temperature is 25° Celsius and remains constant throughout the entirety of the analysis. T_{panel} refers to the temperature of the solar

[19] Dobos, 2013.
[20] Dobos, 2013.

cell itself and is more complicated. NASA's Jet Propulsion Laboratory created a model[21] used to solve for cell temperature:

$$T_{panel} = T_{air} + \frac{NOCT-20}{800} \times I(t)$$

This equation relates the cell temperature of the solar panel to the air temperature, a value known as NOCT, and solar insolation. The air temperature and insolation value, provided by the weather station dataset, is used at each time step. NOCT refers to Nominal Cell Operating Temperature and is a value that provides a means to describe a solar panel's thermal properties and their effects on power outputs. For this model, a NOCT of 48°C was used because it provided an average baseline[22] that would serve well in a hypothetical array simulation.

1.1.4 Solar Variability Significance Analysis – Only Examining Solar Data

The first significance analysis consisted of examining how much solar power output could vary on short timescales throughout the year. For this part of the analysis, only the weather station data and solar power model were used. This section will isolate solar variability while later analyses will take electricity demand fluctuations into account. A Python script, using the PVWatts model, found the hypothetical power produced at each time step. This script also found the difference between the power productions at each time step and recorded it. This value, the difference in power at time t and $t+1$, represents the amount of variability produced by the solar array. The chosen array size does not matter as it is linearly proportional

[21] Ross, 1981.
[22] Muller, 2010.

to the output power of the model. However, for the purposes of this study, it was set at 100kW.

1.1.5 Solar Variability Significance Analysis – Adding Demand Data into the Model

The second analysis of short term solar variability adds a new variable to the model: electricity demand of a microgrid. The microgrid used in this analysis is made up of the Harvard Business School as well as Harvard Athletics facilities. McCollum substation is the interconnect between this microgrid and the wider electrical grid. McCollum also serves as the station where electricity demand for the grid was measured. A map of the microgrid can be seen below:

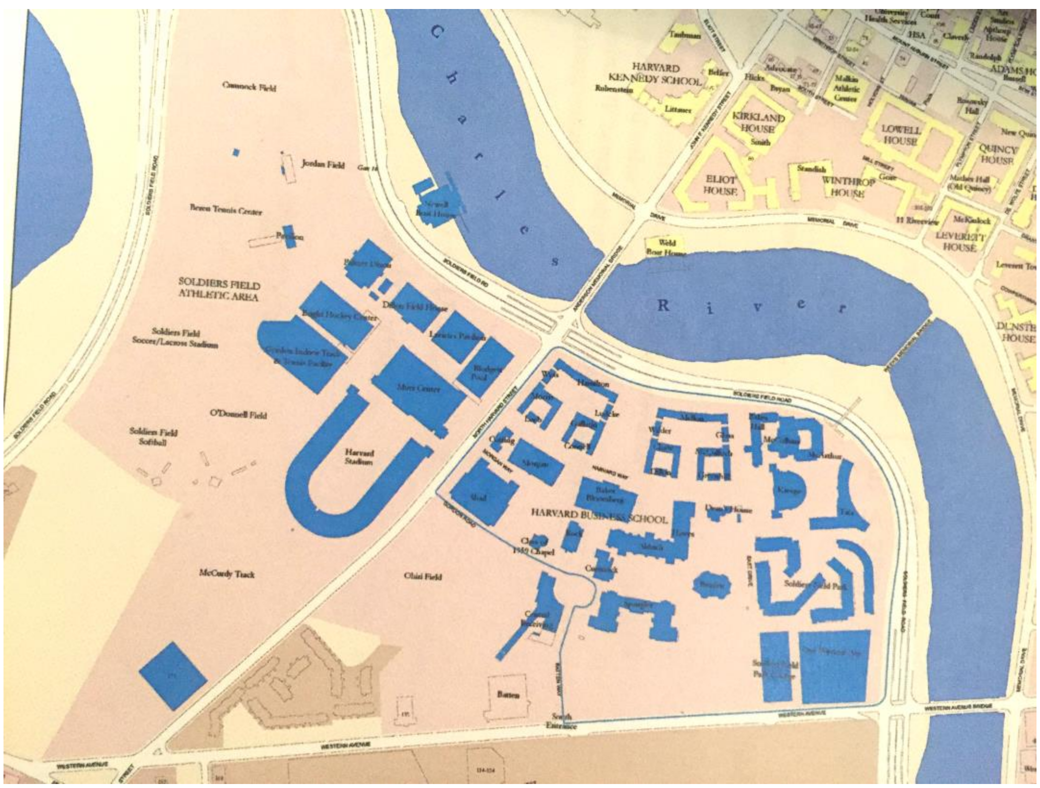


Figure 1.1 | Map of the Harvard microgrid served by McCollum Substation
The buildings included in the microgrid are a dark blue color. The microgrid serves Harvard Business School as well as the athletic complexes in Allston.

Looking at an entire microgrid's demand introduces a new variable into the significance question. Now, rather than solar variability itself being studied, the interesting value is how much power the microdgrid requires from the outside electrical grid at a given time. The changes in the electricity pulled from the outside grid are the interesting value because they represent the stress created on the overall grid by the variability in the microgrid. This value is given as ΔG.

1.1.6 Computer Modeling of Solar Variability

A Python script was used to model the data in terms of ΔG. This script first loops through all of the demand data to find the change in demand for each time step. It then makes two new columns where ΔDemand is added and subtracted to the ΔG_{max} constraint found earlier. These two columns are necessary because the maximum solar change is limited differently depending on how demand is growing or shrinking in the 5 minute timespan. For example, a growth in demand would allow PV output to grow *more* in that time period, hence an addition. If demand fell but PV grew, it could grow *less* because more electricity would be added to the grid, again leading to the addition column because of the way ΔDemand is added to ΔG. See table 1 for more information on the cases. This now provided a framework to see how much solar could be produced in each case, again depending on ΔDemand and ΔPV.

Next, the model uses the temperature and insolation data to calculate the power output at time *t* of a 1 kW array. Then, it finds the difference in output between each PV(t) and puts it in a different column as Δ PV. Next, according to the logic table, the maximum Δ PV is calculated and the array size to create this Δ PV is calculated and stored in another column. Since array size is linearly proportional to power output, the maximum array size is calculated by dividing Δ PV by the power output of the 1 kW array. The output of this division is the number of 1 kW arrays that can exist and still have volatility remain under the given threshold. The minimum of this maximum column was found manually and was the largest array size that could exist in the system to remain within the constraints given. Additionally, the 5th percentile of the arrays (in terms of size) was used to see the differences between the absolute largest array and the largest possible provided looser constraints.

ΔPV positive	ΔD positive	Solar can increase *more*, use addition column
ΔPV positive	ΔD negative	Solar can increase *less,* use addition column
ΔPV negative	ΔD positive	Solar can decrease *less,* use subtraction column
ΔPV negative	ΔD negative	Solar can decrease *more*, use subtraction column

Table 1.1 | Logic for Python code to figure out correct ΔG, ΔD, ΔPV signs
The logic of this table was used to determine the correct function of the model. In essence, it tells the model what to do for every situation that can be encountered. The columns referred to in the table are from the solar dataset. The addition column refers to ΔD being added to ΔPV to determine the constraint at the given timestep. The subtraction column refers to ΔPV being subtracted from ΔD. How the model remains within the constraint is determined by the absolute values of these additions or subtractions remaining below the constraint.

1.2 Results

1.2.1 Absolute Changes in a Model Array

The results of the significance analysis that focused on the solar variable showed variability that was large in magnitude as well as frequency. This section explores the variability of solar power production over the course of one year in the Northeastern United States. In particular, this section analyzes the data from the weather station at Gund Hall on Harvard's campus. The results focus only on how much solar power itself can vary; there are no other variables being considered. The purpose of this initial data analysis is to isolate the amount that solar photovoltaic power can vary on short timescales. Later sections will introduce other variables to see if the variability of those quantities effects the overall microgrid system.

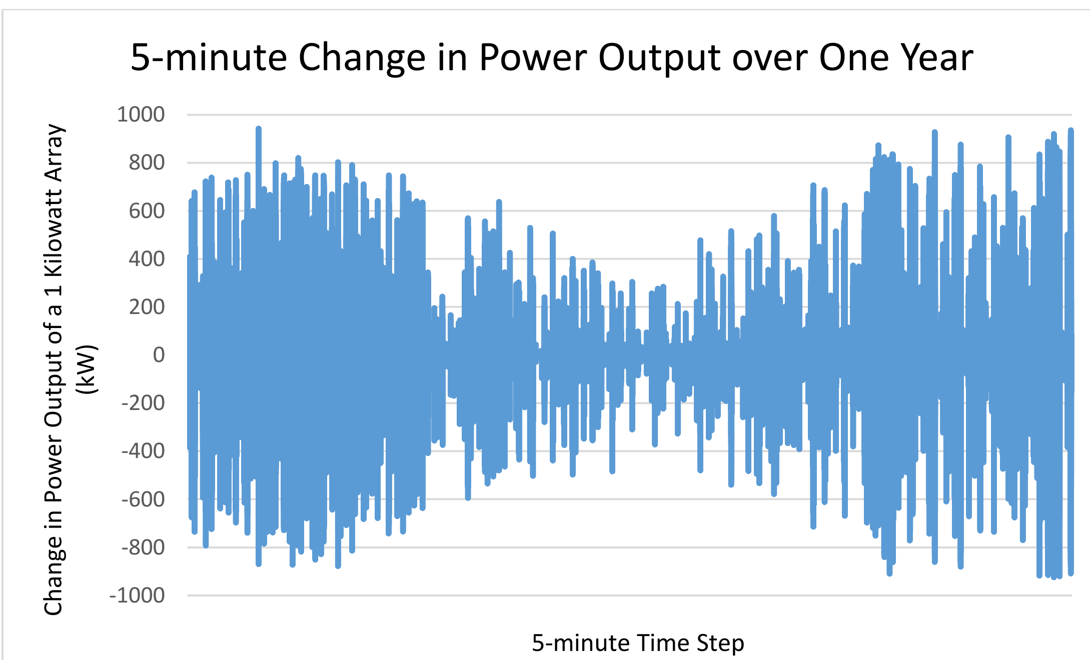


Figure 1.2 | Fluctuations of a solar panel array over one year
This plots the data points taken over the 2014-2015 year and shows the difference in power output at each 5 minute timestep.

This figure shows the variability of solar power output over one year for each 5 minute timestep. Solar radiation and temperature data were used with a model to determine the amount of power output of a hypothetical 1 kilowatt array at each time. To determine the variability, the difference between each power output was plotted. The left-hand side of the graph marks June 2014 and the right-hand side is the data from July 2015. In between the data from every month except January 2015 is plotted.

Overall, this graph shows that there is a significant amount of variability within the system. The magnitude of the largest changes in power output is large and the frequency of these large changes in power output is considerable. The other interesting part of this graph is that there is positive and negative variability. There are relatively equal instances of power output jumping or falling drastically within a 5 minute time period.

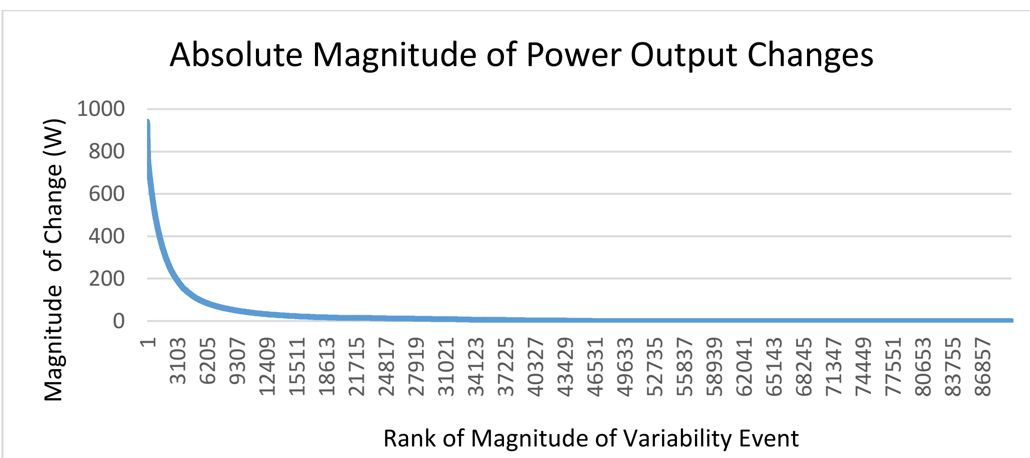
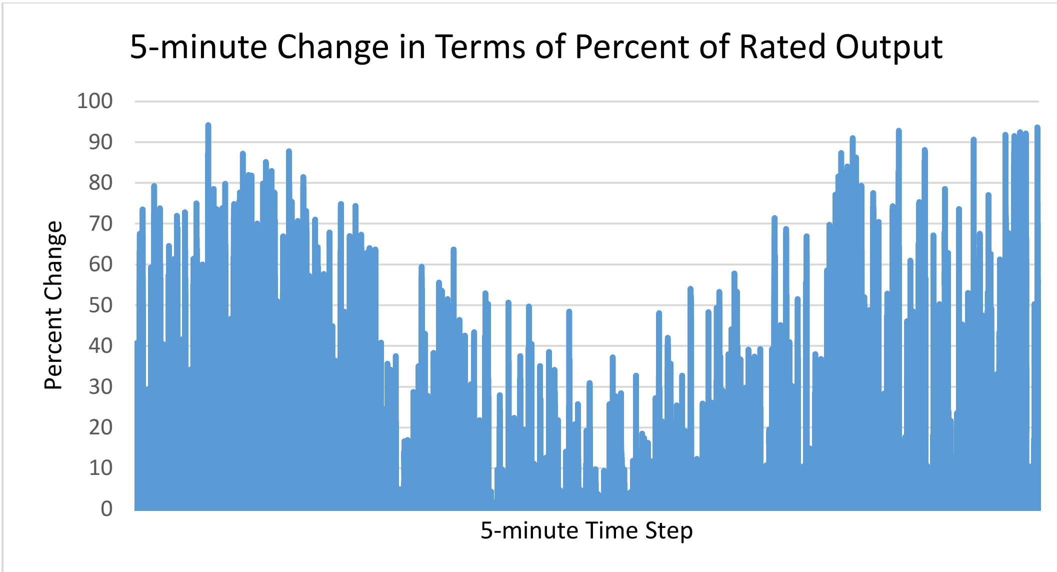


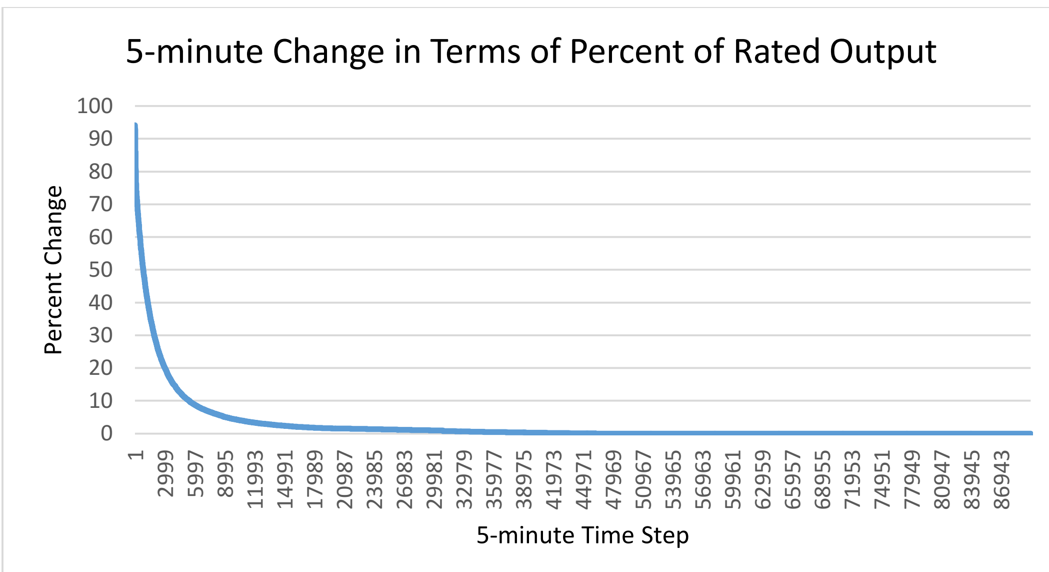
Figure 1.3 | Power output changes
The changes in power output were ordered from greatest to least and then plotted to show the relative amounts of each power output change. As night time data was also used in this analysis, about half of the tail of 0 output change can be accounted for due to the lack of sunlight during the night.

To get a better sense of the frequency of variability events as compared to their magnitude, the above figure plots the absolute magnitude of each change in power output. The magnitudes were ordered from greatest to least. This gives a sense of how frequent large variability events occur. From the graph, it is apparent that events with large magnitude are relatively rare. The plot drops off drastically in a 'hockey-stick' fashion. Most of the time, there is little to no variability at all. It is important to note, however, that for roughly half the time there will be no variability because it will be night time. Additionally, the magnitude of power output was plotted in terms of Watts rather than relative change to capture the scale of how large the variability can be. In other words, a 100% change in output over 5 minutes is not significant if the power being produced was only 50W in a one kilowatt system. A smaller relative change may have a larger magnitude, and thus would be more important, if a large amount of power was being produced at that given time.

The important conclusion to draw from this graph is that variability events with large magnitudes do happen. However, their quantity is not overwhelming, as seen by the considerable drop in the graph. In an absolute sense, there are a good amount of variability events with a large magnitude. On the other hand, in a relative sense, the frequency is not as large. Overall, there are a substantial number of high variability events but the inverse relationship between magnitude of variability and frequency is strong.

1.2.2 Proportional Changes in a Model Array





Figures 1.4 and 1.5 | Relative change in power output
These graphs show the change in power output in terms of a percentage of the size of the array. By showing the data in this manner, the analysis can be applied different array sizes than the standard 1 kilowatt used earlier.

The next set of graphs translates the absolute data from the model run into relative numbers based on array size and shows that panels can be expected to have short term variability events on the order of 95% of their rated maximum power output. By looking at changes in power output as a percentage of array size, these charts are more applicable to looking at a general case. From these values, one would be able to infer the variability that would occur in power output for any reasonable array size. An estimate could be made of how much raw volatility, in terms of Watts, would be introduced into a system by adding a solar photovoltaic array of any size. The relationships outlined in the absolute magnitude figures hold here; the general trend of events of significant occurring with a strong inverse relationship to frequency holds.

1.2.3 Analyzing Monthly Distributions of Variability

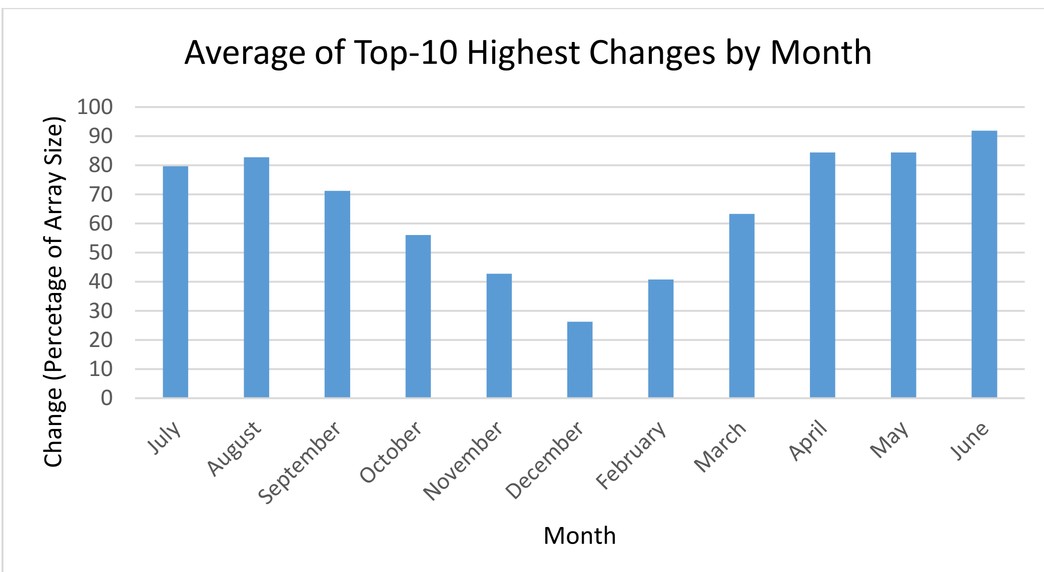


Figure 1.6 | Maximum power output changes by month
The average of the top 10 power output changes was taken for each month and plotted here. Notice the seasonal variability with winter having the lowest power output volatility.

Solar variability has a strong seasonal relationship; it is at its minimum in the winter and peaks in the late spring and early autumn. When split into monthly timescales, an interesting trend emerges. This graph shows the average of the top ten highest variability events for each month. The average of the top ten was taken to capture the magnitude of the maximum amount of variability one could expect. The average helps to eliminate the effect of any one outlier having too much of an effect on the results.

There is a clear trend between season and variability. Summer months experience the highest level of variability, with power output being able to vary over 80% of the maximum array size. The maximum variability falls off sharply, however, as the transition to winter occurs. In December, the month with the lowest variability, the *maximum* amount of variability the system experienced was less than 30% of its rated output. Compared to the summer months, this is a significant drop in the amount of variability the same system can experience over a yearly timespan. Reasons for this strong seasonal dependence will be explored further in the discussion section.

1.2.4 Adding Demand to the Model

The next part of the significance analysis section introduces another variable, electrical demand, into the model of power volatility within a system with a solar photovoltaic array and found that the variability of the system only increased with this additional variable. The system is the microgrid serviced by McCollum

Substation (see figure 1.1). By adding demand data, the variability analysis shifts solely from solar power output to the variability of the grid's input of power into the system. In other words, the subject is now a microgrid system and its power demand rather than strictly a photovoltaic array and its power output. By modeling the microgrid with a hypothetical solar photovoltaic array, a better estimate of the strain the system puts on the electrical grid can be made. At each moment, the overall electrical grid must input enough power into the microgrid to perfectly match demand. However, demand alone can vary, which introduces a small amount of stress into the system. When one adds a photovoltaic array to the system, the effective demand that the overall grid sees changes. This is because the power produced by the photovoltaic array will meet demand within the microgrid system first, which changes the amount of electricity the overall grid would have to input into the system.

Rather than looking at the raw amount of variability that a solar photovoltaic array introduces into the microgrid, a new measure was used to explore the significance of the volatility introduced by the solar power system. For part of this analysis, the output of the model was the largest solar array that could exist within the system if given a certain volatility constraint. The larger the solar array, the larger the amount of variability in the system. The constraint is on the 5-minute change in the amount of power the overall grid must input into the microgrid. At each time, solar array output, microgrid demand, and electrical grid power input must match. Within this system, the constraint was placed on the amount the input power from the electrical grid can vary. As a general rule, the smaller the array that can exist within the system, the larger the amount of solar volatility.

Month	**18%**	**24%**	**30%**	**36%**	**1500 kW**
July	1478	2147	2722	3279	2086
August	1195	1701	2207	2713	1972
September	1560	2291	2963	3637	2073
October	1342	2047	2732	3460	2425
November	1886	2584	3280	3951	3154
December	2049	2892	3609	4388	3861
February	2030	2647	3262	3881	3272
March	1098	1549	2002	2454	2093
April	844	1270	1696	2120	1635
May	1305	1837	2354	2810	2056
June	1109	1529	1948	2367	1801
Minimum	*844*	*1270*	*1696*	*2120*	*1635*

Table 1.2 | Short Term variability model results
The top row refers to the constraint given to the model for that specific run. The percentage refers to the percentage of maximum demand, given in kW, that was used as the constraint.

The above table shows the results of five different model runs using different constraints. For four of the runs, the constraint was determined by taking a percentage of the maximum electricity demand for the given month. For example, '18% July' had its constraint given by finding the maximum demand of McCollum substation in July and taking 18% of that. The last column, '1500kW', had a hard constraint of 1500 kW given for each month when the model was run. *Minimum* refers to the largest photovoltaic array size that could exist within the system under the strictest constraint. In other words, it is the maximum array size that could be in the system to remain within the given constraints for the entire year. The values of the table are the hypothetical array sizes in the system given in kilowatts.

1.2.5 Model Results under a Fixed Constraint

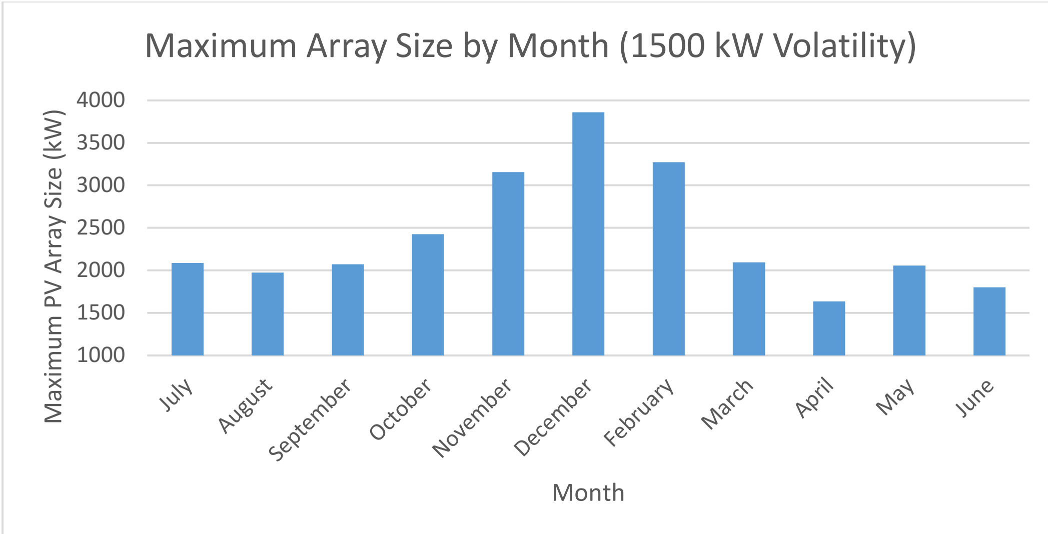


Figure 1.7 | Model results by month, fixed constraint
The maximum array size that could exist in the system while still meeting the constraints given (in this case, 1500 kW variability) is plotted. Note the strong seasonal effect on variability.

The above graph shows the largest array size that would remain within a hard constraint of 1500 kW variability. The 1500 kW represents a 5-minute change of the electrical grid having to supply 1500 kW more or less electricity to the McCollum microgrid. The hard constraint of 1500 kW was applied equally to each month when the model was run. The larger the maximum size of the array for each month, the smaller the amount of variability that occurred. As noted earlier, this variability takes into account both fluctuations in solar power output as well as demand fluctuations from the buildings within the McCollum microgrid.

There is a strong seasonal dependence visible in this graph. Winter months experienced the lowest amount of variability and thus had the largest array size that could remain within the 1500 kW constraint. This matches with the earlier analysis that focused strictly on solar power output without factoring in demand. In particular, April is interesting. It has the smallest maximum array size out of any month.

1.2.6 Model Results under a Variable Constraint

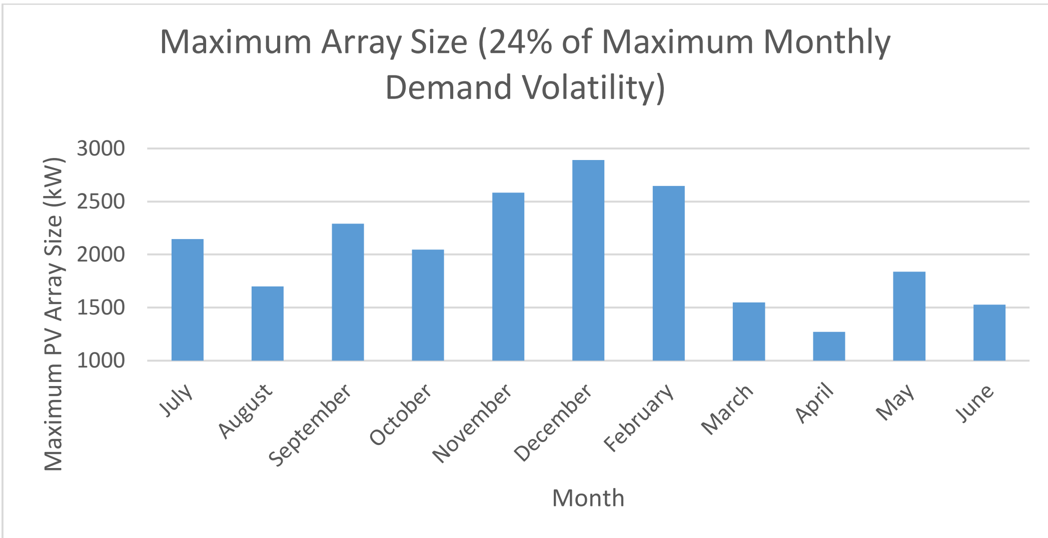


Figure 1.8 | Model results by month, variable constraint
The maximum array size that could exist in the system while still meeting the constraints given is plotted. The constraint for this model run varied by month and was set to 24% of the maximum electrical demand reached during that month.

Rather than using a constant 1500 kW constraint, this graph shows the results of using the model with varied constraints for each month. Rather than a blanket constraint given over the year, the variability constraint was determined as a percentage of maximum demand for each individual month. This has the effect of matching the variability the system is constrained by with the amount of power flowing through the system itself. Months with higher demand, namely the summer, would have larger variability constraints. This leads to the seasonal effect being not quite as drastic as the hard 1500 kW constraint for every month. There is still a seasonal dependence; however the correlation is not nearly as strong.

1.2.7 Demand Increases Total Volatility in the System

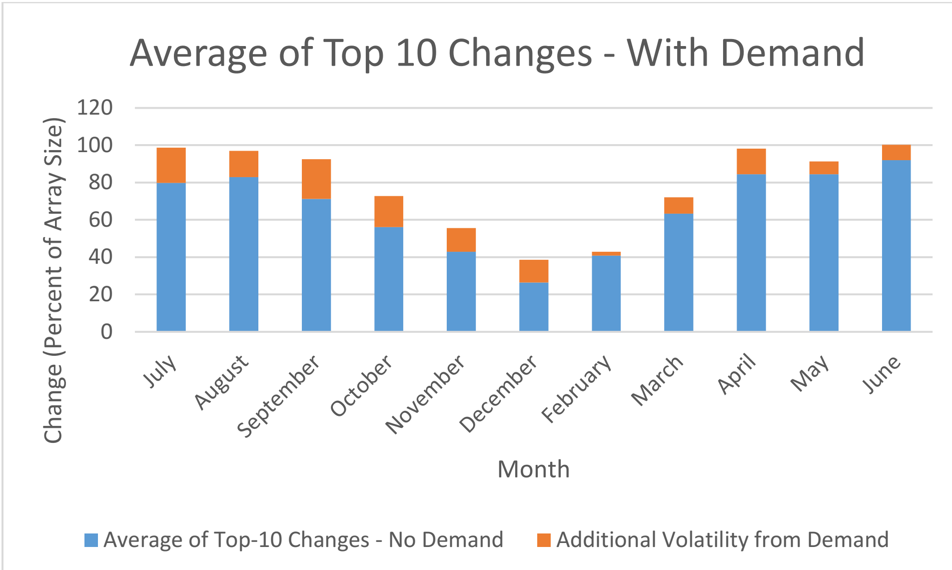


Figure 1.9 | Demand and solar variability
This graph shows the average of the top-10 variations in the system for each month. The important piece of this graph is that demand variability always increases the total variability the system experiences. In no month does demand variability help to cancel solar variability.

Adding demand data to the model resulted in an increase in system variability in every month. This graph plots the average of the top-10 variability events in the system by month. Unlike the earlier graph, this includes fluctuations in demand rather than solely solar fluctuations. In every month, the magnitude of the variability events actually increased. The blue bar represents the variability as seen by solar only. The orange bar is the increase in variability the system saw when demand was introduced into the model. In no months did random variability in demand cancel out variability introduced by a hypothetical solar array.

1.3 Discussion

1.3.1 Importance of Short Term Variability

Short term variability of solar power matters because as more solar is installed on the electrical grid, the greater the effect variability can have on the infrastructure of the grid. Currently, over 22 gigawatts of solar capacity exist in the United States. This capacity is expected to double in the next two years.[23] Thus, solar is beginning to have an impact on the makeup of the electrical grid. As solar is a non-dispatchable power source, there are challenges when adding solar photovoltaic capacity to the grid. One such problem is the so called 'duck-curve' where the diurnal cycle of the sun combines with the typical electrical demand curve to produce large ramp-up or ramp-down times for conventional power plants. In other words, when the sun goes down in the late afternoon and solar power goes offline, demand must be met quickly by conventional power sources. However, while important, the 'duck-curve' has received a tremendous amount of research. There exists another problem: solar fluctuations on short timescales. As supply must always meet demand on the electrical grid, short term fluctuations would have an impact. If the magnitude of the fluctuations were too great, the quality of the electricity supply would decrease drastically and the infrastructure of the grid could be harmed. Thus, studying short term variability is important because solar capacity is increasing around the United States and its effect on the grid must be anticipated.

[23] SEIA, 2015.

In Massachusetts, there is a cap on the amount of grid-connected solar that can be built in the state. One such reason for this cap is because of short-term variability and its effect on the health of the infrastructure of the grid. However, this cap is calculated somewhat arbitrarily: it is a set percentage of peak demand that the grid faces in a given year. By studying solar variability and quantifying the data, a better constraint could be put on the cap. Thus, the significance analysis from Harvard's campus will give a better idea of how much power volatility is induced by solar photovoltaic power which could lead to better policy decisions regarding the amount of solar power on the electrical grid.

1.3.2 Overall Significance – The Magnitude and Frequency of Variability Events

The results of the significance analysis were striking: variability from solar power was considerable in both magnitude and frequency. Overall, the magnitude and frequency of these large variability events were higher than expected. Figure 1.2 shows the fluctuations in solar power that occurred over just one year. From the graph, it is clear that solar power production is nowhere near constant. There are constantly large fluctuations occurring in power production. Figures 1.4 and 1.5 show these fluctuations in more general terms that could be applied to any photovoltaic system. These graphs show power variability in terms of percent of array size. Thus, the numbers shown could be applied to a solar photovoltaic array of any size to figure out how much variability, in terms of Watts, it could introduce into a system. The surprising part of the analysis comes from just how large the magnitude of the fluctuations can be. There are a non-negligible number of events with fluctuations over 90% of rated power output. This means that, in New England, any solar photovoltaic array could be expected to have its power output fluctuate by the entirety of its capacity in a very short amount of time.

The magnitude and frequency of short term volatility of solar power has implications for its future as well as for the electrical grid that it will be connected to. As solar photovoltaic power has been shown to fluctuate to nearly its rated capacity in a short timescale, solar capacity on the grid will require significant electrical grid reserves (power plant reserves) in order to guarantee the quality and constancy of the electricity supply. This is because solar cannot be guaranteed to not lose all of its electrical production immediately. In other words, even if a panel is producing 100% of its rated capacity, it may drop to 0% in a short timeframe. Thus, to ensure the correct operation of the grid, spinning reserves would have to be ready to back up solar capacity in the system. As spinning reserves are expensive to operate and are expensive environmentally, this would be a significant drawback to solar.

While the short-term variability significance analysis showed that there are concerns for the future of large amounts of solar power on the grid, this is the worst-case scenario. As Tarroja, Mueller, and Samuelsen showed, short-term variability can be mitigated if solar arrays are spread out geographically. However, in the worst case scenario, short-term fluctuations could have an impact on the functioning of the grid or the reserve system that is in place.

1.3.3 Seasonal Variability – New England's Climate is a Factor

An interesting result that came from the significance analysis was a strong seasonal trend for short term variability. As seen in Figure 1.6, volatility is highest in the spring, summer, and autumn while the lowest in the winter. This seasonal dependence is not a small effect either; the maximum amount of variability can be over three times higher during June versus December. Thus, if planning for short term variability while building a solar array or while deciding on the optimum use of reserves in the grid, the time of year is important to consider.

One possible explanation for this comes from the climate of Cambridge and Boston. According to NOAA, the area is classified as a "moist, subtropical mid-latitude climate"[24] which has implications for how solar resources behave throughout the year. This climate classification is characterized as being dominated by convective thunderstorms in the summer months. Large amounts of convection in these months leads to the conditions that cause the highest amount of solar variability. Convection in the atmosphere can be caused when sunlight warms the surface of the Earth early in the morning. This causes the atmosphere to become unstable and convection occurs. Convection can lead to cumulus clouds forming.[25] This causes problems for solar power because it has both high amounts of radiation (required to heat the surface of the Earth) and also intermittent, cumulus clouds. Thus, the conditions are perfect for large amounts of short term variability as there is a large amount of solar radiation hitting the ground that is broken up by the

[24] National Weather Service, 2008.
[25] Convective Clouds

shadows of passing cumulus clouds. In summary, the convective atmosphere during the summer months in Cambridge and Boston leads to the formation of cumulus clouds during sunny days that leads to a significant amount of variation in solar power production on short timescales.

1.3.4 Seasonal Variability – Upper Limit of Variability Shifts throughout the Year

Another possible reason for the seasonal dependence of short term variability is the differing amounts of radiation that occur during each season in Cambridge. In the spring, summer, and autumn, maximum insolation values can reach over 1000 W/m^2 in Cambridge. However, in the winter, these maximum values drop to less than 800 W/m^2.[26] This means that in winter, a solar panel array can never approach producing its rated power. This is because panel outputs are rated according to a standard insolation value of 1000 W/m^2. If the maximum amount of radiation that is possible is only 800 W/m^2, then the panel can only produce 80% of its rated output. Thus, even in the worst case scenario of full sun to full shade quickly, the panel output changes less in the winter than the summer. In other words, higher insolation levels in non-winter months allow the power output of a panel to fluctuate more because there is more room to fluctuate.

[26] Calculation of Solar Insolation

1.3.5 Adding Demand Data to the Model Increases Variability in the System

Adding a demand variable to the model resulted in an increase in variability in the system. The initial analysis of the significance of short term variability in solar power only took into account production of solar power itself. This next section will examine when the system is complicated and acts more like a real scenario: the addition of demand data into the model. Since the model is now behaving more like a real system, the measure of variability is changed into how large of an array can exist within the given constraints of the system. A larger arrays means there is less variability while a small array indicates more variability. This is because power variability is directly proportional to the size of the photovoltaic array.

With a hard constraint of 1500 kW prescribed to the model for each month, adding in demand data had the result of variability acting exactly how it would be predicted to. There was a strong seasonal dependence in the amount of variability in the system. Adding demand data did not do much to change this earlier conclusion from the initial significance analysis. If remaining constrained to a given level of variability, December would be able to have the largest solar array and April the smallest (Figure 1.7).

However, if the variability constraint is allowed to change for each month, the results are slightly different. This model run (Figure 1.8) is interesting because the constraint varies according to the maximum demand in the system. By setting the constraint to be a given proportion of maximum demand, the system can behave more realistically. A grid operator will account for the variability in one part of the grid as a proportion of how much demand is typical in the area. Thus, higher demand areas will be allowed more variance. Following this logic, peak demand for McCollum substation changes month-to-month so the variability in the system would also be expected to change. Thus, having a varied volatility constraint makes sense.

When the volatility constraint is varied according to monthly demand, the strict seasonal correlation is weakened. The least amount of variability still occurs in December. Some months, such as July, actually end up being less relatively variable with the new constraint (see Figure 1.8).

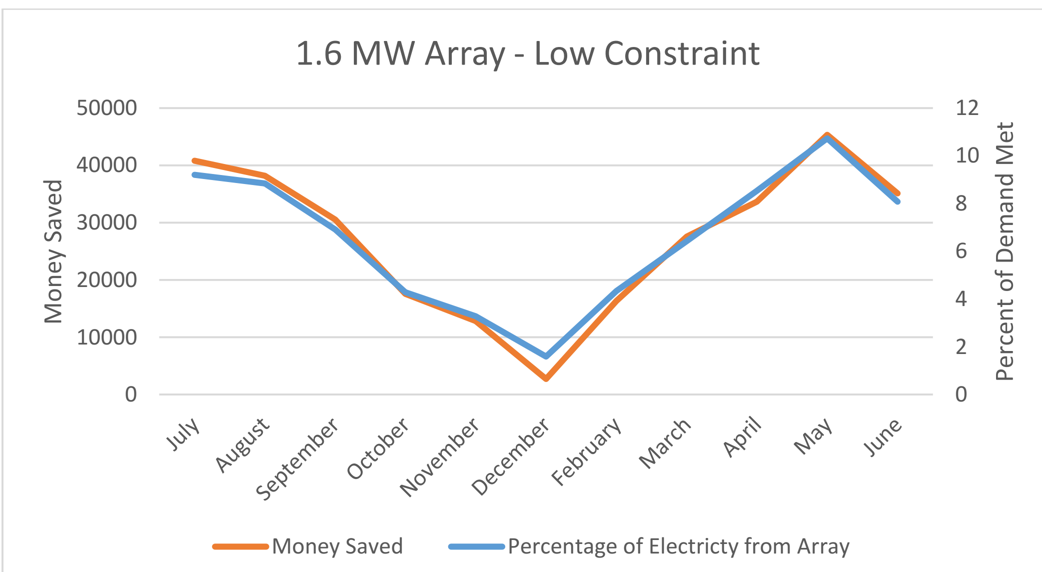
1.3.6 How Maximum Variability Changes when Demand is Introduced

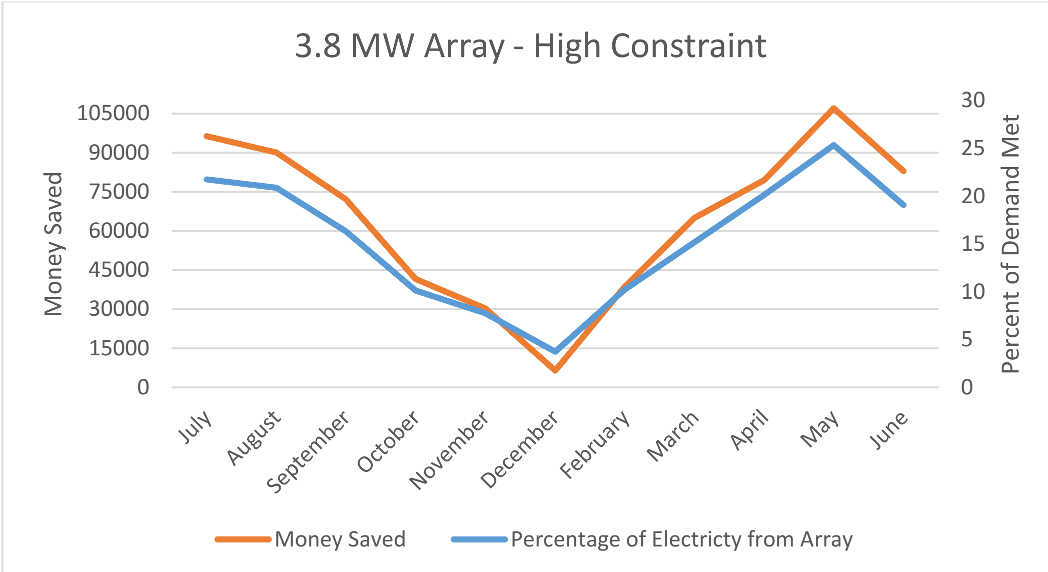
On the whole, the variability in the overall system increased when the demand variable was added to the model. The final part of the significance analysis deals with the question of whether or not introducing demand (which is itself variable) could affect the volatility of the system. The idea behind this is that, by random chance, demand variability and solar variability would cancel out. For instance, if the power output from the array dropped, but demand also dropped, some of the variability of the solar array would be canceled out.

In the end, demand variability did not help to cancel solar variability. Instead, the amount of variability in the system increased dramatically. The average of the top 10 most variable events in each month increased in every single month. The average amount of increase was over 10% of the panel rating. Thus, adding in demand actually significantly increased the variability of the system rather than decreasing it. In conclusion, this means that the natural variability of the electrical grid is unlikely to cancel out the variability introduced by solar photovoltaic arrays.

1.3.7 Variability and the Impact on Solar Photovoltaic Arrays

If short term variability is a constraint, it has a tremendous impact on how much solar can be added to the electrical grid. To illustrate this, an analysis was created that looked at the impact of a solar array with lowest constraint (April) versus the impact of a solar array with the highest constraint (December). The results are below:





Figures 1.10 and 1.11 | Hypothetical arrays in McCollum
These figures demonstrate the difference the choice of constraint can make in terms of variables that matter heavily in the real world. The high constraint allows for an array that is over double the size of the low constraint, leading to real monetary savings as well as allowing for a higher percentage of renewable energy. The orange line represents money saved[27] *and is on the left axis, while the blue line represents how much power the array is providing to the grid.*

Figures 1.10 and 1.11 show the impact of two different array sizes in McCollum substation's microgrid. This analysis shows the impact that a volatility constraint can have on a system that would like to add solar photovoltaic arrays as a power source. If using the low volatility constraint, the amount of solar that can be added to the system is small. If using the high volatility constraint, the size of the array can be more than doubled. The impacts of this are tremendous. The larger array is able to meet a much higher proportion of demand than is the smaller array.[28] This illustrates how much a variability constraint can impact the potential of a solar photovoltaic array.

[27] 'Money Saved' was calculated using the Cambridge average of $0.16 per kWh
[28] The large array meets 15.5% of overall electricity demand. The small array meets 5.6% of overall annual demand.

CHAPTER 2 – Mitigation Analysis of Short Term Variability of Solar Power

After determining that short term volatility of solar power was a significant issue for the future of solar power, exploring ways to mitigate this volatility became important. The volatility analysis showed that in New England, the amount of short term variability that can occur with solar photovoltaic panels is substantial. The magnitude and frequency of high variability events was greater than expected. This means that as more solar photovoltaic power gets added to the electrical grid, short term variability must be taken into consideration.

One such way to take short term variability into consideration is to look at ways to mitigate the variability at its source. This chapter explores the addition of a storage source to a hypothetical solar photovoltaic array that is optimized to minimize short term variability. In other words, the storage system's only function is to fill in the valleys and clip the peaks of solar panel power output. As the variability events with large magnitudes were relatively infrequent, the hope was that a small, cheap storage system could make a meaningful impact on mitigating short term variability.

2.1 Methods

2.1.1 Designing a Model that Utilizes a Storage System to Minimize Volatility

The second part of this thesis explores basic mitigation techniques for short term solar power variability and utilizes a model created for that analysis. After determining the significance of short term volatility in the first section, the amount of how much variability could be mitigated with a simple and small storage solution was explored. To model how a battery could affect the system, linear programming methods were utilized to find how an optimally designed system would act.

To model a contained microgrid system, data from McCollum substation as well as the Harvard GSD weather station was used. The new element, the storage system, required two parameters to be put in the model: maximum power input/output as well as total energy storage capacity. To find data for these storage devices, currently available electricity options were researched and a variety were chosen, ranging from lithium ion batteries to flywheels. The different storage scenarios are listed below:

Storage Method	S_{max} (capacity, kWh)	r_{max} (power, kW)
Tesla Powerwall/Telecom flywheel	500	165
Tesla Powerwall/Telecom flywheel	1000	330
T-1275 12V lead acid	497.5	225
T-1275 12V lead acid	995	450
T-105 6V lead acid	499.5	149.85

T-105 6V lead acid	999	299.7
Velkess Flywheel	500	100
Velkess Flywheel	1000	200

Table 2.1 | Stats of storage systems analyzed
The above table lists the different storage methods tested within the model. The important specifications, capacity and maximum power output, are represented in terms of kWh and kW, respectively.

2.1.2 Mathematical Equations Utilized in the Model

The model equations are listed below:

Objective

Maximize A

S.T.

$$G(t) = D(t) - P(t) + r(t)$$

$$\Delta G = |G(t) - G(t-1)|$$

$$S(t) = S(t-1) + (r * 0.0834)$$

$\Delta G \leq 1500$ (or decided upon constraint)

$$0 \leq S \leq S_{max}$$

$$-r_{max} \leq r(t) \leq r_{max}$$

$$P(t) \begin{cases} \dfrac{I(t)}{1000} \times A_{std} \times \left[1 + \gamma\left(T_{panel} - T_{std}\right)\right], & I(t) \geq 80 \\ \dfrac{0.008 \times I(t)^2}{1000} \times A_{std} \times \left[1 + \gamma\left(T_{panel} - T_{std}\right)\right], & I(t) < 80 \end{cases}$$

$$T_{panel} = T_{air} + \frac{NOCT - 20}{800} \times I(t)$$

Testing the system with a battery uses a very similar setup to the significance analysis. However, two new elements, *r* and *S* are added into the system. *r* refers to the power output or input of the storage system at a given time.

It is measured in kilowatts. *S* refers to the energy storage capacity of the storage system. It is measured in kWh.

To run the model, Matlab's linear programming toolbox was utilized. A script was written that would utilize the weather station data, McCollum demand data, and storage data to output the maximum size of a solar panel array that could exist within the constraints of the system. The linprog function of Matlab was used to optimize the function of the battery to minimize short term volatility.

2.2 Results

2.2.1 Adding a Storage System to Minimize Short Term Variability in the System

This section provides the results of adding a hypothetical battery to the system in order to mitigate variability and shows that storage systems can be effective methods to mitigate short term variability. The model was run with the same data as was used with the significance analysis. However, in this scenario, a hypothetical storage solution was optimized to mitigate variability the system would experience. Multiple types of storage solutions, including batteries and flywheels, were tested to see how well they could manage the volatility in the system.

Variability Constraint (kW)	kWh Capacity	Maximum Power (kW)	Array Size (output)	generation/demand
1500	0	0	1635	6.92%
. 1500	500	100	1911	8.09%
1500	499.5	149.85	2048	8.67%
1500	500	165	2090	8.84%
1500	1000	200	2187	9.25%
1500	497.5	225	2256	9.54%
1500	999	299.7	2449	10.36%
1500	1000	330	2524	10.68%
1500	995	450	2820	11.93%

Table 2.2 | Results of mitigation modeling
The outputs of the model that utilized the optimized storage system are listed above. The larger the array size, the better the storage system at mitigating short term variability.

The above table is the set of results received from running the model with different storage scenarios. The variability constraint was held constant for each run in order to have a fair comparison between types of storage. Listed are the stats for the storage system analyzed in that run, including the capacity of the storage system as well as its maximum power output. The model output the maximum array size that could exist within the given constraint. In terms of solar capacity, the larger the array size, the better. Finally, each array size is put into terms of how much of the annual demand it would meet within McCollum substation's microgrid. Another important note is that the top row of this chart shows the 'no-storage' model run, which provides a useful comparison for how well each storage solution works.

2.2.2 The Effect of Storage on the Maximum Array Size allowed by the Constraint

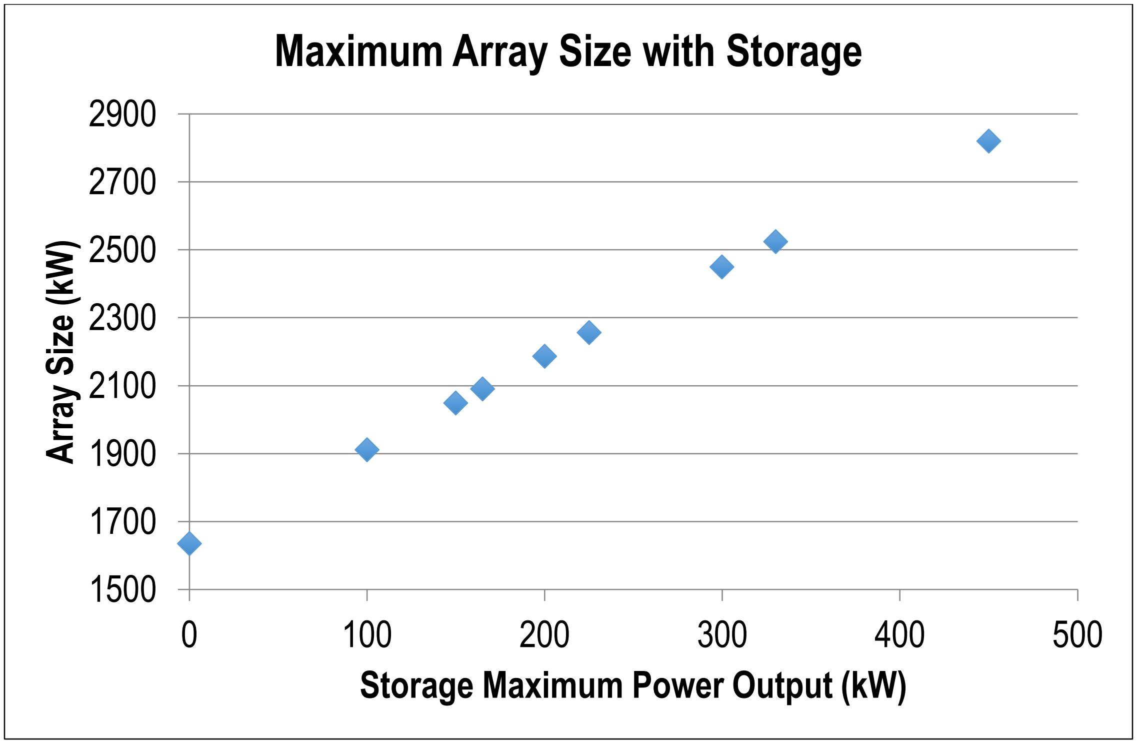


Figure 2.1 | Relationship of array size and storage power output
The relationship between maximum power output and model output of array size is plotted above. The larger the array size, the better the performance of the storage system in mitigating short term variability.

This graph depicts the relationship between the maximum array size that would be possible within the constraints of the system versus the maximum power output of the storage system. There is a clear positive correlation between the maximum power output achieved by the storage system and how well it works to mitigate short term variability. An important note is that storage capacity does not effect this relationship at all; the only thing affecting the ability of the storage system to mitigate short term variability is its maximum power output.

2.3 Discussion

2.3.1 A Small Storage System can make a Significant Impact on Short Term Variability

The results of this analysis show that relatively small storage options could potentially make a significant impact in managing volatility introduced by solar photovoltaic arrays. The power output or input of the storage unit helps to fill in the valleys and trim the peaks of the variability in the system. As see in the significance analysis, events with large magnitudes of variability are rare. The storage unit comes into play by managing those few, yet large, events. This allows the system to have a larger amount of solar power yet still remain within variability constraints.

2.3.2 Maximum Power Output is the Driving Factor in Effectiveness of Mitigation

The other point to note in these results is that the power output of the storage option was the driving factor in how well it performed whilst managing variability. Storage capacity did not play any role in how well a storage solution was able to manage volatility. Additionally, it is also interesting that the relationship between how well a storage option managed variability in this model and how the magnitude of its maximum power output has a linear relationship.

2.3.3 Impact of Storage Systems

Overall, if a solar installation was constrained by short term variability, this initial analysis shows that a storage option would be able to have a significant impact. Storage solutions can effectively manage short term volatility. They work best when they are optimized to only mitigate short term variability rather than store power for any large amounts of time. Additionally, the analysis shows that storage capacity is not a meaningful factor when determining how well a given storage system can mitigate the power output volatility of a solar photovoltaic array. The best plan would be to have a cheap storage option that is capable of a high maximum power output. The results of this analysis are encouraging for the potential of mitigation of short term power variability by an electricity storage system.

CHAPTER 3 – Solar Resources in a Changing Climate

Solar photovoltaic power production is directly related to the climate of the area it is located in. Solar requires clear skies with high levels of solar radiation in order to perform optimally. Therefore, certain regions of the United States are better suited for solar photovoltaic arrays than others. However, the Earth's climate is currently changing due to human activity.[29] This changing climate causes problems for solar resources as they are directly related to the climate of the region in which photovoltaic arrays are built. If a region is sunny now, will it remain so in the future?

Why the Long-Term Future Climate of a Region Matters to Solar

The long-term future of a region's solar resources is important because of the cost and lifetime of infrastructure that may be built to fully exploit renewable energy resources. High voltage direct current electricity transmission lines are seen as one possible answer to boosting the amount of renewable energy being used in the United States.[30] These transmission lines will require a significant investment in time, money, and space. The general idea is to build high voltage direct current transmission lines from areas with high quality renewable energy resources, such as windy plains and sunny deserts. These transmission lines would link these renewable energy resources to the large power markets in more heavily populated

[29] IPCC, 2007.
[30] Kollipara, 2016.

areas, such as California and the East Coast. In terms of solar power, this makes the future climate of the Southwest in the United States even more important. Currently, there are plans for two large direct current transmission lines to be built from the Southwest to large electricity markets.[31] These transmission lines will have a lifetime on the order of tens of decades and represent a commitment to building renewable energy sources in the Southwest. Thus, it is crucial to study the future of the region to be certain its prime renewable energy resources will remain so in the future.

Current research suggests that climate change could affect the positioning of Hadley Cells on Earth. Hadley Cells are circulation patterns where warm air rises from the equator and travels poleward before sinking at 30 degrees latitude. This sinking air is dry and generally causes deserts to form at 30 degrees across the Earth. This dry climate is favorable for solar power. However, some scientists are proposing that climate change can affect the positioning of Hadley Cells on the Earth which would dramatically affect the climate at 30 degrees of latitude. One study suggests that Hadley Cells extended all the way to the poles in ancient climate regimes. Anthropogenic forcing of the climate could cause this 'equable climate' to return, which would dramatically affect the regions of the world that currently have great solar resources. [32] Thus, proposed mechanisms for shifting the climate of regions with high quality solar resources exists. If climate change causes the

[31] Clean Line Energy Partners, 2016.
[32] Farrell, 1990

regions of the world with dry climates to shift, it could adversely affect the solar resources of those regions.

Global Climate Models (GCMs) provide an excellent way to answer the question of how solar resources are projected to change over the coming century. They allow for flexibility in emissions scenarios which is important because there is no certainty regarding the amount of carbon dioxide emissions humans will emit throughout the 21st century. This allows for different scenarios to be studied which provides additional insight into how solar resources are projected to change.

3.1 Methods

The third part of this thesis investigates how solar resources are projected to change over the coming century due to climate change. To thoroughly explore this problem, current literature in the field was reviewed. An analysis on global climate model data was performed to explore this topic in a more in depth manner.

3.1.1 Literature Review of Current Research of Changing Clouds and Aerosols

To begin investigating the topic of changing solar resources, a literature review of relevant studies was conducted. In particular, aerosol and cloud studies were focused on. Aerosols were chosen because they play an important role in cloud formation as well as the transparency of the atmosphere, which affects how well sunlight can pass through to the ground. Clouds were chosen because of their outsized impact on short term variability as well as the overall amount of solar radiation that reaches the ground. Clouds are important because they can be opaque to sunlight and are a driver of the quality of solar resources in a given region. First, how aerosols and clouds affect solar irradiation levels was researched. Then, research on how aerosols and clouds are expected to change was conducted. This two-step process allowed for a link to be made between clouds, aerosols, and the future of solar power.

3.1.2 Analyzing Data from the Source – Global Climate Models

The literature review did not answer the question in the depth required. Not enough relevant research has been done on the subject. In particular, how clouds are expected to change spatially as well as how cloud types could change over the coming century was not addressed. Thus, an analysis was made directly from the source – global climate model data. Global climate model data was chosen because it was created using various carbon dioxide emissions scenarios for the coming century. As it is unknown was the future of the climate will look like, GCMs were valuable because they allowed as many scenarios as possible to be studied.

The data used came from the National Center for Atmospheric Research (NCAR) CCSM4. Two runs were used, rcp45 and rcp85, which correspond to a model run that uses 4.5 W/m^2 and 8.5 W/m^2 of radiative forcing, respectively. Each emissions scenario was run 3 times by NCAR. To get the best results, all three runs were averaged for each emissions scenario, giving me an average dataset for each emissions scenario. By averaging three runs of the NCAR model, the internal variability within the model itself was minimized. Thus, a better prediction about real climate fluctuations could be made rather than focusing on the variability of the model.

3.1.3 GCM Variables Investigated

Three NCAR model outputs were analyzed: cloud cover, shortwave radiation reaching the ground, and shortwave radiation reaching the ground while assuming a clear sky. Matlab was then utilized to examine the data present in each emissions scenario in three different years, 2015, 2050 and 2100. To begin, two variables to be examined were established: cloud cover and blocked radiation. Blocked radiation is the difference between the shortwave radiation reaching the ground while assuming a clear sky minus the shortwave radiation reaching the ground. The difference between these two variables is the amount of radiation the model is projecting to be ‘blocked’, or unable to hit the ground. If radiation is blocked, it cannot reach solar photovoltaic arrays on the ground. Thus, more blocked radiation is bad for solar power. Cloud cover and blocked radiation were plotted on a map of the United States using Matlab for each emissions scenario and for 2015, 2050, and 2100.

3.1.4 GCM Data Manipulation

After plotting the initial data for each year to get a general idea of what it looked like, the next step was to compare the changes by year for each variable and each emissions scenario. To find the changes, the base year of 2015 was subtracted from the year to be plotted. Thus, the change that occurred between the reference year, 2015, and the analyzed year was plotted. This was done for clouds and blocked radiation in both emissions scenarios.

Finally, the difference was taken between each emissions scenario in a given year to isolate the effect that a medium or high emissions scenario would have on the variables that were examined. The medium emissions scenario dataset (rcp45) was subtracted from the high emissions scenario dataset (rcp85) to find the difference. Thus, the value calculated would be the difference in response of the variable to a medium versus a high emissions scenario.

3.2 Results

3.2.1 Literature Review

The literature review focused on examining current research on clouds and aerosols and how they may change due to climate change. One study simulated aerosol-cloud feedbacks over the continental United States and found that there was a considerable decrease of solar radiation reaching the ground in July due to aerosols. This decrease was on the order of 10 W/m^2 averaged across the country. This study also showed that aerosols can reduce incoming shortwave radiation via backscattering.[33] In another study, by Lohmann, increasing aerosol emissions were shown to cause a decrease in solar radiation at the surface by increasing optical depth in the atmosphere directly and through cloud feedbacks.[34] Additionally, the literature review also showed two interesting effects: 1) cloud optical depth increases with concentration of cloud droplets and 2) aerosols lead to a decrease in

[33] Zhang *et al.* 2010
[34] Lohmann, 2005

cloud droplet size, leading to longer cloud lifetimes.[35] These two findings show that increasing aerosols can lead to non-negligible effects on solar radiation reaching the ground through their impact on clouds. Thus, the first step of the literature reviewed confirmed a strong link between aerosols, clouds, and solar radiation.

The link between aerosols, clouds, and solar power was established in the first part of the literature review so determining how these factors will change in the coming century will provide insight into how solar resources may also change. In the 2013 IPCC report, it was stated that GCMs suggest climate warming will cause ice clouds to transition to water clouds and become more opaque. However, middle and high latitude cloud cover is projected to decrease.[36] The White House Climate remote said that the Southwest is projected to become hotter and drier, which would be beneficial to solar resources. However, the same report also stated that there is an increased risk for wildfires, which would bring smoke and aerosols to the region and negatively affect solar resources.[37] Hence, there is nothing conclusive that can be drawn from the report. Another study showed that precipitation in the subtropics and tropics will decrease but will increase in higher latitudes. Additionally, climate regimes that are determined by cyclonic activity will have more storminess, leading to more cloudy skies and less solar radiation.[38] The first point about precipitation gives little information about solar resources. Precipitation may change but that does not necessarily clouds will be affected in

[35] Boucher, 2015
[36] IPCC, 2013
[37] Melillo, Richmond, and Yohe, 2014
[38] Trenberth, 2010

the same way. Since clouds are the driver of the quality of a solar resource, this point provides no insight. The second point about the effect of climate change on cyclonic activity does provide more information. However, this is not enough information to answer the question posed earlier – "If a region is sunny now, will it remain so in the future?"

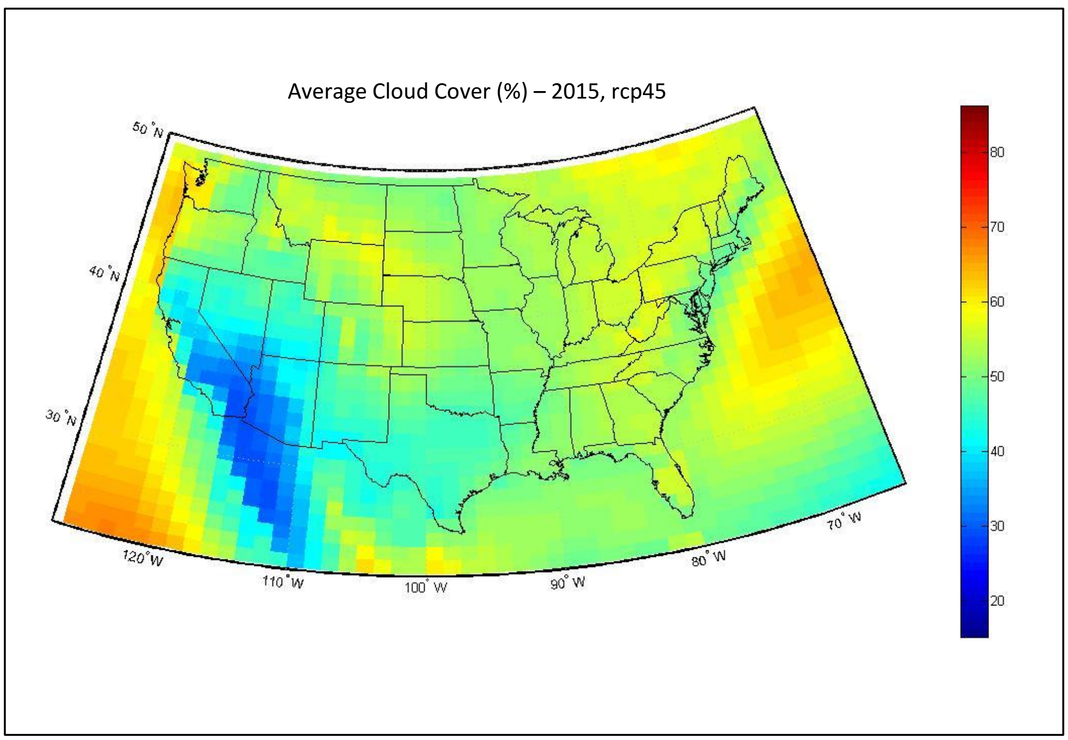
Overall, the literature review yielded interesting information regarding variables that can affect solar resources; however, it did not provide information that was precise or relevant enough to analyze the future of solar resources in the United States. It provides a good groundwork for understanding complicated processes that are utilized by GCMs to make projections about the future. All in all, the literature review provides useful context but was not able to answer the main question of this section.

3.2.2 Global Climate Model Analysis

This section explores the output of a global climate model, NCAR CCSM4, to look at how solar resources are projected to change over the coming century. The data represented focuses on the United States. Each grid square was calculated by the model for the given time period and variable and then plotted on a map of the United States. The data explores two different emissions scenarios: rcp45 and rcp85. These emissions scenarios represent different levels of climate forcing put into the system by 2100 and are directly set in the model run. rcp45 means that the model was run with 4.5 W/m^2 of forcing by 2100 and rcp85 had 8.5 W/m^2 of radiative forcing by the end of the century as its input. As it stands, these are medium and high emissions scenarios, respectively.

The first set of figures show the amount of cloud cover across the United States. Blocked radiation is the difference between the actual modeled insolation and the ‘clear-sky’ level of insolation. The data for 2015, 2050, and 2100 is represented for both rcp45 and rcp85. Following the cloud cover maps are the figures depicting the amount of blocked radiation across the United States. These again follow the convention of 2015, 2050, and 2100 for both rcp45 and rcp85. Next comes the changes in clouds and blocked radiation. The change is represented as the difference between projected values in 2050 and 2100 versus 2015. The changes are depicted for both emissions scenarios. The final set of figures shows the difference between the emissions scenarios for blocked radiation and clouds.

3.2.3 Cloud Cover across the United States – Medium Emissions Scenario



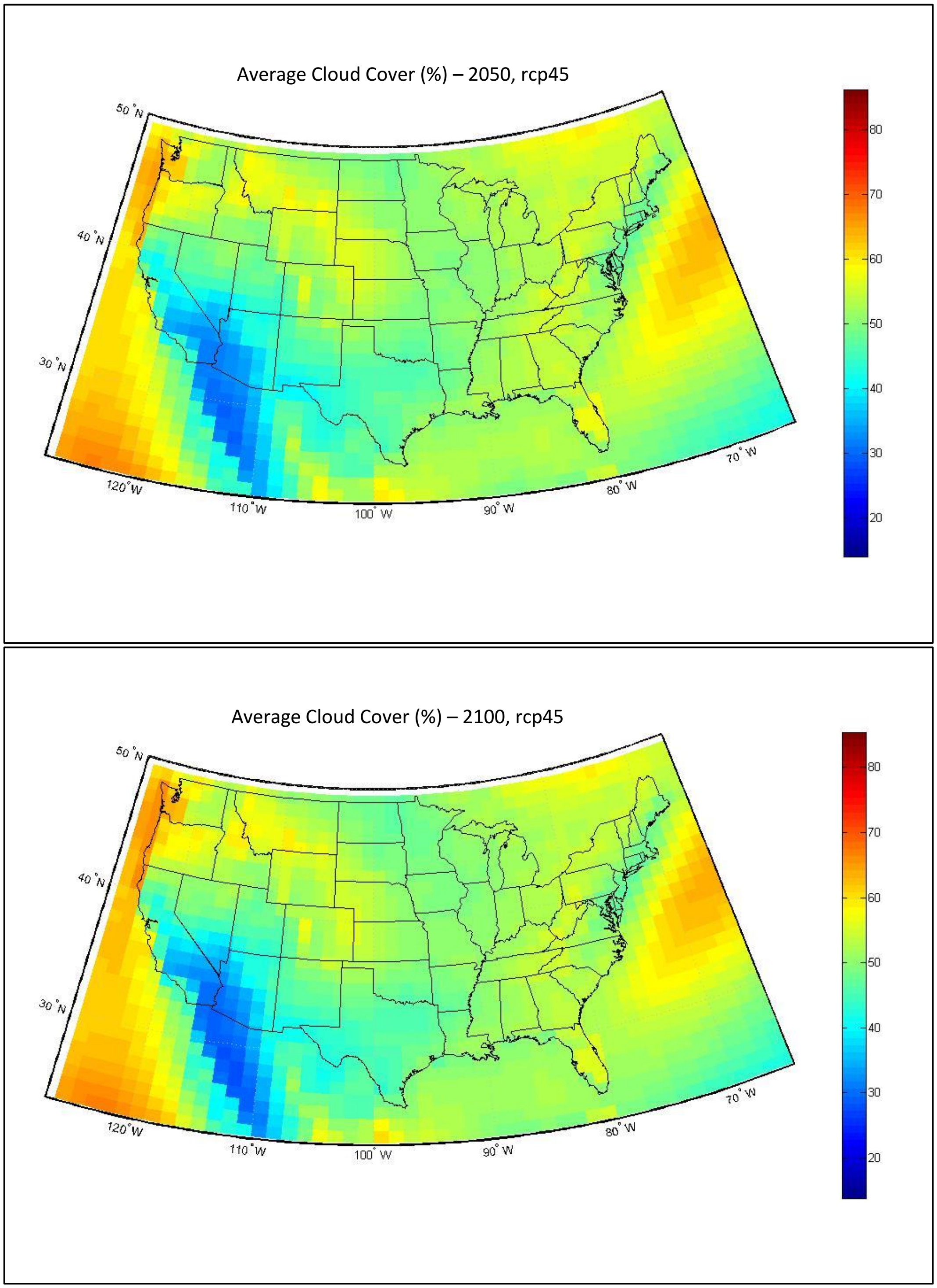


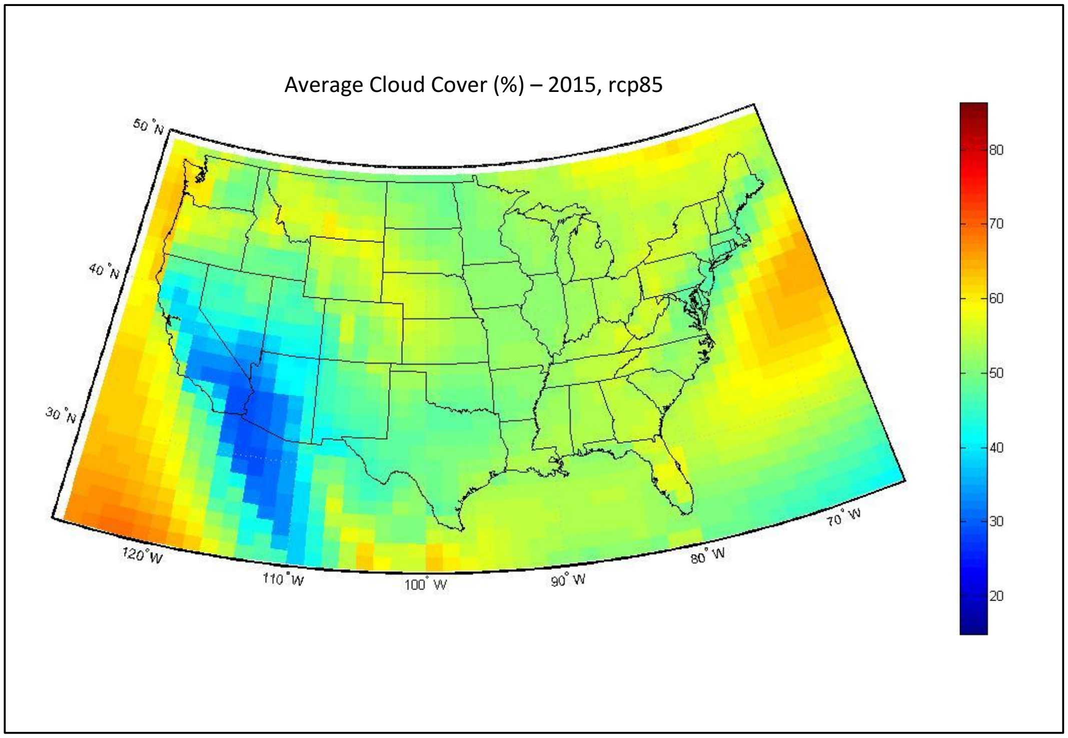
Figure 3.1 | 21st century average cloud cover, medium emissions

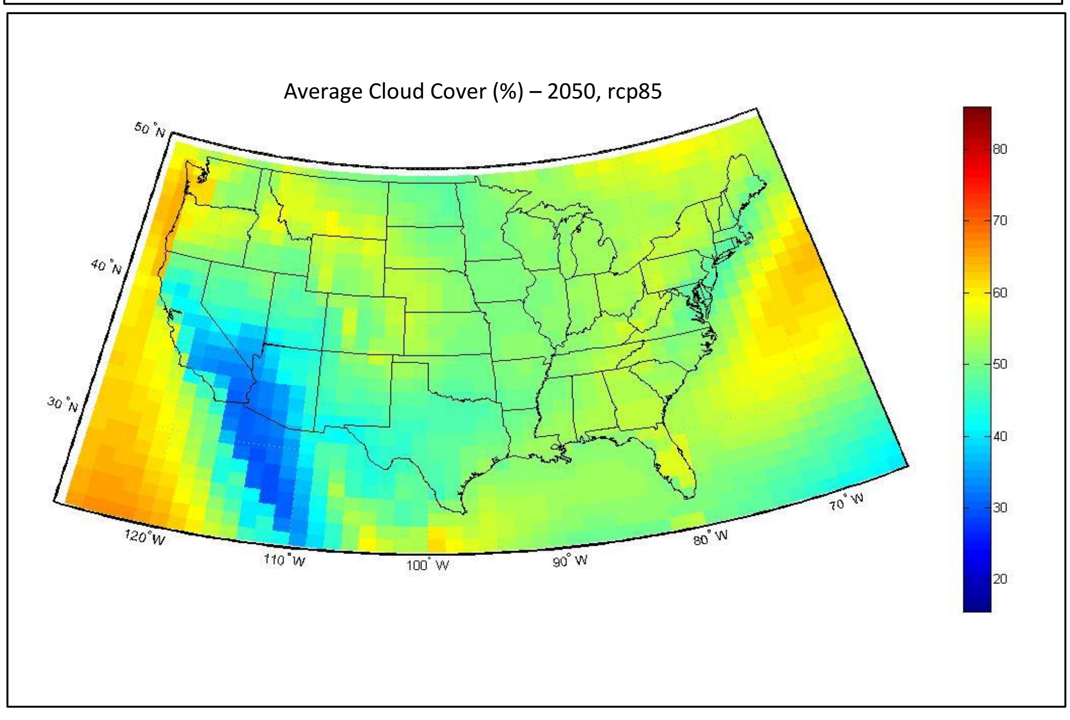
The three figures show the output of the model under a medium, 4.5 W/m² emissions scenario. Warmer colors denote higher average cloud cover than cooler colors. The colors themselves represent the average cloud cover in that grid square. The first map is 2015, the second 2050, and the last is 2100.

The first set of maps depict average cloud cover in each grid square over the United States under a medium emissions scenario. Average cloud cover means the portion of the sky that is filled with clouds, not how much time is spent completely cloudy. Overall, the amount of clouds across the United States does not seem to change considerably over the coming century under rcp45. The values remain within a relatively small range and there are no standout features of change.

The most visible region in the cloudiness map is the Southwest. These region has extremely low cloud cover compared to the rest of the US. The low level of clouds begins in southern California, Nevada, and Utah and extends through Arizona into Baja California. Values in this region range between 20% and 30% cloudiness. These low values explain why the Southwest represents such a good solar resource. Its changes will be explored in much more depth later in this chapter.

3.2.4 Cloud Cover Across the United States – High Emissions Scenario





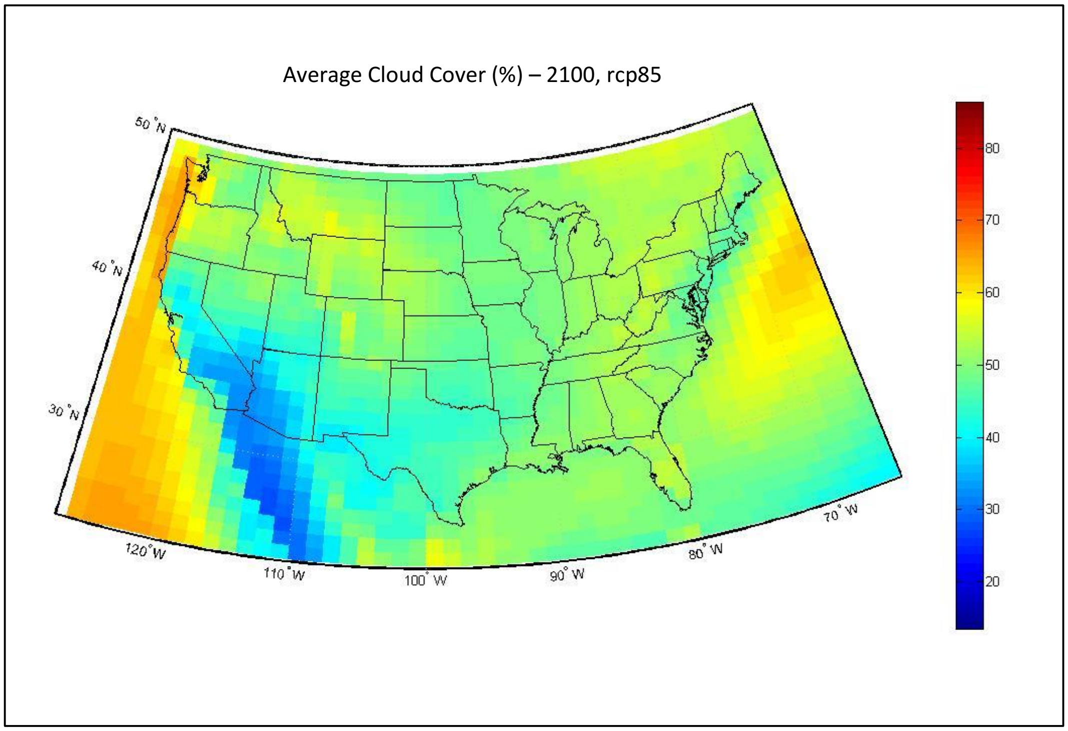
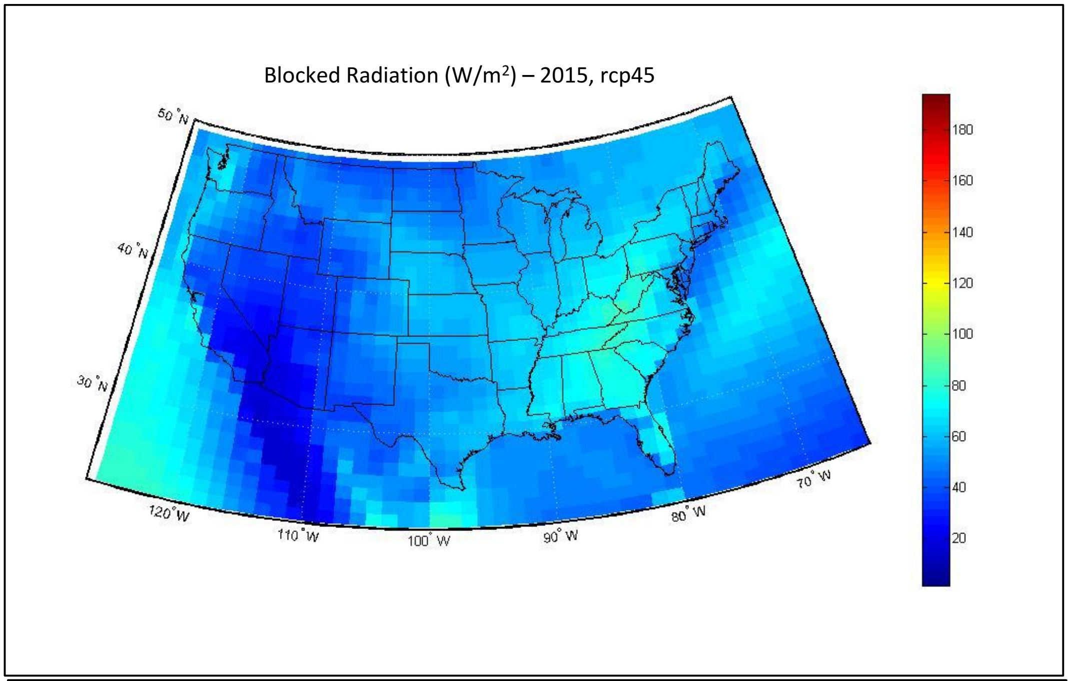
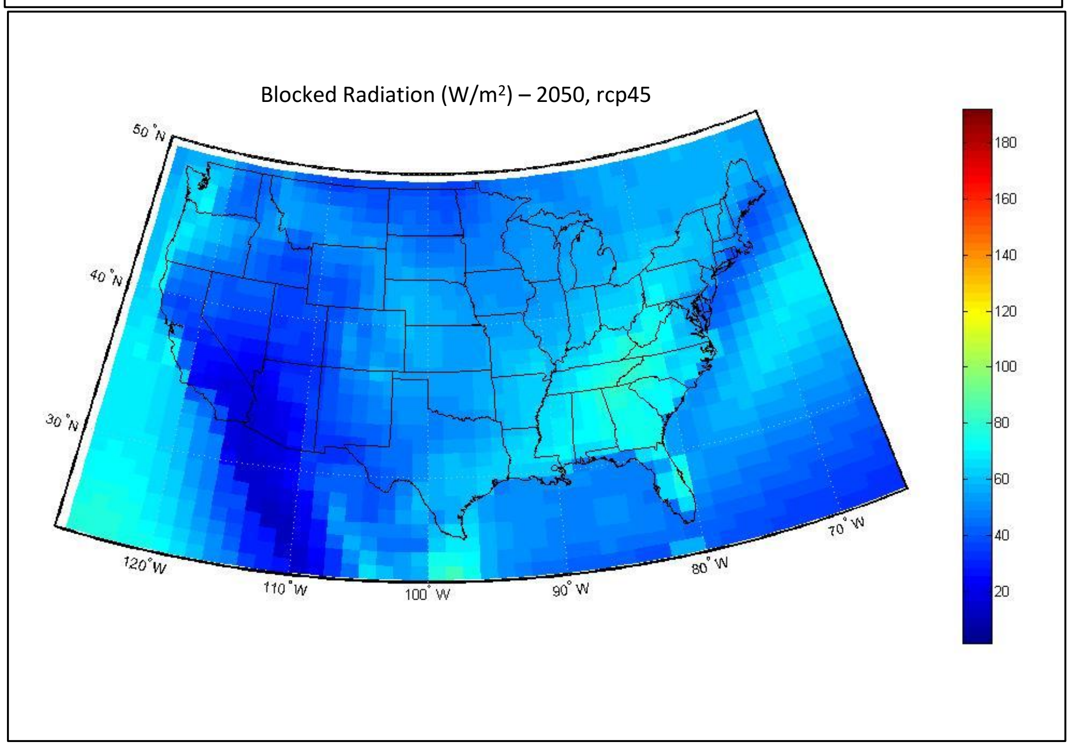


Figure 3.2 | 21st century average cloud cover, high emissions
The three figures show the output of the model under a high, 8.5 W/m² emissions scenario. Warmer colors denote higher average cloud cover than cooler colors. The colors themselves represent the average cloud cover in that grid square. The first map is 2015, the second 2050, and the last is 2100.

Cloudiness in rcp85 has similar qualities to rcp45. Again, the most striking region is the Southwestern United States. Values also do not appear to change considerably over the century. However, since cloudiness is of utmost important to determining the quality of solar resources, the changes under a high emissions scenario will be explored in more depth later in the section.

3.2.5 Blocked Radiation – Medium Emissions Scenario





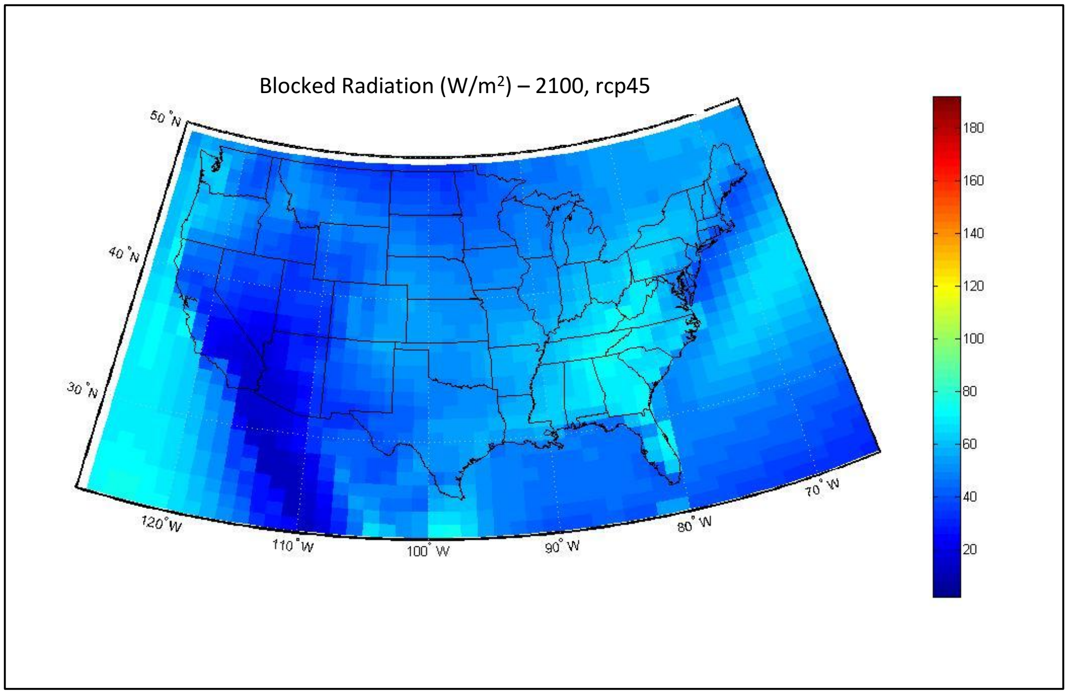


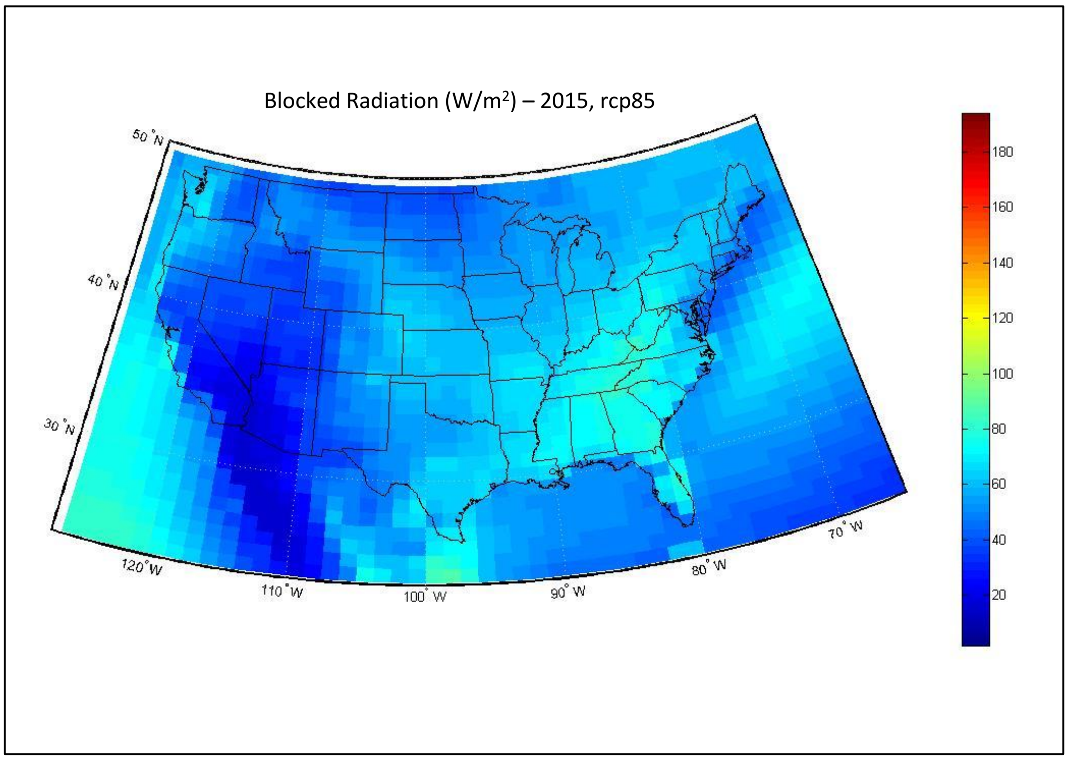
Figure 3.3 | 21st century blocked radiation, medium emissions
The series of maps depicts how blocked radiation will change over the coming century under a 4.5W/m² forcing scenario. The first map is 2015, the second 2050, and the last is 2100. The colors represent the amount of radiation that is being blocked in the atmosphere. The warmer the color, the more radiation that is being blocked and not reaching the ground. The numbers are in W/m².

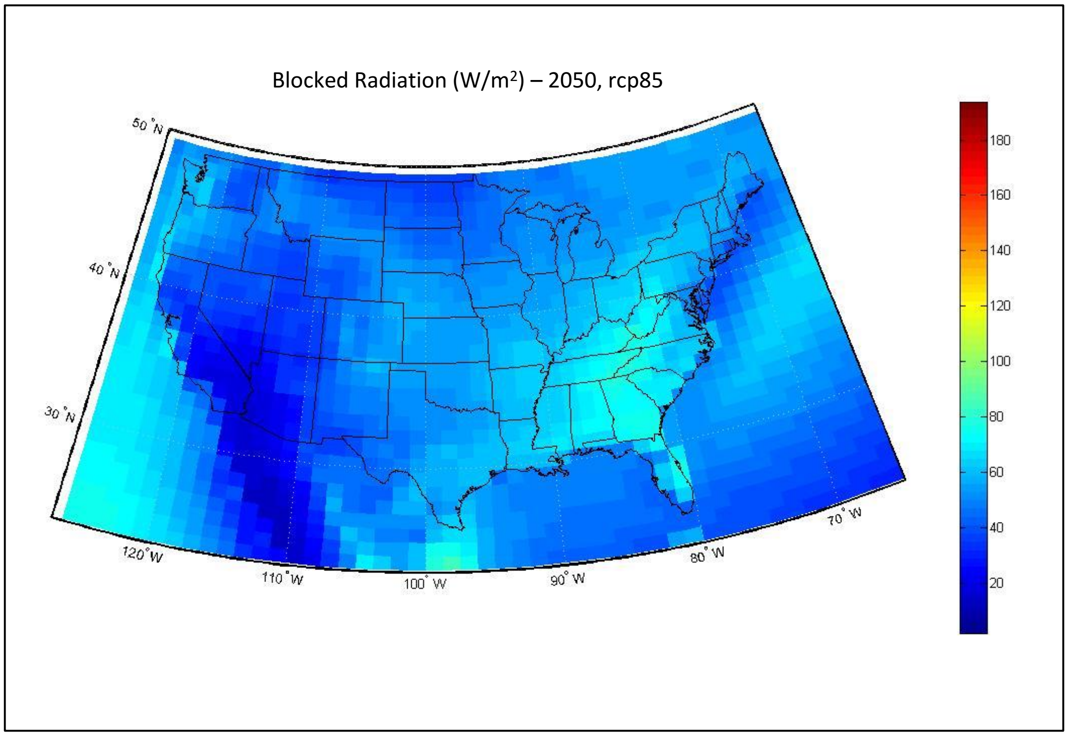
The three maps above depict the amount of blocked radiation across the United States from 2015 to 2100 under a medium emissions scenario. There are two main regions of interest: the Southwest and east of the Mississippi. These regions are interesting because they have the lowest and highest values of blocked radiation on the map.

The region of low amounts of blocked radiation begins in southern Nevada, Utah, and California and runs all the way down Baja California. This region represents the lowest amount of blocked radiation on the map. Values here are around 20 W/m^2 blocked, meaning that most of the time the sun is shining its light is reaching the ground. At first glance, it also seems that the region is not changing that drastically over the coming century in the medium emissions scenario. However, these changes will be explored in more depth later in this section.

East of the Mississippi, especially the Southeast, has the largest amount of blocked radiation. Values for the amount of radiation blocked here are on the order of 80 W/m^2. This is four times more radiation being blocked than in the Southwest. This region also experiences more changes in its values over the century than the Southwest.

3.2.6 Blocked Radiation – High Emissions Scenario





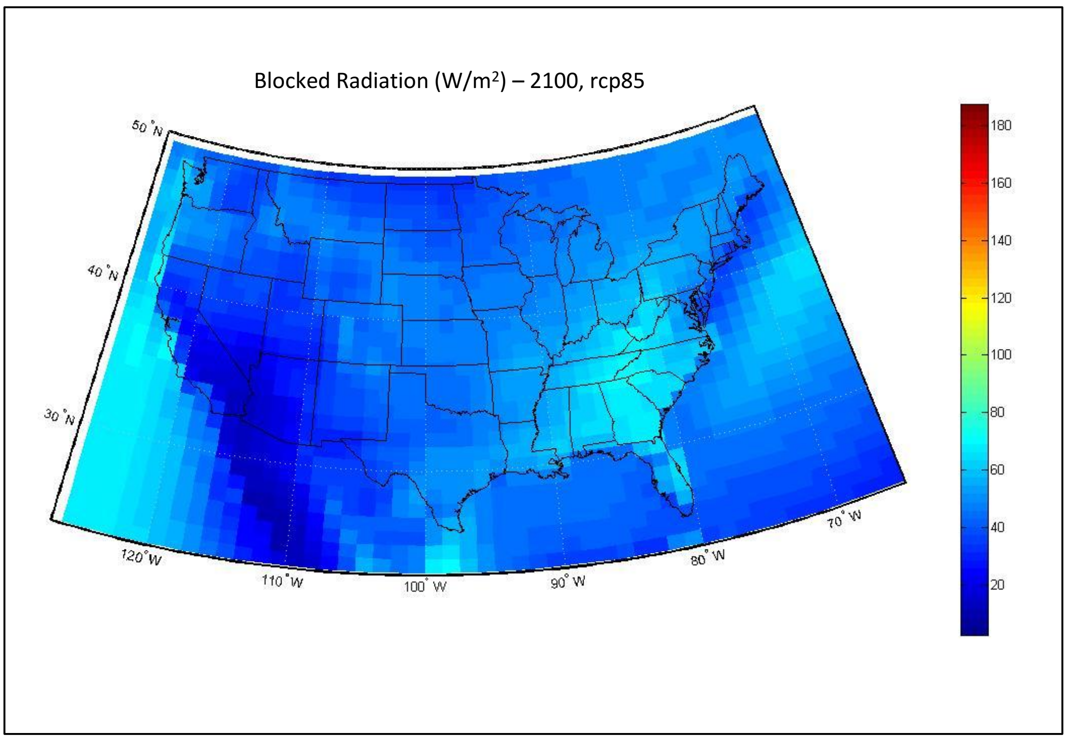
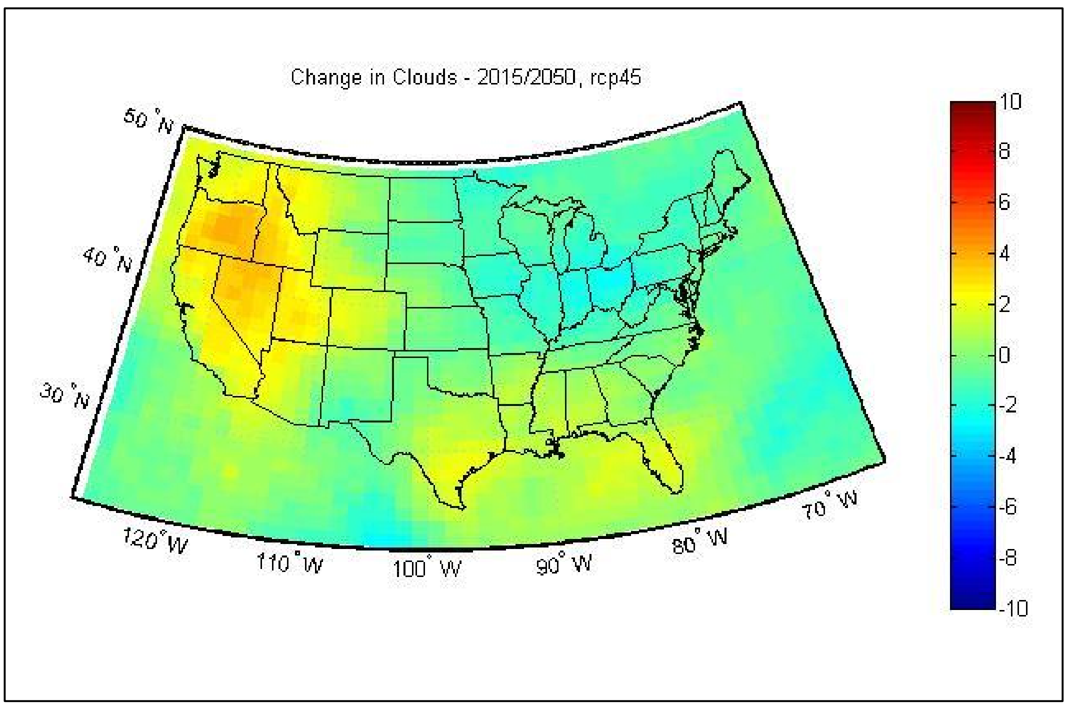


Figure 3.4 | 21st century blocked radiation, high emissions

The series of maps depicts how blocked radiation will change over the coming century under an 8.5W/m² forcing scenario. The first map is 2015, the second 2050, and the last is 2100. The colors represent the amount of radiation that is being blocked in the atmosphere. The warmer the color, the more radiation that is being blocked and not reaching the ground. The numbers are in W/m².

The above set of figures shows the CCSM4 output of blocked radiation values for rcp85, the high emissions scenario, between 2015 and 2100. Similar to rcp45, the two main areas of interest are the Southwest and east of the Mississippi because of their blocked radiation values on either end of the spectrum. As with rcp45, the Southwest has very low blocked radiation values that remain relatively constant throughout the century. The region east of the Mississippi is interesting in the high emissions scenario because its blocked radiation values change a considerable amount over the century. In particular, the change between 2050 and 2100 seems to be large and will be explored further in this chapter.

3.2.7 Changes in Clouds over the 21st Century – Medium Emissions Scenario



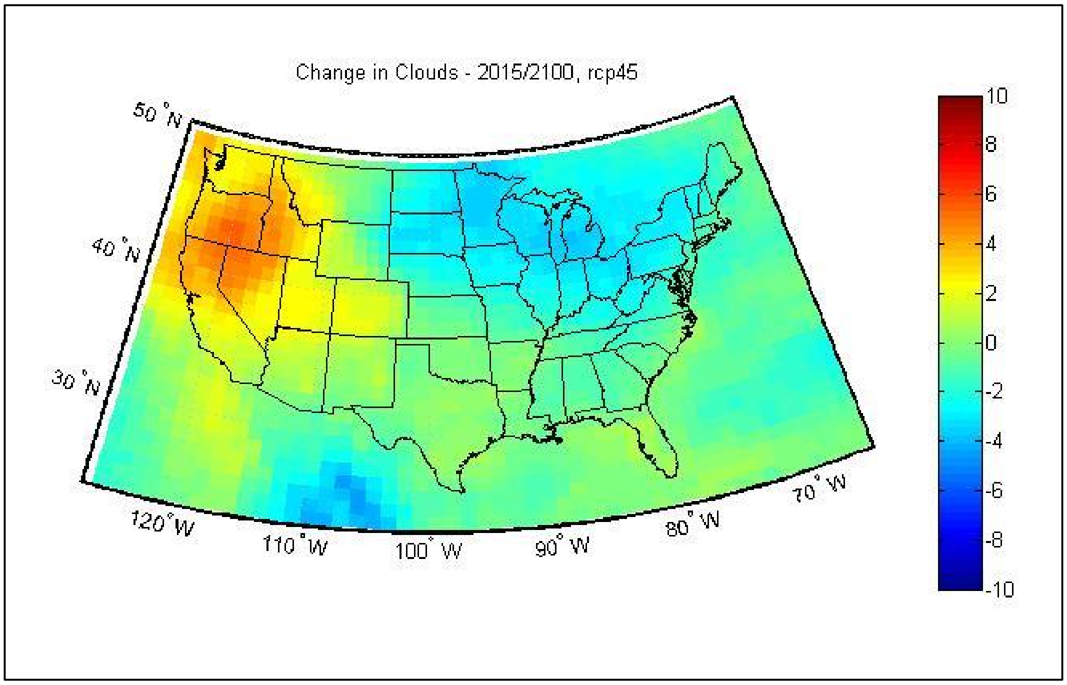


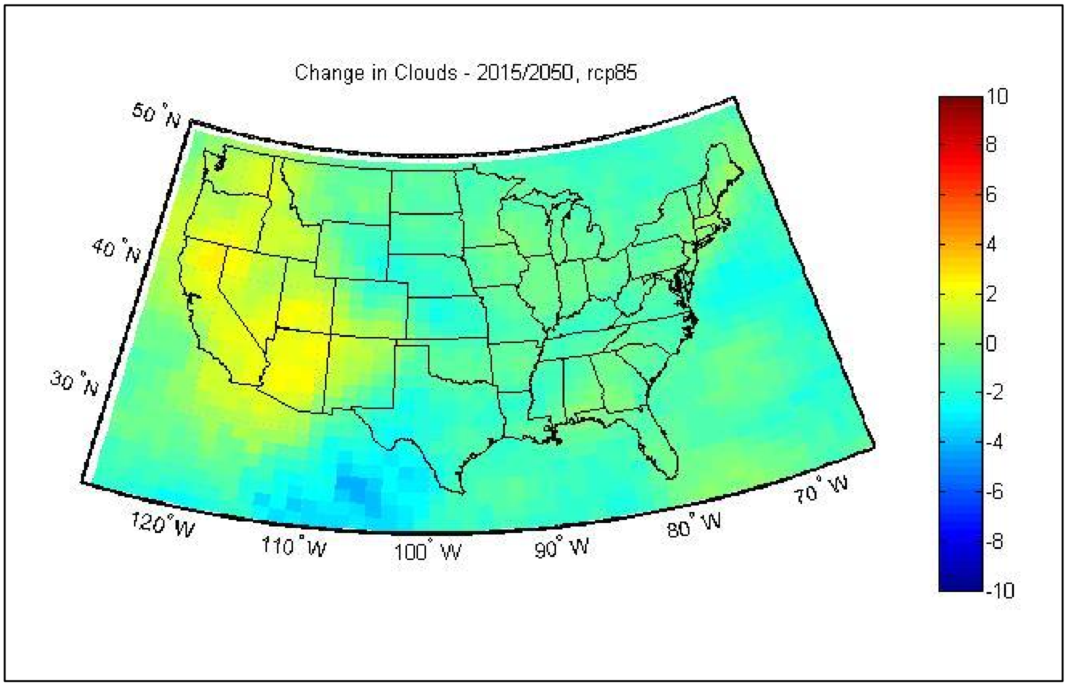
Figure 3.5 | Medium emissions changes in clouds
These figures highlight the temporal changes projected for cloud cover in the 21st century under a 4.5 W/m² forcing scenario. The first map is the change from 2015 to 2050 and the second map is the change from 2015 to 2100. The colors represent the absolute change in average cloud cover in terms of a percentage. For example, going from 30% cloud cover to 25% would be represented as -5% on these maps.

This set of maps shows the change in cloud cover over the United States under a medium (4.5 W/m² of forcing) emissions scenario. By 2050, some areas see significant change. The Western United States sees an increase in projected cloud cover. The largest amount of increase in in the Northwest. The states along the Gulf of Mexico also see an increase in cloud cover. The Midwest sees the most significant decrease in cloud cover compared to anywhere else during this time period.

By 2100, the trends from 2050 for the Pacific Northwest and Midwest strengthen. The Pacific Northwest sees even more projected cloud cover and the decrease in cloud cover in the Midwest continues. Of interest is the Southern United

States – both the Southwest and Southeast. These areas saw increases in cloud cover by 2050 under this emissions scenario but the increase tapers off by 2100. The overall values tend to a low amount of cloud cover increase, roughly on the order of 1%.

3.2.8 Changes in Clouds over the 21st Century – High Emissions Scenario



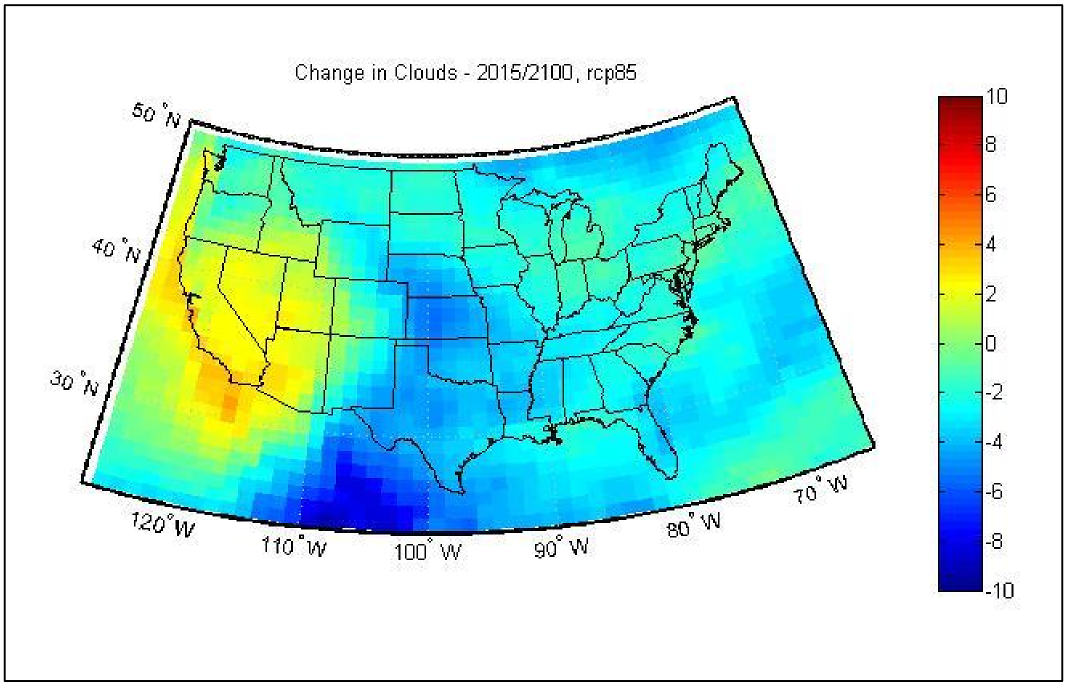
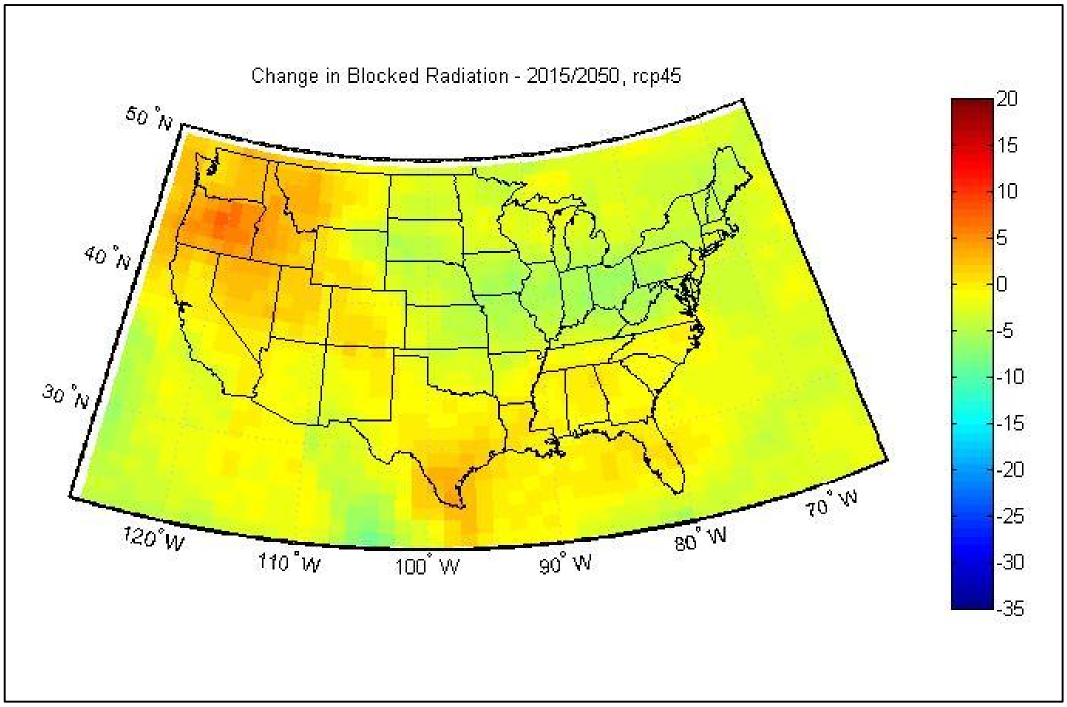


Figure 3.6 | High emissions changes in clouds
These figures highlight the temporal changes projected for cloud cover in the 21st century under a 8.5 W/m² forcing scenario. The first map is the change from 2015 to 2050 and the second map is the change from 2015 to 2100. The colors represent the absolute change in average cloud cover in terms of a percentage. For example, going from 30% cloud cover to 25% would be represented as -5% on these maps.

The high emissions scenario has some interesting results when looking at projected cloud cover change. There are two big regions of change: the West Coast and the rest of the United States. By 2050, the West coast sees a projected increase in total cloud cover. Of note is the fact that the largest increase is centered around the Southwest. The rest of the United States (except for a small portion of New England) sees a projected decrease in cloud cover. The decrease is not large in magnitude but it is spatially significant because it covers such a large area.

By 2100, the changes in cloud cover mellow out. The Southwest holds its projected increase of ~2% from 2050. Thus, from 2050 through 2100 not much changed in the area. The rest of the United States, however, sees its initial decrease in cloud cover continue over the latter half of the 21st century. The Great Plains in particular see a significant drop (on the order of 5%) of cloud cover in the high emissions scenario.

3.2.9 Changes in Blocked Radiation Over the 21st Century – Medium Emissions Scenario



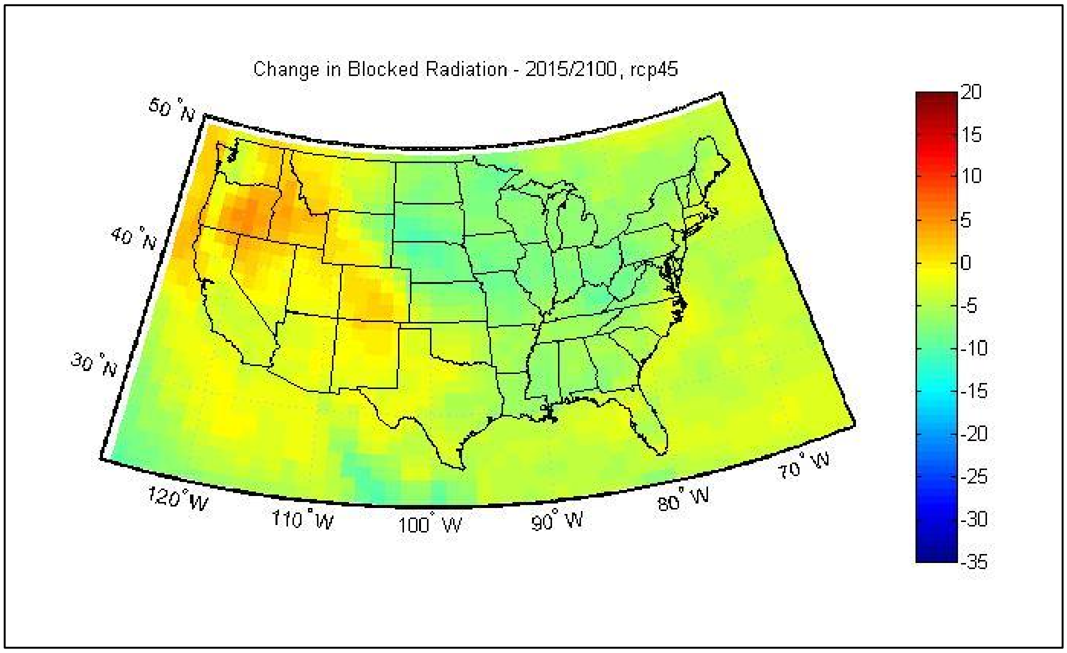


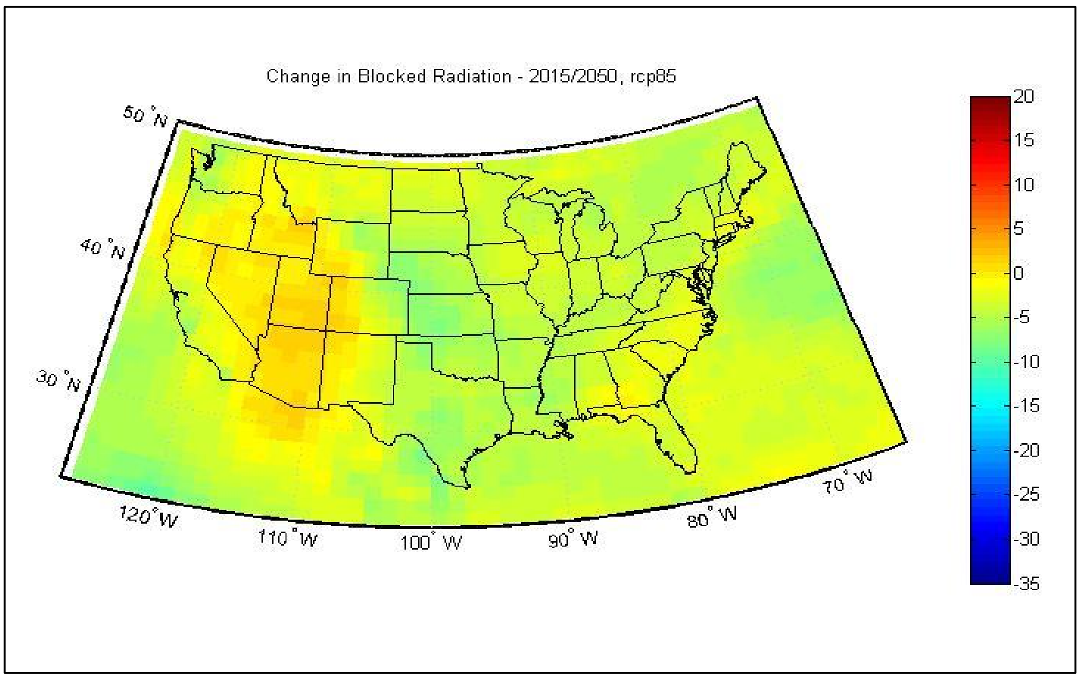
Figure 3.7 | Medium emissions changes in blocked radiation
These figures highlight the temporal changes projected for blocked radiation in the 21st century under a 4.5 W/m² forcing scenario. The first map is the change from 2015 to 2050 and the second map is the change from 2015 to 2100. The colors represent the absolute change in blocked radiation in terms of W/m².

The first figure shows the change in blocked radiation between 2015 and 2050 using rcp45. Warmer colors denote an increase in blocked radiation while cooler colors denote a decrease. In the context of solar resources, warm colors are undesirable. A striking feature of this map is the sizeable increase in blocked radiation in the Pacific Northwest. This region, centered around Oregon, sees an increase of roughly 6 W/m² increase in blocked radiation. The Midwest, on the other hand, sees a considerable decrease in blocked radiation by 2050 under rcp45.

The second map shows the total change in blocked radiation from 2015 to 2100 in rcp45. The map provides CCSM4's projection on how much blocked radiation will change over the entire 21st century. The first point of interest is the

Pacific Northwest. This region saw a considerable increase in blocked radiation between 2015 and 2050. An additional 50 years tempered some of this increase around Oregon and even decreased blocked radiation in areas closer to the coast. The Great Plains and Midwest saw decreases in blocked radiation overall. Another region of interest, the Southwest, saw blocked radiation levels remain relatively stable throughout the entire century.

3.2.10 Changes in Blocked Radiation over the 21st Century – High Emissions Scenario



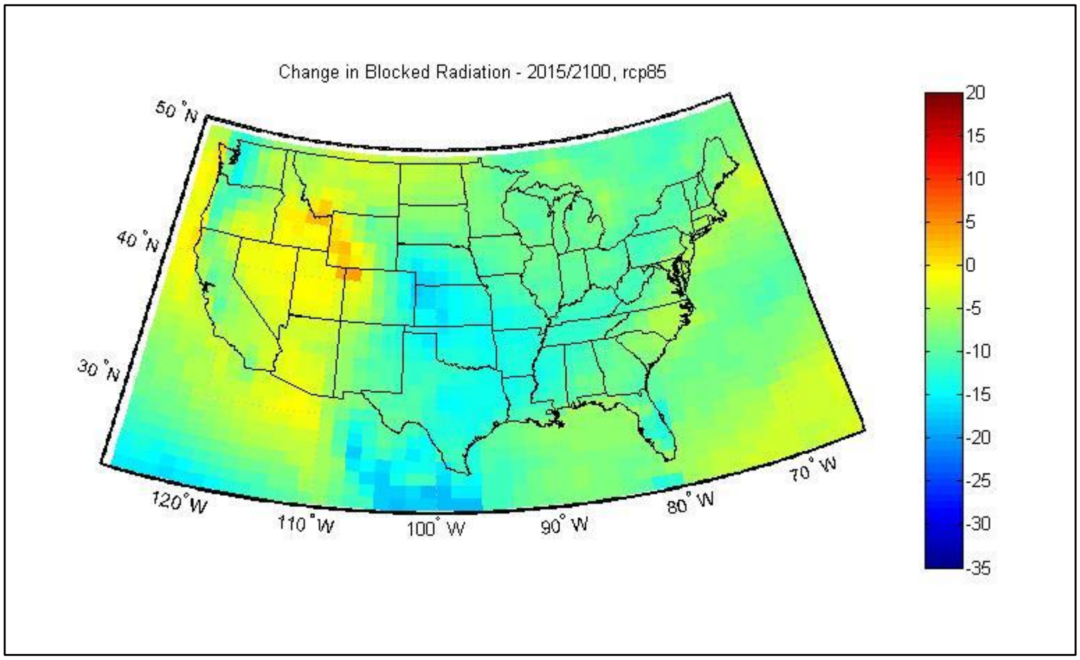
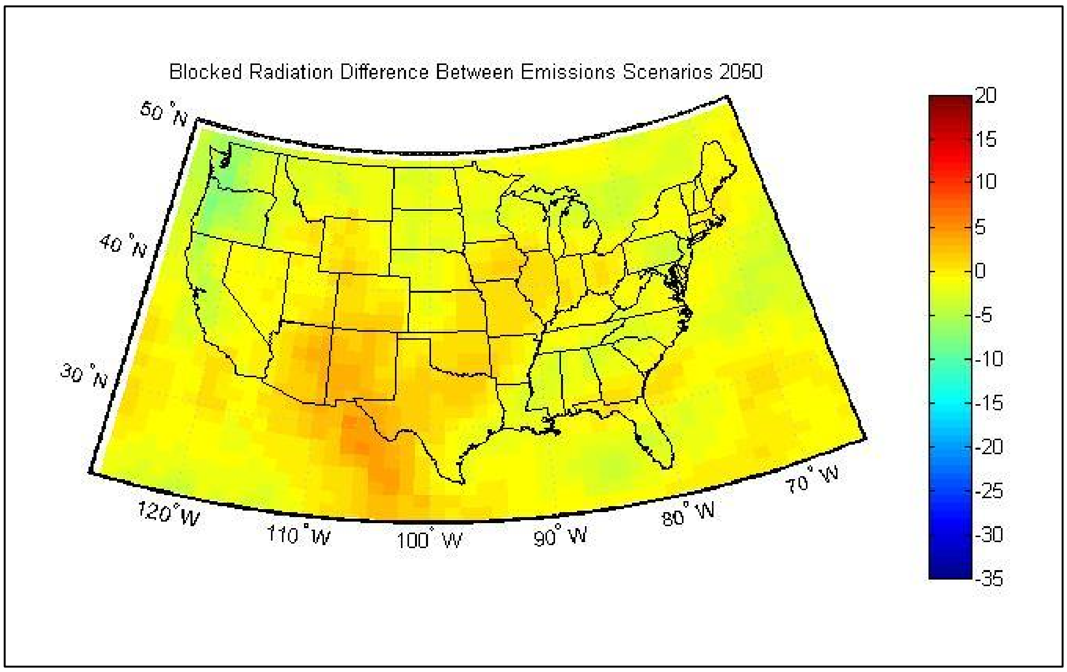


Figure 3.8 | High emissions changes in blocked radiation
These figures highlight the temporal changes projected for blocked radiation in the 21st century under a 8.5 W/m² forcing scenario. The first map is the change from 2015 to 2050 and the second map is the change from 2015 to 2100. The colors represent the absolute change in blocked radiation in terms of W/m².

The next set of maps depict the change in blocked radiation over the 21st century with rcp85, the high emissions scenario. By 2050, blocked radiation levels do not change significantly for large portions of the United States. The Southwest sees very little change overall. However, a swath of the Great Plains through Texas sees a considerable decrease in blocked radiation levels. The Northeast and Southeast see some drop in blocked radiation but, for the most part, values stay relatively stable.

At first glance, it looks as though the stability of blocked radiation levels under a high emissions scenario hold through from 2050 to 2100. However, it is important to note the changes in values represented by the colors. East of the Mississippi, blocked radiation decreases overall with some areas seeing decreases of over 10 W/m^2. The Great Plains and Texas see large magnitudes of decrease, with some places seeing decreases of blocked radiation on the order of 20 W/m^2. The Southwest United States, of interest because of its great solar resources, sees surprisingly little change in blocked radiation in the high emissions scenario.

3.2.11 Differences between Emissions Scenarios



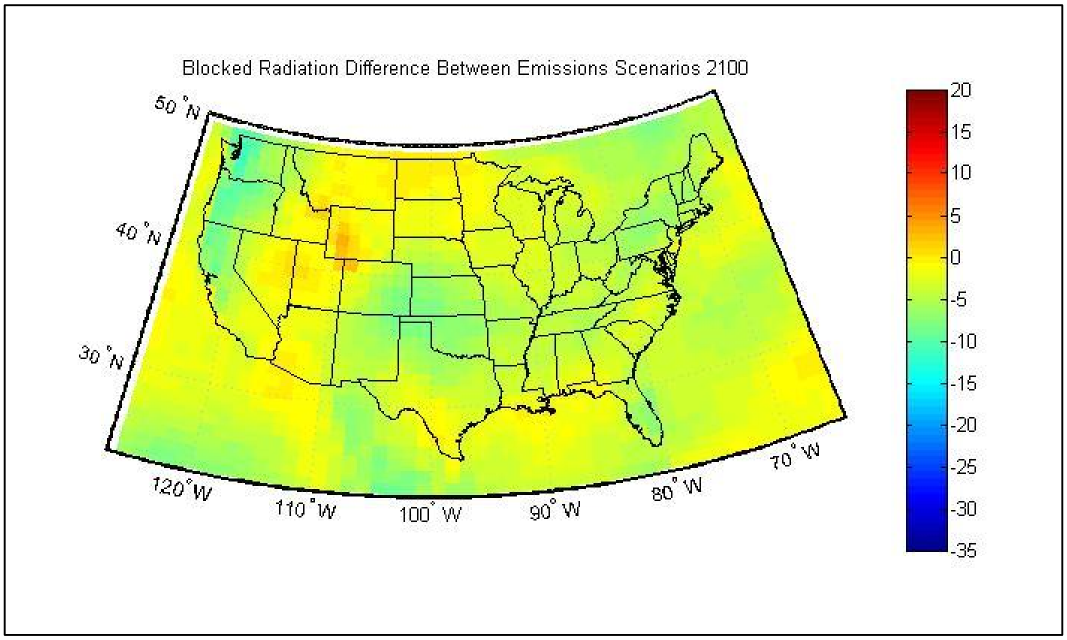
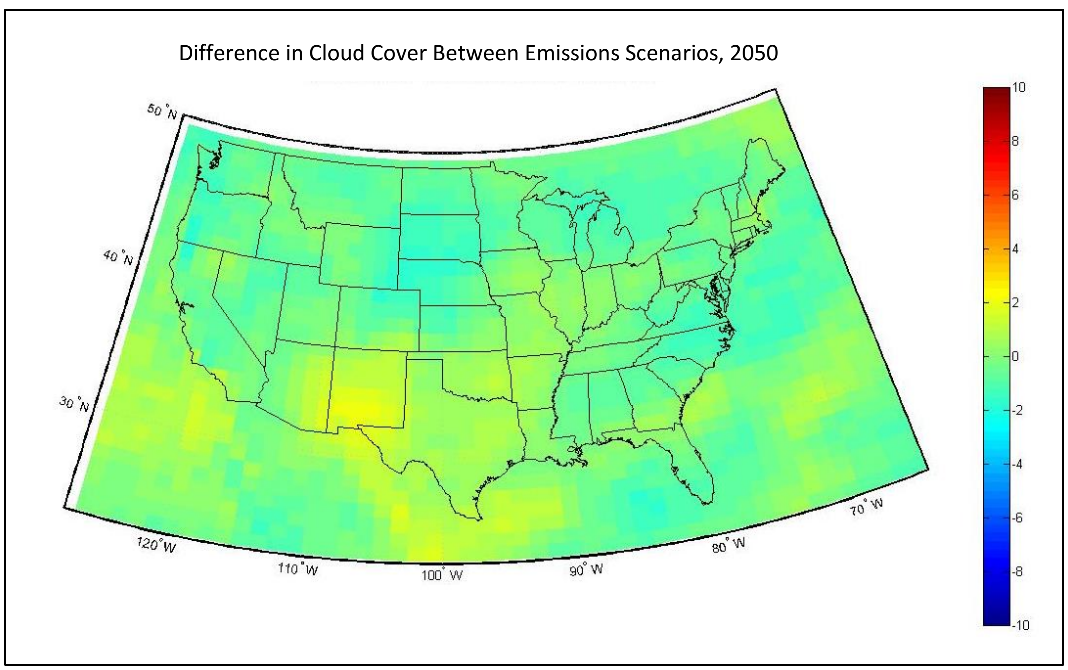


Figure 3.9 | Difference in emissions scenarios, blockd radiation
The figures show the difference in the medium and high emissions scenario for blocked radiation for each year analyzed. Warmer colors denote that the given grid square had more blocked radiation in the high emissions scenario than it did in the medium emissions scenario. The numbers are in terms of W/m^2.



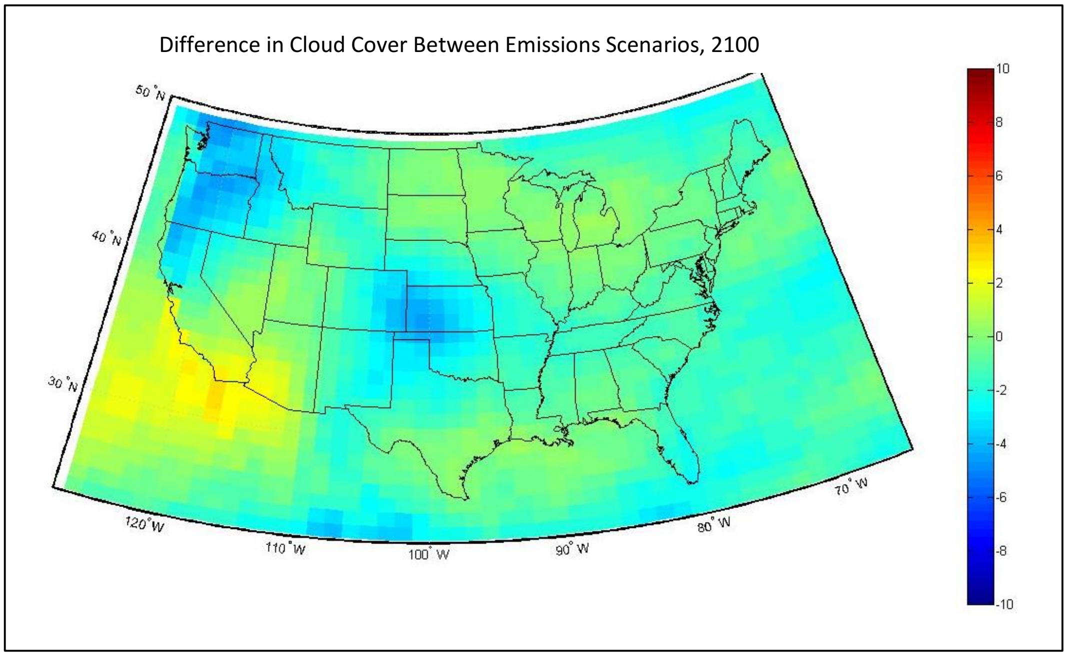


Figure 3.10 | Difference in emissions scenarios, clouds
The figures show the difference in the medium and high emissions scenario for average cloud cover for each year analyzed. Warmer colors denote that the given grid square had more cloud cover in the high emissions scenario than it did in the medium emissions scenario. The numbers are in terms of percentages.

The final set of maps show the changes between the medium and high emissions scenarios. They are in terms of (high emissions values) – (medium emissions values). This means that a negative value for the blocked radiation maps indicates that, for that grid square, there is more blocked radiation under a medium emissions scenario than a high emissions scenario. For cloud cover, a positive value indicates that there is more cloud cover in the high emissions scenario than the low emissions scenario. Maps are provided for both 2050 and 2100.

The difference in blocked radiation for the emissions scenarios shows not too much of a difference between the model runs except for the Pacific Northwest and Southwest in 2050. The Pacific Northwest has negative values, indicating that there is more blocked radiation under a medium emissions scenario than a high emissions scenario. In the Southwest, the values are positive which indicates that there is more blocked radiation in the high emissions scenario than the medium scenario. It is also interesting to note that the difference between the emissions scenarios mellows out through 2100. Much of the United States is within +/- 5 W/m^2 of difference between the model runs. The other point of note is that when there are differences, they tend to be negative. This indicates that a higher emissions scenario would lead to less blocked radiation than a medium emissions scenario.

The differences in cloud cover between the models is more interesting. In 2050, there is a large section centered around New Mexico that has more clouds in the high emissions scenario than the medium scenario. Three other sections, including the Northern Plains, Pacific Northwest, and North Carolina/Virginia show lower amounts of cloud cover. By 2100, much of the United States shows not much of a difference in cloud cover in a high emissions scenario than a medium emissions scenario. Yellow and orange colors denote a low magnitude of difference and much of the United States falls within that range. The Southwest, however, is showing a higher amount of cloud cover in the high emissions scenario than the medium emissions scenario. The Pacific Northwest and Oklahoma see significantly less clouds in a high emissions scenario than a medium emissions scenario.

3.3 Discussion

Solar photovoltaic power is becoming a more important source of electricity in the United States. The amount of solar capacity being installed every year continues to increase but this is not spread equally across the country. The top 3 out of 4 states with the highest amount of solar installed are located in the Southwest (Arizona, Nevada, California) and are only beaten by Hawaii.[39] California itself has nearly 10 GW of solar capacity installed, equivalent to 10 full-size nuclear power plants. It is clear that the most important region for solar power in the United States is the Southwest.

Since the Southwest is the most important region for solar power in the United States, it will be the focus of the analysis of changing solar resources over the 21st century. Any change in cloudiness or blocked radiation could potentially have a large impact on the solar that is installed in the region or would be installed in the future. The climate of this region, as well as how it will change, is integral to the future of solar photovoltaic power in the United States.

3.3.1 Solar Resources under a 'Medium' Emissions Scenario (4.5 W/m^2 of forcing by 2100)

According to the NCAR CCSM4 rcp45 model, the western part of the United States will become cloudier throughout the 21st century. The increase in cloudiness will be centered in Oregon, with the state seeing an increase of almost 5% in average cloud cover. In this scenario, even the Southwest will see an increase

[39] SEIA, 2016.

in average cloud cover. The increase will not be as high as the Pacific Northwest, however, and would be on the order of 2%. This does not mean good news for the Southwest and the quality of its solar resources. Increased amounts of clouds in the atmosphere would be expected to decrease the quantity of the solar radiation reaching the ground. Fortunately, this can be tested with another variable, blocked radiation.

Under the medium emissions scenario, blocked radiation behaves in an interesting manner. Since the western part of the United States showed an increase in average cloud cover, it would be expected that blocked radiation would increase across the entire region. However, this is not the case. In Oregon and the Pacific Northwest, blocked radiation does indeed increase. The Southwest, on the other hand, does not see this increase in blocked radiation. Rather, blocked radiation registers no meaningful change in either 2050 or 2100 for the Southwest. This creates a conundrum: how does the cloudiness of an area increase yet the amount of solar radiation reaching the ground remain relatively constant?

A possible explanation for how the Southwest can be cloudier and still retain the same level of blocked radiation is the temporal distribution of the increase in cloudiness. In other words, the timing of cloudiness matters. Since solar radiation would only be affected by clouds increasing during daylight hours, any increase in clouds that occurred overnight would have no effect on the blocked radiation in the region. Thus, since cloudiness of the Southwest increases but blocked radiation remains constant, the increase in cloud cover must be occurring during the night.

3.3.2 Solar Resources under a 'High' Emissions Scenario (8.5 W/m^2 of forcing by 2100)

The high emissions scenario, like the medium emissions scenario, causes the western United States to increase in cloudiness. However, unlike the medium emissions scenario, this increase in cloudiness is center around the Southwest. By 2050, the average cloud cover is projected to increase by about 2%. By 2100, this increase reaches 4% in some areas of the Southwest with the entire region seeing an increase in cloudiness.

As for blocked radiation, these values remain relatively constant through 2050. Small portions of Arizona may see a slight decrease (less than 5 W/m^2) but the entire region of the Southwest sees little change. By 2100, the Southwest is projected to see either no increase in blocked radiation or even a slight decrease.

The dichotomy between increasing clouds and unchanged (or even decreasing) blocked radiation occurs in the high emissions scenario. In this model run, the Southwest increases its average cloudiness yet sees little to no change in the amount of solar radiation reaching the ground. Thus, the temporal distribution of clouds must be important in this scenario as well. In both the medium and high emissions scenario the timing of changes in clouds proved to be important in their effect on solar resources. Therefore, this is an important consideration that must be taken into account when analyzing how the solar resources of a region could change in coming years.

3.3.3 Differences in Emissions Scenarios – Blocked Radiation

The difference in the projected change of blocked radiation between emissions scenarios is interesting because they will be mostly anthropogenic in origin. In other words, the choices that humans make will determine whether the 21st century sees a medium or high emissions scenario which directly effects the variables studied in the solar resources analysis.

In 2050, the differences in blocked radiation in the Southwest United States between emissions scenarios are small except for Arizona and New Mexico. Besides these two states, there is little difference in the amount of blocked radiation under the different emissions scenarios. In Arizona and New Mexico, however, there is about 5 W/m^2 more blocked radiation under a high emissions scenario than a medium emissions scenario. Consequently, these states will see benefits for their solar industries if emissions remain relatively constrained. Besides the Southwest, the Pacific Northwest is interesting to view in terms of differences between emissions scenarios. By 2050, the blocked radiation of these regions already begins to diverge. A high emissions scenario sees much less blocked radiation than a medium emissions scenario. Thus, solar resources in the Pacific Northwest will be better under a high emissions scenario.

By 2100, the differences between emissions scenarios in the Southwest all but disappear. The discrepancy between the scenarios seen in Arizona and New Mexico in 2050 dissipates to a negligible level by 2050. Thus, by the end of the century, there does not seem to be much hinging on the level of CO_2 emissions in regards to solar resources in the Southwest United States. The Pacific Northwest, however, is another story. These region sees a significant difference between emissions scenarios. Under the high emissions scenario, the lower levels of blocked radiation seen in 2050 become even lower in 2100. For the Pacific Northwest, the higher the emissions of the 21st century, the better the solar resources of the region.

3.3.4 Difference in Emissions Scenarios – Clouds

In 2050, the difference between emissions scenarios in terms of clouds is relatively negligible. However, there are more clouds in the high emissions scenario in Arizona and New Mexico than in the medium emissions scenario. This difference in cloudiness helps to explain the difference in blocked radiation that was discussed above. In terms of differences between emissions scenarios, it seems that cloudiness does have an effect. This is a departure from what was seen earlier in analyzing the changes in blocked radiation and clouds throughout the 21st century.

By 2100, differences in average cloud cover in the Southwest disappear. The region is more or less unchanged in terms of cloudiness under either scenario. There is one interesting region in 2100, however. The Pacific Northwest sees a dramatic difference in the level of cloudiness between emissions scenarios. In the high emissions scenarios, the average cloud cover is on the order of 5% lower than the medium emissions scenario. This helps to explain the difference between blocked radiation in this region under the two emissions scenarios. As outlined above, the amount of blocked radiation in the Pacific Northwest is significantly lower under a high emissions scenario than a medium emissions scenario. The best explanation for this is the substantial difference in average cloud cover seen between the emissions scenarios.

3.3.5 Conclusions

The solar resources analysis using a GCM provided interesting insight into how the future of solar power in the United States may change. One particularly noteworthy region was the Pacific Northwest. The Pacific Northwest is interesting because of the considerable difference between emissions scenarios. Under a high emissions scenario, the solar resources of the Pacific Northwest will be in a much better place than under a medium emissions scenario. More emissions drives a decrease in average cloud cover which leads to a decrease in blocked radiation. However, this finding may prove to be unimportant. The Pacific Northwest is not known for solar power. One reason is because of its climate. The region is cloudy and sits at a higher latitude, leaving little opportunity to gather significant amounts of energy from the sun. The other reason is because the Pacific Northwest has a substantial amount of hydroelectric power. The large amount of hydroelectric power leads to low electricity prices, which makes installing solar photovoltaic power unattractive. Thus, while the solar resources of the Pacific Northwest would be affected differently under emissions scenarios, the impact would be inconsequential.

On the other hand, the Southwest of the United States is the best place in the country for solar power. As one would expect, the country has most of its solar power capacity installed in this region. Thus, any changes in its climate over the coming century could have a significant impact on the state of solar power. However, the region is not expected to see drastic changes in its solar resources. Under both emissions scenarios, clouds are expected to increase in this region. However, analysis of blocked radiation values shows that the solar radiation reaching the ground will remain relatively constant. Thus, the impact of the increase in clouds is negligible. Overall, the Southwest is projected to remain an area with outstanding solar resources.

Finally, the analysis of solar resources provided insight into an unexpected phenomenon. Typically, one of the driving forces of the quality of solar resources in a region is the level of clouds that are usually in the atmosphere. Clouds are excellent at blocking solar radiation from reaching the ground so the more clouds an area has, the worse the quality of its solar resources. However, this analysis showed that some regions can increase their average cloud cover yet have no significant change in the amount of blocked radiation in the area. Thus, the increase in clouds had a negligible effect on the solar resources of the area. One possible explanation for this is that the increase in clouds happens at night. If the amount of nighttime clouds increases while the average cloud cover of the day remains constant, the total average cloud cover will go up with no effect on solar radiation. This is an important finding that should be taken into consideration when analyzing how solar resources could change in an area.

CONCLUSION

The Significance of Short Term Variability

` The results of the short term variability analysis show that solar photovoltaic power production can fluctuate considerably in 5 minute timescales in New England. One year's worth of data demonstrates that the magnitude of fluctuations approaches 100% of the rated capacity of a given array. This means that an array producing its maximum amount of power can drop to zero production in a short time period. The consequences of this are significant. Current electrical grid operation has systems designed to fix the sudden loss of power production, called contingencies, and maintain normal operation. What would the result be if a large portion of production capacity on the grid became solar and contingency plans became normal operation?

This study provides a possible scenario on how the electrical grid may have to operate if large amounts of solar power capacity are added in the future. Since solar power production can fluctuate so considerably, its power production must be backed up by other power reserves on the grid. In the worst-case scenario, every kW of installed solar capacity would have to be backed up with an equal amount of reserves that could act on at least a 5 minute timescale. Geographic variation of panels will help to mitigate this worst case scenario, but the analysis showed that there is no upper bound for reserves required due to weather-related events.

Another outcome of the significance analysis of short term variability is the discovery of a strong correlation between season and short term variability. Variability reaches a minimum in winter. Maximum variability values from the late spring, summer, and early fall can reach three times the maximum variability experienced in December. Two reasons have been proposed for this seasonal correlation. The first is that New England's climate is a driver of the different levels of variability witnessed. In the summer, a convective atmosphere provides the right conditions for sunny days with intermittent cumulus clouds. The combination of these factors leads to high levels of variability as a solar panel can be fully irradiated and then have a shadow from a cloud quickly fall over it. Another reason for the seasonal correlation is that the winter has low levels of maximum insolation as compared to the other seasons. Since the maximum amount of insolation is lower, the maximum power production of the panels is lower. With a lower maximum power production, the magnitude of maximum change is lower. In other words, a lower amount of maximum insolation constrains the maximum amount of change that can occur.

Short term variability of solar power production has been shown to be an important problem that must be considered when determining the future of solar power. Power production can be highly variable and this has consequences for the current electrical grid. In order to maintain the quality and supply of electricity, the short term variability of solar power must be effectively managed. Overall, short term variability must be considered when examining the addition of solar photovoltaic power to the electricity system.

Mitigation of Short Term Variability

Storage systems are able to make a meaningful impact on mitigating short term variability. Using an optimized mathematical model, it has been shown that a storage system is able to reduce the variability caused by a solar array in a system considerably. Thus, using storage systems would be an option to mitigate solar photovoltaic power variability at the source. Further research is required to design an optimal system, but this analysis has proven the concept.

The best option to manage short term variability would be a storage system with a small capacity and high maximum power output that is optimized to focus on short term variability. In the analysis, the driving factor of mitigation of variability was the storage system's maximum power output. Capacity of the storage system had no effect. Thus, when considering systems to mitigate variability, the best option would be a system that is able to obtain a high maximum power output. On the whole, storage systems would be an effective option in dealing with short term solar power variability.

The ability to mitigate short term variability of solar photovoltaic panels effectively would be an important advancement in adding solar capacity to the electrical grid. As shown in the significance analysis, short term volatility can have a large enough magnitude and frequency to be a considerable problem. Short term variability causes problems for grid operators and is detrimental to the infrastructure of the grid. Storage solutions focused on mitigating variability that are coupled with arrays themselves could have a significant impact in solving this problem. If short term variability mitigating storage systems became common, there would no longer be any worry about having enough spinning reserves backing up solar photovoltaic panels. This is an important step in the future of a renewable electrical grid that takes advantage of solar photovoltaic power.

Solar Resources and the 21st Century

The analysis of how solar resources may change over the 21st century indicated that the high quality of solar resources in the Southwestern United States is secure. Even under a high emissions scenario, the climate of the Southwest is not projected to change drastically. It will maintain its sunny conditions throughout the century, making it a prime location for solar power installations.

Within the analysis, an interesting point was uncovered. In the Southwest, cloudiness is projected to increase under some emissions scenarios. However, under the same emissions scenarios, the amount of radiation being blocked by the atmosphere (mainly by clouds) is projected to remain the same. If clouds become increasingly common but the amount of radiation blocked by clouds remains the same, this would imply that cloud cover would mainly be increasing during the night. Under this scenario, the temporal distribution of the change in cloudiness proves to be a driving factor in how solar resources will respond to climate change.

The results of this analysis are important because they provide a level of certainty about the future of solar resources in the Southwestern United States. Expensive infrastructure projects like high-voltage direct current transmission lines are not at risk of becoming obsolete in the next century due to a changing climate. In other words, if infrastructure to take advantage of sunny skies in the Southwestern United States is built, the region becoming cloudy is not one of the possible reasons of failure. This analysis showed solar resources will remain of high quality which provides a level of confidence for any future solar or infrastructure projects in the region. The Southwest will continue to be a tremendous opportunity for renewable solar power in the United States and is not at risk of losing this quality in the next century. The region is suitable for the investment and development of solar power in the near and long term.

Directions for Future Research

Solar photovoltaic power will be an important part of any renewable energy-based society of the future. This thesis has shown that short term variability is a significant problem that must be recognized in the New England region. Further research should expand the geographic extent of this analysis to see if it remains significant across the United States. The mitigation analysis proved that a battery could be an effective tool in reducing volatility; however the exact design of a mitigation system must still be designed and optimized. The Southwest is one region of the United States with high quality solar resources that will remain so throughout the next century in spite of climate change. Other regions of the world where large solar installations and infrastructure have been proposed, such as the Sahara and Gobi Deserts, would also benefit from an analysis of future climate to reduce the risk of future solar projects. Further research will ensure a bright future for solar photovoltaic power.

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