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A Study Of The Sensitivity Of Solar Power Generation To Varying Weather Conditions

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A STUDY OF THE SENSITIVITY OF SOLAR POWER GENERATION TO VARYING WEATHER CONDITIONS

by

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This thesis, submitted by Nathaniel Jeffrey Smith in partial fulfillment of the requirements for the Degree of Master of Science from the University of North Dakota, has been ready by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

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Nathaniel Jeffrey Smith
April 29, 2018

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In loving memory of Leon F. Osborne,
a great advisor, instructor, and friend.

ABSTRACT

Solar energy has seen ever-increasing implementation as a power source throughout the world since its introduction into the energy production market. Meteorological parameters including temperature, wind speed and albedo can have significant impacts on the amount of power that is produced at a utility-scale solar farm. This study sought to review the sensitivity of solar energy production to these varying weather parameters. The modeled sensitivity was tested by running simulations using modified weather data and comparing the power output to a baseline simulation. Results show that temperature has a significant effect in the efficiency of the solar panels, and by extension, the power produced. Wind speed plays a significant role in heat dissipation, while modifying albedo results in a change in the power produced as well, albeit to a lesser extent.

CHAPTER 1

INTRODUCTION

Why Renewable Energy?

For decades, the primary sources of energy within the United States have come from fossil fuel sources, such as oil and coal. Unfortunately, the burning of these fuels gives off large amounts of carbon dioxide, among other pollutants. Kreith et al. (1990) suggested that the amount of carbon dioxide produced by natural gas, coal and oil was up to 45.5, 81.9 and 127.4 metric tons per gigawatt hour of energy produced, respectively. Evans et al. (2009), reported that the global energy production in the year 2005 was 17,450 TWh, of which, 67% of the total energy production was sourced from the fossil fuels of coal, oil and natural gas, while the remaining 33% was comprised of 16% nuclear, 16% hydro power and 1% renewable energies (geothermal, solar, wind, combustible renewables and waste). Evans et al. (2009) also reported that coal is known to have the highest carbon dioxide emissions per kWh and is known to emit other pollutants at high levels. They also noted the main reason these fossil fuels are used is due to their low cost and high availability.

Despite the ease and cost effectiveness of using fossil fuels for power production in the United States and across the world, there are very serious drawbacks. The primary concern of burning fossil fuels to create power are the greenhouse gasses these power plants are emitting into the atmosphere. Carbon dioxide and other greenhouse gasses have been shown to have a global impact on climate (IPCC 2014). These greenhouse gasses contribute to climate change by absorbing longwave radiation that has been emitted from the surface of the Earth, and reemitting it back towards the surface, thus causing a slow increase in the average temperature of the Earth. The use of renewable energy technologies in place of conventional fossil fuel plants can significantly reduce the carbon footprint of energy companies, in terms of the amount of carbon dioxide and other pollutants being emitted into the atmosphere per GWh of energy being produced. Kreith et al. (1990) compared two 100 MW photovoltaic (PV) plants to a 747 MW fluidized-bed coal plant over a 30-year lifetime, and found that the coal plant emitted 1041 metric tons of carbon dioxide per gigawatt hour of energy produced, of which five metric tons were produced during construction and 28 metric tons during operation and maintenance. The remaining 1008 metric tons were produced from the burning of fossil fuels. The solar plants emitted on average 26.5 metric tons of carbon dioxide per gigawatt hour of electricity, 16.5 metric tons on average from construction and 10 metric tons on average from operation and maintenance. None of the reported CO_2 contribution resulted directly from the conversion of solar irradiance to AC power through the panels or inverters.

History of Solar Energy

Just as with fossil fuels, solar energy production technologies are not entirely new. According to the United States Department of Energy (DOE), one of the first examples of storing and harnessing solar technology occurred in 1767. "Swiss scientist Horace de Saussure was credited with building the world's first solar collector, later used by Sir John Herschel to cook food during his South Africa expedition in the 1830s" (DOE 2005). However, the modern development of solar energy technology did not truly begin until the late 1940s and early 1950s. In 1954 Bell Lab scientists Daryl Chapin, Calvin Fuller and Gerald Pearson developed the silicon photovoltaic (PV) solar cell. This was a significant development, mainly due to the fact that this was the first solar cell that was capable of producing enough solar power to operate everyday electrical equipment. This first solar cell had a conversion efficiency of 4% (DOE 2005). These solar power arrays quickly became popular in space agencies throughout the world, and small arrays were used to power radios and telecommunications on many satellites such as the Vanguard I, Vanguard II, Explorer III, and Sputnik-3, which were all launched in 1958. However, attempts to commercialize the solar industry on the ground at the time were, for the most part, faltering.

One of the primary reasons that solar energy struggled to gain traction in commercial and residential industries prior to 1970 was the cost of production. In 1970, Dr. Elliot Berman developed a significantly less costly solar cell. He, in a partnership with Exxon Corporation, designed a solar cell at a cost of $20 per cell, down from the prior cost of $100 per cell, to help power warning lights and horns on offshore oil and gas rigs (Department of Energy 2005). With this reduction in cost, the solar energy industry has seen substantial growth, and in 1977, the U.S. Department of Energy launched the Solar Energy Research Institute, which was re-designated as the National Renewable Energy Laboratory (NREL) in 1991 by then President George H.W. Bush.

More recently, solar energy has become a viable option for producing electricity at a commercial utility scale. This is particularly true for areas within the desert southwest, where there is minimal cloud cover and long periods of sun throughout the year. In 2000, a concentrating solar power plant was constructed that was capable of producing 150 MW of electricity, which could provide power to 150,000 homes when operating at capacity (DOE 2005). On 31 August 2017, NextEra Energy released an energy resources portfolio describing all the different forms of energy production used by the company and mentioned the amount of power produced by each form from the sites that are owned/co-owned and operated by the company. Of the 21,368 gross MW of power capability when all systems are operating at capacity, 2,673 MW of that are produced by solar energy plants located throughout the United States, Canada and one site in Spain (NextEra Energy 2018) (Fig. 1).

Figure 1. A solar farm in operation (NextEra Energy 2018).

The solar energy industry as a whole has made large advancements in conversion efficiency, cost of production and total production capacity over the past 60 years. Solar energy currently meets about 2% of the global energy needs (Evans et al. 2009) and produces many thousands of megawatts of electricity per year. Not only has its cost of production decreased, it has also been highlighted as a viable option when it comes to generating electricity at a utility scale.

As currently applied, some of the parameters that affect solar power production the most are atmospheric conditions. Being able to determine how much energy is being lost to these atmospheric conditions is therefore worth exploring when designing future solar projects to obtain the most realistic results possible. This study will examine the effects of several atmospheric parameters on the irradiance and module temperature and will include ambient air temperature, wind speed, and surface albedo. In the past it has been shown that module temperature, which is affected by plane-of-array irradiance and ambient temperature, has a significant impact on the performance of solar modules (Kurnik et al. 2010). The accepted "reference" temperature used to simulate module performance conditions is 25 °C. As temperature increases, losses occur due to excessive heat affecting module efficiency (King et al. 2004). A module, by definition, is "a unit comprised of several photovoltaic (PV) cells that is the principal unit of a PV array and is intended to convert solar radiation to energy" (NREL 2018). It is expected that an increase in temperature will cause a decrease in power production with this study as well, and vice versa. Wind has also been shown to affect power production levels, as wind helps to dissipate heat away from solar modules and increase conversion efficiency. Kurnik et al. (2010) found in their research that the difference between the PV array temperature and ambient air temperature was halved when the winds were increased from zero to 12 m s^{-1}, for any non-zero conversion efficiency. This type of result is expected in this study as well, as the wind should help dissipate heat during the simulations. The third parameter to be considered in this study is albedo. This is a measure of the fraction of incident sunlight that is reflected off the Earth's surface surrounding the solar panels. A portion of this reflected energy will strike the panels, adding to the direct and diffuse irradiance from the sun and atmospheric refraction, respectively. It is worthwhile to investigate whether the different surfaces at each location result in different power production levels, particularly at locations with seasonally changing surfaces (i.e. summer grass versus winter snow). It is expected that modifying albedo will result in small changes in power production values.

Objective

The objective of this research is to determine the relative effect of several weather parameters on modeled energy output. This knowledge will help modelers and engineers determine the best locations for constructing solar plants, based on where the atmospheric phenomena in question are most favorable. This study will utilize the System Advisor Model (SAM), a solar energy prediction model. It will be initialized with varying atmospheric parameters to observe which parameters limit energy output the most.

CHAPTER 2

BACKGROUND

System Advisor Model Background

Many factors need to be considered when siting a commercial solar array. Land acquisition and production capacity of the solar farm are a couple of factors to consider when going through the design process before moving to construction. The primary focus of this study is the design process of solar farms and what meteorological parameters have the greatest overall impact on power production. This is where SAM becomes useful. As stated by NREL (2017): "The System Advisor Model (SAM) is a performance and financial model designed to facilitate decision making for people involved in the renewable energy industry. SAM makes performance predictions and cost of energy estimates for grid-connected power projects based on installation and operating costs and system design parameters that you specify as inputs to the model". SAM is a very comprehensive model and simulates power production for not only many different solar module types, but also for wind energy, geothermal energy, solar water heating, and biomass-based energy. SAM also has financial models that can simulate cash flow based on cost of construction and operation and agreed upon sale price of electricity between the owner of the power plant and the utility company. The latter is known as a Power Purchase Agreement, which can be implemented for commercial and utility power plants, as well as residential systems. For the purpose of this study, the focus is solar power generation, and so other types of energy production and the financial models are not used.

SAM was originally developed in 2005 by NREL, in collaboration with Sandia National Laboratories. It was originally called the "Solar Advisor Model" because it was "used internally by the U.S. Department of Energy's Solar Energy Technologies Program for systems-based analysis of solar technology improvement opportunities within the program" (NREL 2017). The name of the model was changed to System Advisor Model in 2010, due to the addition of the modeling of alternate forms of renewable energy (NREL 2017). The current list of SAM users includes several government agencies (DOE, NREL and Sandia) for the purpose of program planning and grant programs and project developers who use SAM to configure a solar farm in a way to achieve maximum earnings from electricity sales (NREL 2017).

Of the many performance models that are included within SAM, this study used the "Detailed Photovoltaic" solar prediction model (Fig. 2). This model was chosen in part because it gives the user the capability to select specific solar modules and inverters that will be used when designing the solar farm. As the name suggests, many other parameters within this model are user determined, including the sub-models within the detailed photovoltaic model that are used to simulate how much solar energy is created by the solar panels from the incoming irradiance. Another sub-model within the detailed photovoltaic model is the inverter model. This sub-model takes the simulated DC energy output that was created by the solar array sub-model and uses that as an input to a series of equations that are used to convert the DC power to AC and output it to the grid. The detailed photovoltaic model also simulates energy losses due to excessive module temperatures, and gives the option to simulate other losses such as module shading, soiling, and other mechanical losses (NREL 2017).

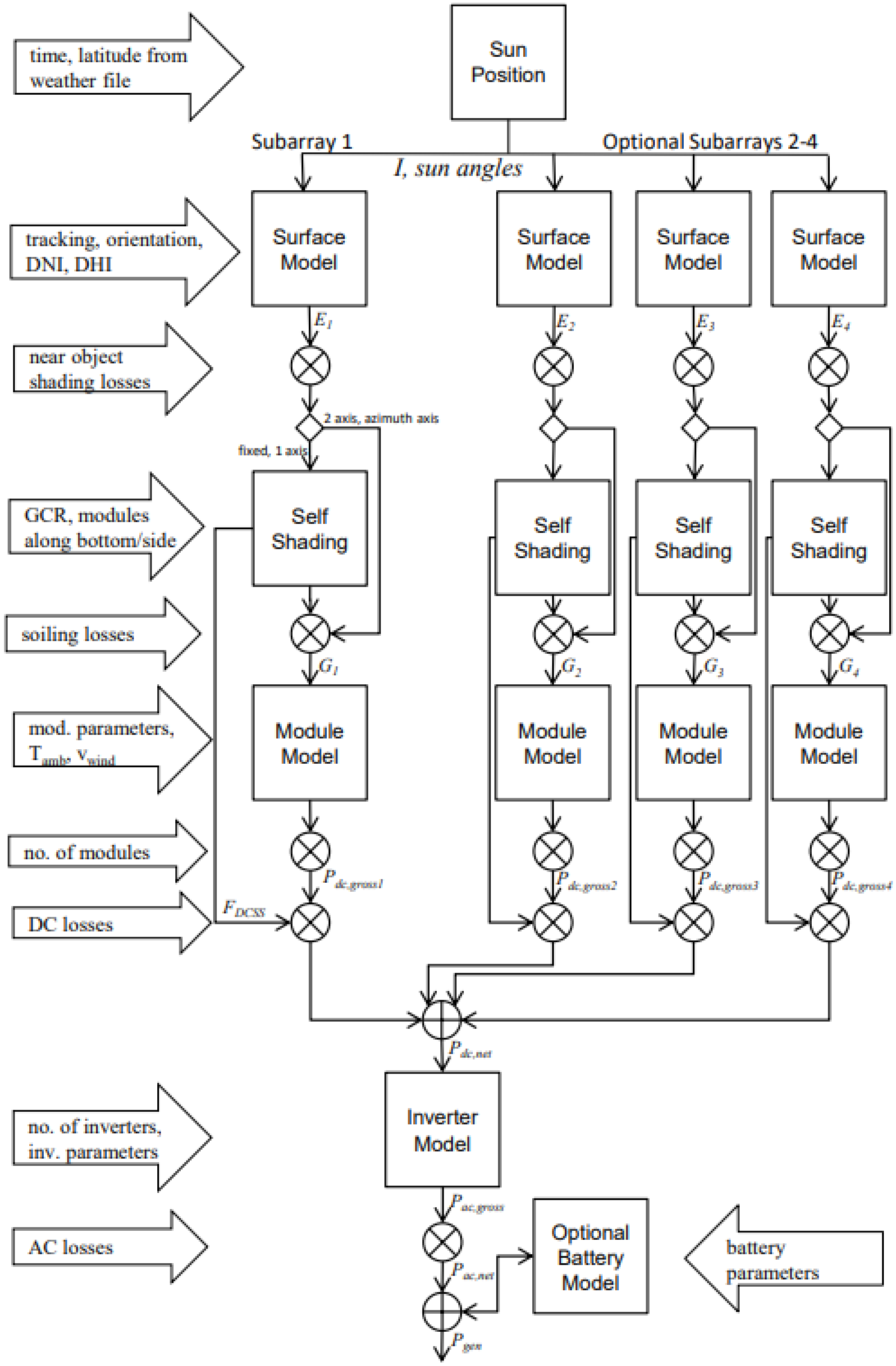

Figure 2. Block diagram of the operation of the Detailed Photovoltaic Model (NREL 2015).

The other common solar model chosen within SAM is the PVWatts model. PVWatts allows the user to enter a few basic inputs for the potential solar farm, such as, power generation capacity (henceforth nameplate capacity), the orientation of the array, how it is mounted, and what types of losses can be expected within the system (NREL 2017). However, PVWatts makes internal assumptions about module and inverter characteristics for three types of modules (NREL 2017). These internal assumptions limit the customization abilities when designing a solar farm for a specific area, which is the primary reason why the detailed photovoltaic model was chosen instead.

One factor that is consistent with both solar models is the need for input data. For this, SAM uses a database of compiled observational data taken from locations around the world. This database was assembled by NREL and is named the National Solar Radiation Database (NREL 2017). Observed data in the files include 2 m temperature, dew point temperature, relative humidity, sea level pressure, wind speed, wind direction, albedo measurements, global horizontal irradiance, direct normal irradiance, and diffuse horizontal irradiance. These data are collected at hourly increments for an entire year, resulting in 8,760 hourly observations for each site. The irradiance data are the primary input data that SAM uses when simulating the energy prediction values at a specific location. Weather data are also used in SAM to model effects of atmospheric parameters, such as temperature and wind, and their impact on the overall prediction estimates, and can act to increase or decrease those estimates accordingly (NREL 2017).

As mentioned previously, a feature that is unique with the detailed prediction model within SAM, as compared to PVWatts, is the customizability of the solar farm the user wants to build. With the detailed solar model, the user can select both the solar modules and power inverters they wish to use from a list of thousands. The libraries for both the solar modules and inverters used by SAM were composed by a company called Go Solar California, and contain the manufacturer specifications for most solar modules and inverters on the market today (NREL 2017). Once the specific modules and inverters have been chosen, the detailed model gives the user the option to select submodels that determine the following: how the model simulates diffuse radiation; how the solar modules convert the solar radiation to DC power; and how the DC power is converted to AC through the power inverters.

The first routine has to do with how SAM simulates diffuse atmospheric irradiance. Three process options are available with this step, each with varying complexity, depending how simplified the user wants this part of the simulation to be. The first process is the simplest: an isotropic model that assumes that diffuse radiation is evenly distributed across the sky, regardless of zenith angle (NREL 2015). The second available process for diffuse sky irradiance is the Hay, Davies, Klucher and Reindl model (HDKR). This model is similar to the isotropic model, in that, it assumes isotropic conditions everywhere except at angles close to solar zenith, where it assumes higher diffuse irradiance numbers (NREL 2015). Finally, the third process is the Perez model. Developed in 1990, SAM incorporates a modified version of the model, which assumes isotropic conditions only within 2.5° of the 0° zenith angle. Beyond that range, the values of the diffuse radiation are determined by coefficients that are empirically derived from a series of sky conditions and locations. This differentiates the Perez model from the isotropic model and the HDKR model, which were both mathematically derived instead being derived empirically (NREL 2015). Owing to its accuracy, the Perez model was chosen for this study. All atmospheric data, including albedo, irradiance and other atmospheric parameters are used as input data in the detailed photovoltaic model. SAM utilizes the atmospheric data and simulates the amount of DC power produced by solar modules and, ultimately, the amount of power that is converted to AC and sent out to the grid.

PV Array Performance submodel Options

One of the major components of the detailed solar performance model is the submodel that simulates the amount of power produced from incoming solar irradiance. With SAM, there are four available submodels to choose from when choosing the array performance model. The first of the four options is the Simple Efficiency Module Model. This model is designed to give preliminary results, before the user has chosen a specific module. The requirements for this submodel include the module area, a set of conversion efficiency values, and any temperature correction parameters (NREL 2015). Due to the fact that it only requires this limited information and nothing about specific modules or inverters, it is the least accurate of the four submodels in terms of predicting the performance of the modules, and is more suited for sensitivity studies and parametric analysis (NREL 2015).

The second and third submodel options are nearly identical to each other, as they both use the same base submodel, the California Energy commission (CEC Performance Model; however, the implementation of the submodel varies. One implementation, with the Module Database, uses a five-parameter model that was developed at the University of Wisconsin-Madison and "calculates a module's current and voltage under a range of solar resource conditions using an equivalent electrical circuit whose electrical properties can be determined from a set of five reference parameters" (NREL 2017). The five reference parameters are determined from data obtained during laboratory testing under standard reference conditions or the manufacturer of the module. This submodel pulls the necessary data from eligible modules within SAM's CEC module library, which contains a list of the modules that are maintained by the CEC for the California Solar Initiative (NREL 2017).

There is a secondary implementation of the CEC Performance submodel, but instead of using the module database supplied with SAM, it uses any user specified parameters and calculates module efficiency around those values. The specifications entered are used to calculate a set of coefficients that are used to describe the model performance (NREL 2017). It is worth noting that if the specifications being used are for a module that is also included in the CEC Database, the calculated results may differ from what SAM would use in the module database. The specifications used to generate parameters in the CEC library are based on specifications provided by third party testing facilities, which may differ from data on the manufacturer data sheet (NREL 2017).

The fourth model is the Sandia PV Array Performance Model. The coefficients describing this model's performance, like both versions of the CEC Performance Model, are derived partially from laboratory testing of inverters and manufacturer specifications, however they are also partially derived from measurements taken from operational modules installed on commercial PV systems. Like the CEC Performance model with Module Database, the Sandia PV Array Performance Model has its own database of modules within SAM from which the user can choose (NREL 2017). In addition, the Sandia submodel includes an algorithm that accounts for module efficiency loss due to the increased temperatures of the module when the sun is shining during the day. "The algorithm calculates an hourly module temperature as a function of the solar radiation, ambient temperature, and wind speed in a given hour, and a set of properties describing the thermal characteristics of the cell and module" (NREL 2017). The Sandia PV

Array Performance model is used in this study since its equations were empirically determined from realistic testing conditions (NREL 2015).

Once the submodel determines the amount of solar energy produced by a single solar module, it calculates the overall DC power output supplied to the inverter by taking the amount calculated for one module and multiplying it by the total number of modules in the array. Within the array, there may be multiple strings, which are a series of modules connected in a row leading to the power inverter (NREL 2015):

$$P_{dc,gross} = N_{modules} * N_{parastrings} * P_{dc,m} * F_{dcss}$$

where

- $P_{dc,m}$ = Total array DC string voltage
- $N_{parastrings}$ = Number of strings in parallel
- $N_{modules}$ = Total number of modules in string
- F_{dcss} = Self-shading DC loss factor (only if arrays do not have tracking system)

This does, however, use the assumption that all modules within the solar farm operate at the maximum power point of a single module, which may not be the case in realistic scenarios. However, to calculate the net DC power sent to the inverter, SAM takes the gross DC output and multiplies it by a decimal DC loss factor, which accounts for percentage losses due to array mismatch, diode connections, DC wiring, errors in module solar tracking, and nameplate capacity (NREL 2015). This net DC power output is what is supplied to the inverter for conversion.

Power Inverter Performance Submodel Options

Once the net DC power output data have been obtained from the PV array performance submodel, they are used as input data in the inverter submodel, where they are converted to AC power, before being sent out to the power grid. Like with the PV array performance submodel, SAM gives the user a list of options to choose from when deciding on an inverter submodel to use as well. SAM offers three options to choose from, although the first two options are relatively similar. The first option is the Inverter CEC Database, which is an implementation of the inverter model developed by Sandia National Laboratories. This submodel contains a list of commercially available inverters that is maintained by the California Energy Commission (CEC) (NREL 2017). Any inverters in the list can be used when performing experiments within this submodel. Like the PV array performance submodel, the inverter submodel is also empirically derived using data provided by the manufacturer and field data that are representative of actual operating conditions, which are then used to calculate a series of measured coefficients that help determine the inverter's performance (King et al. 2007).

The second model is another implementation of the Inverter CEC Database model. In this version, only the specifications provided by the manufacturer are used to calculate the coefficients that are used to describe the inverter's performance characteristics. This model does not account for any outdoor field data from operational sites or laboratory testing data (NREL 2017).

The third submodel in called the Inverter Part Load Curve submodel. This inverter model is not based upon the Sandia inverter model at all, and instead bases the inverter performance and efficiency on night-time losses that are provided by the user, as well as efficiency values of the inverter while running at partial load. These values would generally be provided by manufacturer specification sheets (NREL 2017). The efficiency of the inverter would depend on the part-load points chosen for that inverter, from which SAM uses linear interpolation to calculate efficiency values between those part-load points (NREL 2017). The inverter model being used for this study is the Inverter CEC Database. This is because, just like the Sandia PV Performance model, the Inverter CEC Database is partially derived from data taken from operational conditions, as well as laboratory test data and manufacturer specification sheets.

Validation of SAM

In order to build confidence in SAM's ability to accurately predict power production levels, NREL (2013) performed a validation of the model using observed irradiance and meteorological data as input into SAM. NREL then compared the gross AC output of the power predicted by SAM to the power output at operational sites that were used for this validation, due to the measured performance data being measured at the inverter output (NREL 2013). In order to more accurately compare data from SAM to observed data, portions of the datasets were removed. Days where the PV systems were shut down were removed due to the large discrepancies between what the model was outputting and what the plant was actually producing. In addition, days where inverter outages occurred were also removed. They were identified by comparing the output performance of the inverters to each other. If one of the inverters was reporting a much lower value, then it was determined that the inverter was not performing properly, as the inverter outputs should correlate very well when operating properly (NREL 2013). Finally, the last parameter that was removed before performing statistical analysis was nighttime observations. This is because the model does a very good job at determining when it is nighttime and automatically sets the DC output to zero. This would make the mean that SAM would only account for the slight losses due to idle inverter operation. This in turn would "skew hourly statistics by indicating that the mean hourly error and RMSE are much lower than the daytime hourly error" (NREL 2013).

Two major areas of concern were focused on for sources of error within this validation. The first was concerning snowfall and how covering the solar panels affected the output of the plant. NREL theorized that in these situations, SAM could easily overpredict the amount of energy produced by the plant due to snow covering the panels not being taken into account in input solar data (NREL 2013). The second source of error was due to an incorrect algorithm within SAM that is used to calculate backtracking, which is a process used by some energy providers to minimize row-to-row shading between solar modules. This error was discovered during the validation process and was fixed in later versions of the model, of which this study uses. It was discovered that at hours of high zenith angle, SAM did not always implement the backtracking algorithm and instead was setting the tracking angle to the maximum value, causing excess energy loss due to module-to-module shading (NREL 2013).

This validation project included solar arrays of sizes ranging from 205 kW to 25 MW. Several of the solar arrays also tilted along one axis while following the sun as it rose and fell. The sites that had the one-axis tilt were those that saw the error due to the incorrect backtracking algorithm and were the DeSoto site, a 25 MW utility-scale plant located in DeSoto County, FL, and Mesa Top, a smaller 658 kW commercial-scale plant located near the NREL main campus in Golden, CO (NREL 2013).

The results for this validation project were promising. NREL performed hourly root mean squared error (RMSE) calculations at all the sites tested and found that at all locations, with the exception of the Mesa Top and DeSoto systems, (increased error due to the flawed backtracking algorithm), the RMSE was 5.1% or less (Fig. 3). The Mesa Top site had an RMSE just over 10%, while DeSoto had an error slightly larger than 6%. One thing worth noting is that there was no noticeable trend between the size of the plant and the RMSE recorded (NREL 2013).

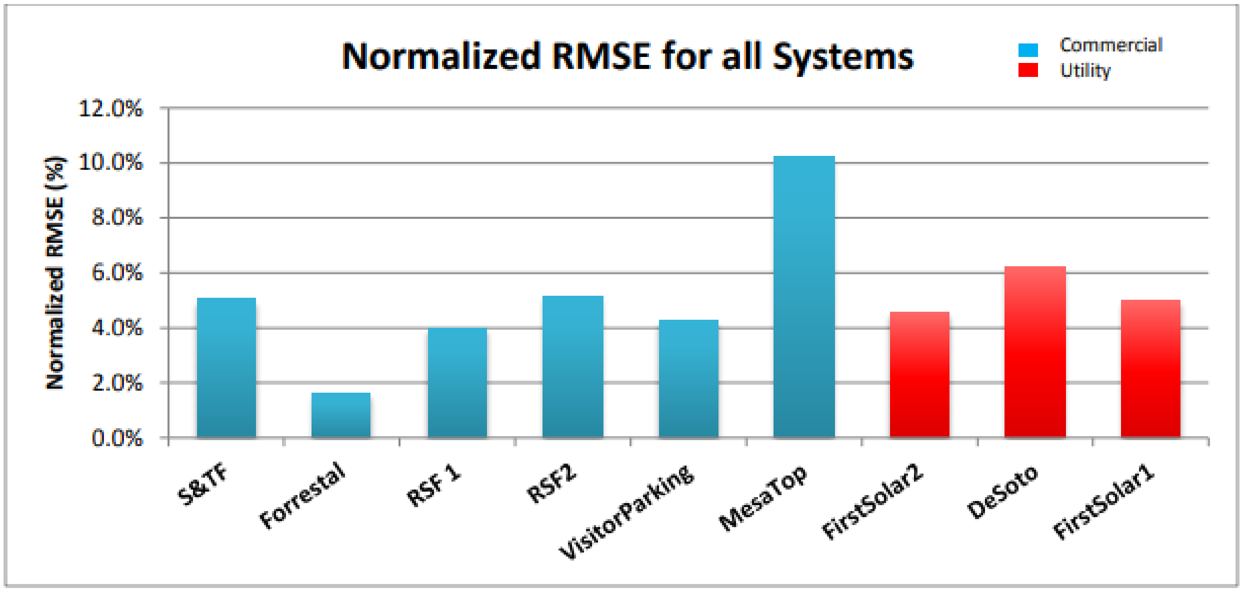

Figure 3. RMSE calculations performed at all sites used in SAM validation report (NREL 2013).

The monthly results indicated that SAM tended to over predict power output in the winter months and under-predict during the summer months. This was also determined by Sandia National Laboratories when they performed similar data analysis (NREL 2013). NREL determined that this may be due to the irradiance transposition models. However, insufficient temperature correction, as well as soiling differences between seasons, could be possible causes of error as well (NREL 2013). Lastly, in terms of the annual results, it was found that the overall error for all systems was less than 3%. This excludes the DeSoto and Mesa Top plants because of the known backtracking error they still contained. NREL found that on a yearly basis, the model tended to under-predict the amount of solar radiation as a whole for a given location. They also concluded that the size of the system had no correlation to the amount of annual error (NREL 2013).

In this validation study, NREL also compared many of the different submodel options within SAM, as well as the different types of irradiance inputs. They compared:

- Sandia Module Model versus CEC Performance Model
- Perez diffuse sky model versus Hay-Davies-Klucher-Reindl (HDKR) diffuse sky model
- "Total and Beam" irradiance inputs versus "Beam and Diffuse" irradiance inputs (NREL 2013).

Ultimately when performing these comparisons using a variety of combinations, they found that the different submodels and irradiance inputs agreed quite well with one another, with the CEC, Perez and Beam and Diffuse combination having the highest RMSE, at only 3.3%. The combination with the lowest error was found to be the Sandia, Perez and Total and Beam combination, with a RMSE of only 1.7% (NREL 2013). This happens to be the combination used for the sensitivity study herein.

CHAPTER 3

METHODOLOGY

Sensitivity Analysis

A sensitivity analysis of environmental conditions was performed on the SAM energy prediction model, to determine which environmental conditions had the greatest effect on the amount of solar energy produced at each of the three locations chosen. This analysis was performed by modifying the input atmospheric variables one at a time and noting changes in the SAM model output. The atmospheric variables that were used with this sensitivity study were: solar irradiance (direct normal (DNI), diffuse horizontal (DHI, global horizontal (GHI)), atmospheric temperature, wind speed, and albedo. This sensitivity analysis was performed by comparing the model output that resulted from changing one specific value to the model output that resulted from the base value of the same parameter.

Location Choices

The research done with this report included a sensitivity analysis at three different geographical locations throughout the United States: Blythe, CA, Tuscaloosa, AL and Grand Forks, ND (Fig 4).

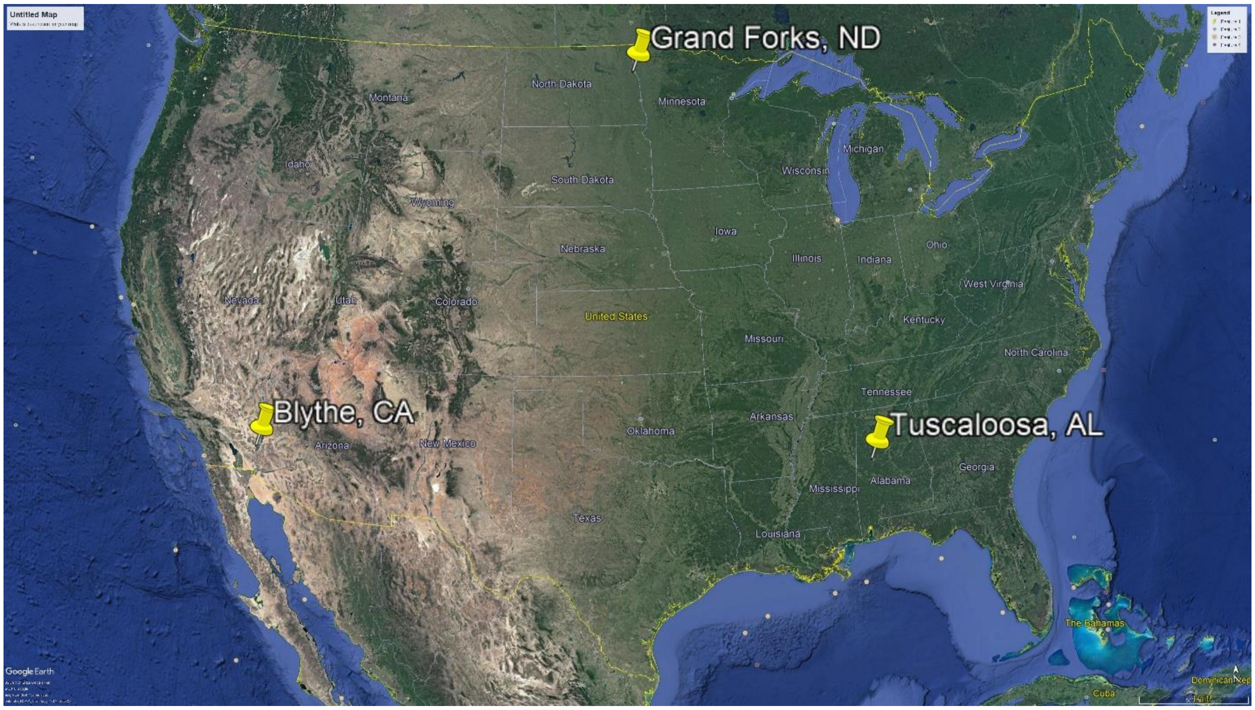

Figure 4. Map identifying the three locations used for this sensitivity study. They include: Blythe, CA, Tuscaloosa, AL and Grand Forks, ND (Google 2018).

This was done in an attempt to see if and how much each of the aforementioned parameters affected the efficiency of the system at each of the different locations. Each location is unique from the others in at least one distinct way, allowing a test of the model in a variety of different atmospheric conditions.

One location that was used for this study was Blythe, California, which is in far southeastern California (Table 1).

Table 1. Climatology Data for Blythe, CA (NCEI 2017)

SEASON	PRECIP (IN)	MIN TMP (°F)	AVG TMP (°F)	MAX TMP (°F)
Annual	3.83	59.5	73.6	87.8
Winter	1.57	42.8	55.6	68.4
Summer	0.81	77.6	92.1	106.5
Spring	0.62	57.1	72.1	87.1
Autumn	0.83	60.1	74.4	88.7

Located in the desert southwest, it is one of the hottest and driest location in the United States (National Centers for Environmental Information (NCEI) 2017). Blythe has an annual daily mean temperature of 23.1°C, with a seasonal daily mean temperature in the summer of 33.4°C. Its annual average precipitation is a mere 3.83 inches, one of the lowest values in the continental United States. This location was chosen mainly to monitor how the solar plant would perform, in terms of solar energy conversion efficiency and overall power production, in an area that receives excessive heat during the day and little rainfall throughout the year. This excessive heat is particularly noticeable during the summer months, where temperatures can exceed 49°C during the afternoon hours. One factor that should contribute to the production of solar energy is Blythe's latitude of 33.6°N. At this latitude, the solar zenith angle is small, particularly during the summer months, which leads to more solar irradiance reaching the solar panels normal to the panel surface.

Tuscaloosa, Alabama was the second location chosen for this study, based on its temperature and precipitation characteristics. Probably the most significant difference between Tuscaloosa, AL and Blythe, CA is the annual mean precipitation of 52.60 inches. Tuscaloosa also has a warm climate, with an annual mean temperature of 17.7°C, slightly cooler than Blythe. The seasonal mean maximum temperature in the summer is 32.8°C with only occasional highs above 37.4°C. The latitude of 33.2°N is nearly equal to that of Blythe.

Table 2. Climatology Data for Tuscaloosa, AL (NCEI 2017)

SEASON	PRECIP (IN)	MIN TMP (°F)	AVG TMP (°F)	MAX TMP (°F)
Annual	52.60	52.5	64.0	75.6
Winter	15.29	35.7	46.7	57.7
Summer	12.47	69.9	80.5	91.1
Spring	12.73	51.2	63.6	76.1
Autumn	12.11	52.8	65.0	77.1

The final location that was used for this study was Grand Forks, North Dakota. Grand Forks is located in east-central North Dakota, along the Minnesota border. At 47.9°N, the latitude of Grand Forks is considerably higher than that of Blythe or Tuscaloosa, resulting in a higher zenith angle, and less direct radiation reaching the panel surface. It is also considerably cooler than Blythe or Tuscaloosa, with an annual mean temperature of 4.4°C (Table 3).

Table 3. Climatology Data for Grand Forks, ND (NCEI 2017)

SEASON	PRECIP (IN)	MIN TMP (°F)	AVG TMP (°F)	MAX TMP (°F)
Annual	20.81	28.9	40.0	51.1
Winter	1.68	0.5	10.0	19.5
Summer	9.51	54.1	66.6	79.1
Spring	4.65	29.2	40.6	52.0
Autumn	4.97	31.1	42.0	53.0

The annual mean precipitation for Grand Forks is 20.81 inches (NCEI 2017) and can be in the form of multiple phases, a feature unique to Grand Forks from the other two locations. The presence of snow is commonplace throughout late fall, the winter months, and even well into spring. This introduces some uncertainty in the model output because, as noted earlier, SAM may not always capture the effects of snow accumulation on the panel face. Secondly, the temperature variation at Grand Forks is considerably larger than that of Blythe or Tuscaloosa. The summer mean for Grand Forks is 26.2°C, while the winter mean temperature is -12.2°C. However, the record temperatures have a greater range, from 42.8°C, to -41.7°C. This provides an opportunity to evaluate how the solar panels perform not only in areas of high temperature, but areas of very low temperature as well. Lastly, the amount of direct solar irradiance reaching the panels is decreased as well, due to the higher latitude of Grand Forks. This affects how much radiation the panels absorb, and therefore, the amount of overall energy the solar plant produces.

Energy Prediction Model Setup

All selected locations have atmospheric data files stored within the model itself, which originate from the National Solar Resource Database (NSRDB), to be used for modeling energy prediction estimates. The atmospheric parameters necessary for SAM to run include: GHI, DNI, DHI, dry bulb temperature, dew point temperature, sea level pressure, wind speed and wind direction. Albedo is another parameter that is made available with the observed dataset supplied with the model. A canned process within the model can be included to calculate the power change due to changing ground albedo. The data in these datasets come from a variety of different sources and were developed using the Physical Solar Model (PSM). The meteorological data are derived using NASA Modern Era-Retrospective Analysis (MERRA) datasets, which are then interpolated down to 4 km by 4 km grids to match the resolution for the NSRDB (NREL 2018). The solar radiation data are produced by using cloud properties from satellite retrievals and calculating surface radiation from those properties. The cloud properties are determined using the AVHRR Pathfinder Atmospheres-Extended (PATMOS-x) algorithms. These algorithms have been adapted for use with GOES data (NREL 2018). NREL developed a model which incorporated aerosol optical depth, precipitable water vapor and the cloud properties from (PATMOS-x) to compute the GHI for cloudy scenes. The DNI for cloudy scenes is modeled by the Direct Insolation Simulation Code (DISC). The REST2 radiation model is then used to model GHI and DNI in clear sky conditions (NREL 2018).

Constructing the plant within the model was the next step. A plant size of 10 megawatts was chosen for the desired power output. This size was chosen due to its relatively small size, making it easier to work with within the model. This is on the low end of what may be considered “utility scale” plants. However, it is still large enough to be considered utility-scale, according to NREL, which set five megawatts as the lower threshold for a utility-scale power plant.

Once the size was determined, the next step was designing the plant itself. For this, solar panels and inverters had to be chosen, as well as design layout (Fig. 5).

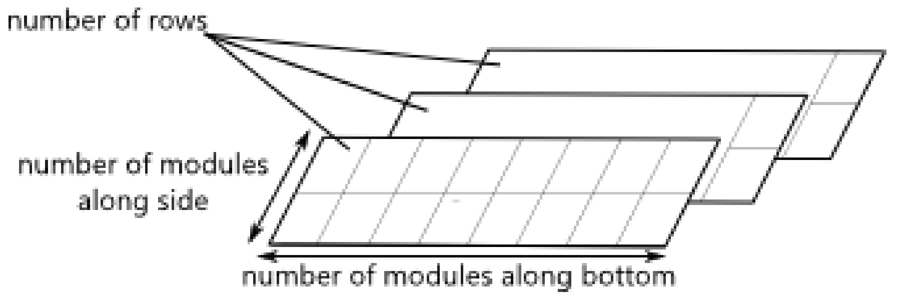

Figure 5. The general configuration of solar panels. The number of rows, modules along the side and modules along the bottom can vary by project (NREL 2018).

Based on personal correspondence with a solar energy expert (Stacy Fleenor, WindLogics, Solar Resource Division), the decision was made to use solar modules produced by the company Canadian Solar. The modules used produce 300 watts of DC power per module at maximum power. 35,154 of these modules were needed to generate the stated 10 MW power capacity of the plant. In order to convert the DC power generated by the solar modules to AC power, power inverters were required. Six SMA inverters were used for this setup, each with the capability of converting nearly 1,700,000 watts DC of power to AC, under full load. The modules have been set up within the model, such that they are mounted on racking systems, to allow for the single-axis tilt. The single axis was enabled within the model to maximize the amount of direct sunlight the modules would receive throughout the day. There is an option for a two-axis tracking system, both in the x and y directions, but it was determined that that method would not be used because it is much more expensive and the amount of extra power produced due to the increase in direct radiation received is not enough to warrant the excess costs (personal correspondence). The tilt at which the modules were oriented was dependent on the location of the site. For Grand

Forks, the tilt angle was equivalent to the latitude, facing towards the south. The tilt was initially set to 35° because of a concern of self-shading between module rows within the plant. Simulations were performed with the tilt set to 35° and then set to the latitude to determine which setting produced the most power. It was found that the plant produced more power with the tilt set to the latitude of Grand Forks and was ultimately kept for subsequent runs. The tilt angles of both Blythe and Tuscaloosa were also set equal to their respective latitudes. This is because the two locations are close enough to the equator, that self-shading was of little concern. These modules also faced directly towards the south. The racking systems at Blythe and Tuscaloosa were set up the same way as Grand Forks, with a one-axis tilt system that would tilt back and forth along the x-axis.

Data Analysis

As mentioned previously, the focus of this study was a sensitivity analysis. This sensitivity analysis involved manipulating the different parameters within the atmospheric input data, and comparing the power output from this simulation with that of a simulation using the unmodified data provided with the model.

The first step in performing this sensitivity analysis involved creating baseline simulations, using the atmospheric data that was provided as an input, without the modification of any of the data variables. This baseline simulation was performed at all three locations, using the solar plant configurations mentioned above. Once the baseline simulation at each location had been performed, each of the atmospheric input parameters was modified individually, and another simulation was performed. Once these data had been changed, each individual run was compared to the baseline run, to observe how much of a difference changing each individual parameter made.

The first parameter modified was the ambient air temperature, which was increased and decreased from the baseline temperature by 5°C and 10°C. This range of temperatures was chosen to maximize the visible effect from temperature if a change was noticeable. In addition, it was chosen to see how close the percent efficiency change was to the 0.477% $°C^{-1}$, recorded for the 300-watt Canadian Solar panels used in this study, under large temperature swings. The wind speed was the second parameter modified. Since the wind speed is variable and cannot be negative, it was decided to run simulations at five static values: 0 m s^{-1}, 3 m s^{-1}, 6 m s^{-1}, 9 m s^{-1} and 12 m s^{-1}. These values were chosen to highlight the heat dissipation capabilities the wind has on the solar modules. This began with calm winds to show module temperatures without heat dissipation, and increased continuously to a realistic value to show power production in wind conditions that could be seen at operational plants. The albedo was the third meteorological parameter adjusted. In the observed data, the albedo values range from 0 to 100%. It was decided to simulate increases and decreases in albedo of 3% and 6% to observe how radiation being reflected off the ground would affect power production based on the reflectivity of the surface. This is a realistic range of albedo changes for a given location, particularly one that experiences variations in surface conditions from winter to summer. Although areas with colder climates can see much larger shifts in albedo, this change is more consistent with what would be seen in regions farther south, where more solar farms are located.

CHAPTER 4

RESULTS

Baseline Model Results

The first step in determining what affect the atmospheric parameters had on the power produced at each site was to run the model with the collected unmodified meteorological data to obtain baseline runs for each location. The three locations produced the following annual power figures:

- Blythe: 24,856,000 kWh
- Tuscaloosa: 16,782,000 kWh
- Grand Forks: 17,233,000 kWh

Blythe produced significantly higher amounts of power for the control run. This is due to having the most cloud-free days, as implied by the lack of precipitation. Tuscaloosa and Grand Forks were much closer to each other in terms of annual power production, although their monthly production values vary rather significantly (Fig 6). Grand Forks produced significantly less power than Tuscaloosa in the winter months, particularly October through December. However, for the vast majority of the summer months, Grand Forks produced significantly more power than Tuscaloosa, compensating for the lower power production in the winter months. This could very well have to do with the annual solar cycle.

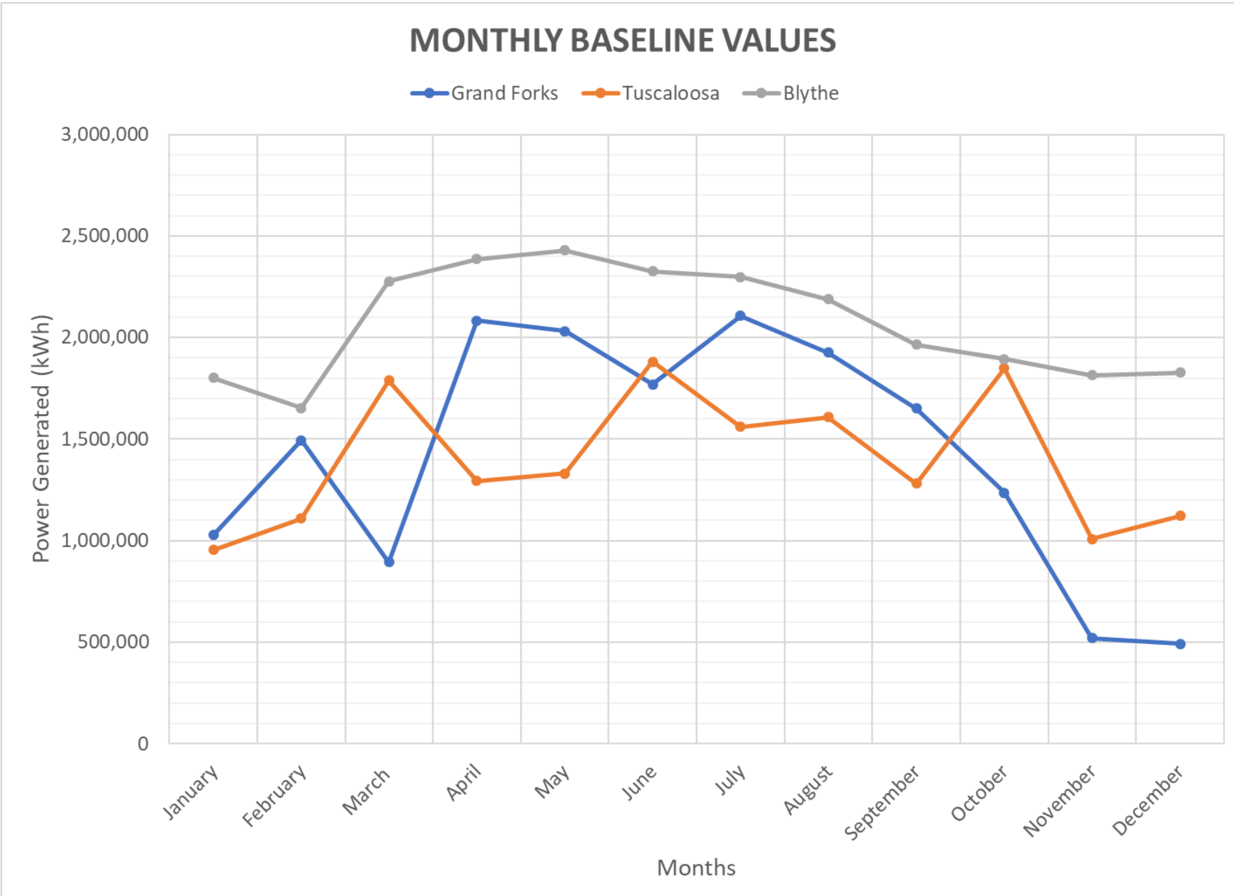

Figure 6. Monthly baseline power production values for Blythe, Tuscaloosa and Grand Forks.

With Grand Forks being located at a much higher latitude than either Tuscaloosa or Blythe, the daily duration of sunlight varies much more depending on the season. At the peak of summer Grand Forks can have 16 hours of sunlight per day, while in the dead of winter that decreases to roughly 9 hours per day. In addition, Grand Forks has a much lower sun angle in the winter, at only 18.5° above the horizon at local noon. Thus, the normal component to the panels is significantly reduced.

SAM Output for Modified Temperature Data

Simulations with the modified temperatures showed that the overall yearly power production had an inverse linear correlation with temperature (Fig. 7).

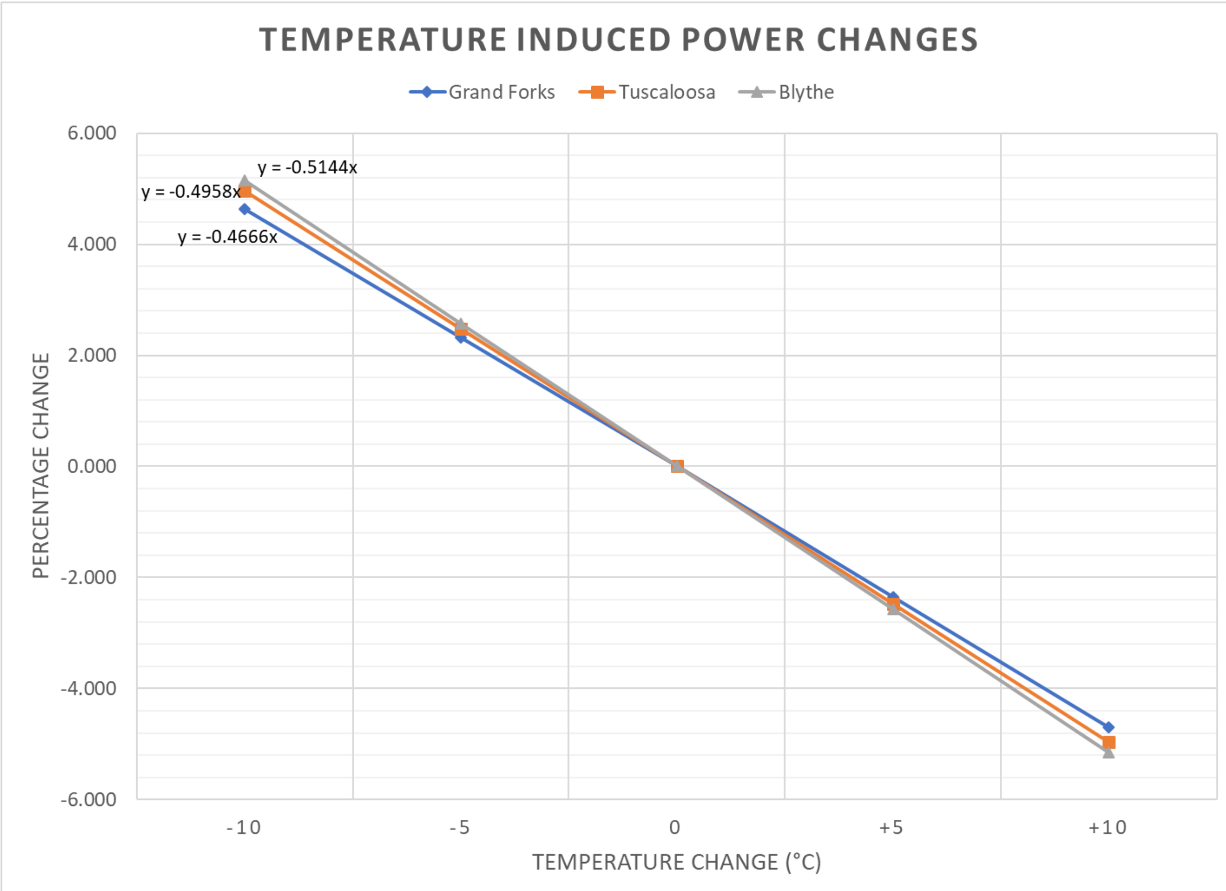

Figure 7. Percent changes in annual power production at Blythe, Tuscaloosa and Grand Forks as a result of changing temperature.

The percentage impact the temperature changes had on power production were the largest at Blythe (-0.51% $°C^{-1}$), which produced the highest overall amount of annual energy (Table 4). Tuscaloosa (-0.49% $°C^{-1}$) produced the least amount of annual solar energy overall, however, it was just behind Blythe in terms of percentage change. Grand Forks (-0.46% $°C^{-1}$) was in the middle in terms of annual solar energy produced, but showed the smallest impact in energy production due to temperature modification.

Table 4. Power Variations to Changing Temperature

Temperature Modification to Power Produced (AC kWh)			
	Grand Forks, ND	Tuscaloosa, AL	Blythe, CA
Baseline	17,233,000	16,782,000	24,856,000
Decreased 10°C	18,032,000 (4.6%)	17,614,000 (5.0%)	26,135,000 (5.1%)
Decreased 5°C	1,7634,000 (2.3%)	17,198,000 (2.5%)	25,495,000 (2.6%)
Increased 5°C	16,829,000 (-2.3%)	16,366,000 (-2.5%)	24,217,000 (-2.6%)
Increased 10°C	16,424,000 (-4.7%)	15,950,000 (-5.0%)	23,578,000 (-5.1%)

While the annual power production change may have been linear with the temperature change, there was a noticeable non-linear trend in the monthly data. This is most likely due to the solar zenith angle. When the sun is higher in the sky, there is more direct solar radiation, and therefore, more reaction with the solar panels. In addition, the days are longer during the summer months, leading to more extended periods of solar radiation and exposing the panels for longer periods of time when compared to winter. This was observed at all three locations, and while the percentage gained or lost in each month varied location to location, the overall trend was relatively consistent.

As was the case with yearly data, Blythe was consistently the most greatly affected month-to-month, deviating from baseline the most during the summer months, when there were greater amounts of direct solar radiation, and deviating the least during the winter months (Fig 8). The same was true for both Tuscaloosa and Grand Forks, with Tuscaloosa seeing larger monthly deviations than Grand Forks, most likely due to Tuscaloosa's lower latitude, which would lead to more direct solar radiation and higher daytime temperatures.

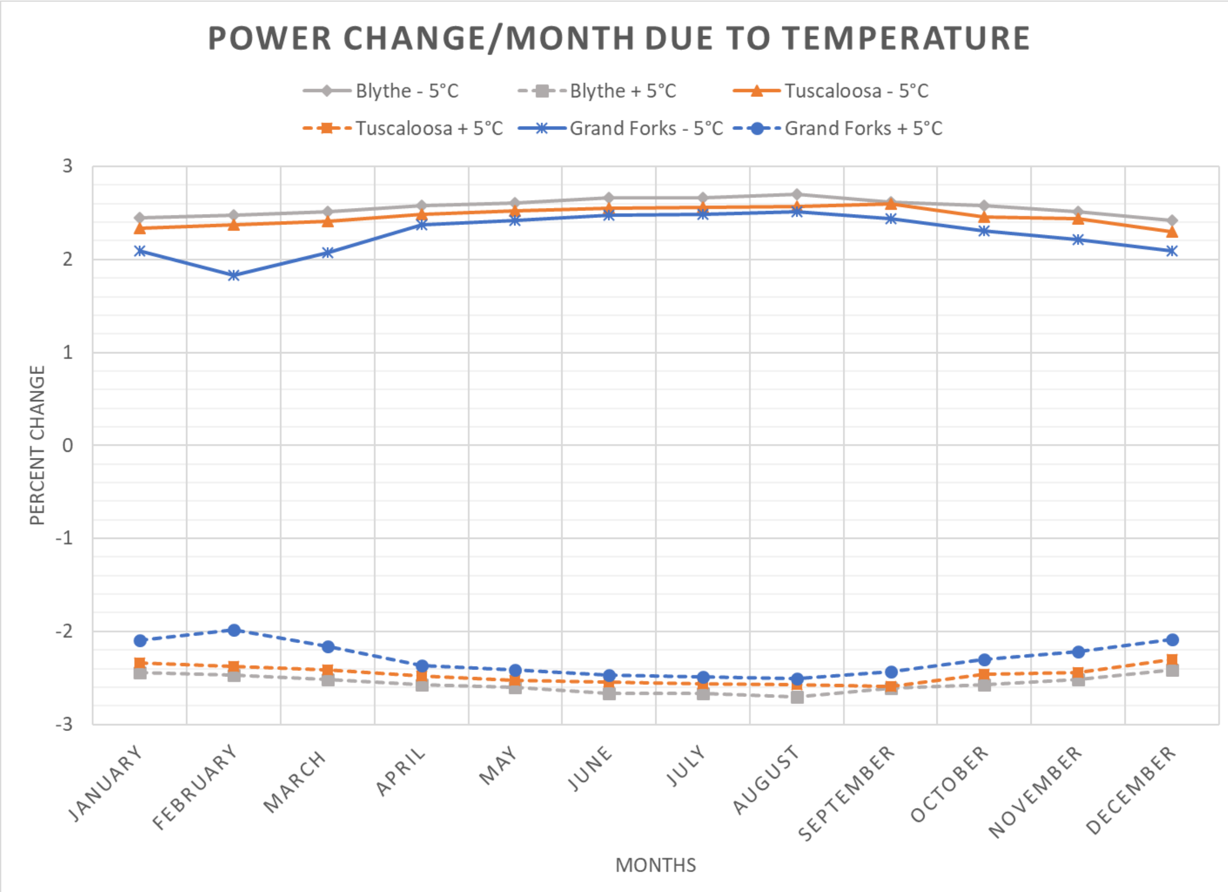

Figure 8. Monthly percent changes in power production at Blythe, Tuscaloosa and Grand Forks as a result of changing temperature within SAM.

As mentioned previously, the yearly trend between temperature change and power produced was linear. This is again shown in the monthly data plots, as the lines showing the power produced due to increased temperature are nearly a mirrored image of the lines showing the power produced due to decreased temperature. As was the case when the temperature was increased, the greatest deviations were once again in the summer months for the examples with decreased temperature. Blythe also saw the largest gains from this decrease in temperature and Grand Forks saw the least benefit.

SAM Output for Modified Wind Speed Data

Wind Speed was another variable that proved to have a significant effect on the amount of energy produced over a given year. As with temperature, the wind speed was increased linearly as from 0-12 m s^{-1}. However, unlike temperature, changing the wind speed at a linear rate did not result in a linear change in the amount of power that was produced. Instead, the change was logarithmic in nature (Fig. 9).

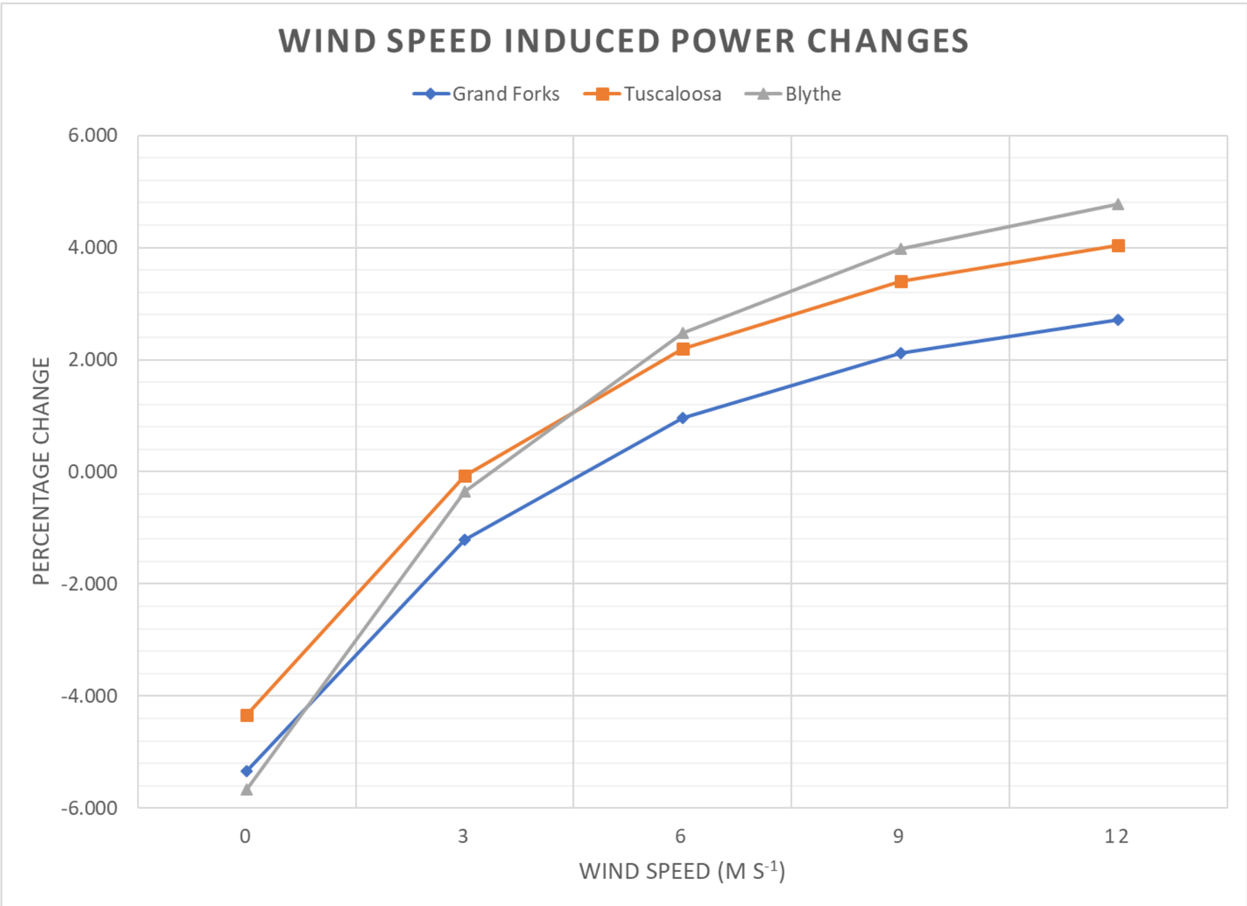

Figure 9. Percent changes in annual power production at Blythe, Tuscaloosa and Grand Forks as a result of changing wind speed.

As was the case with changing temperature, Blythe saw the largest impact due to changing winds speeds, ranging from a nearly -6% loss in efficiency with calm winds, to gaining nearly 5% efficiency with winds set to 12 m s^{-1}. It is noticeable in figure 9 that Blythe saw the greatest benefit from increasing wind speed, as its curve had the steepest slope. Grand Forks and Tuscaloosa saw changes of roughly the same magnitude, although at 12 m s^{-1} Tuscaloosa's efficiency was over a percent higher (Table 5).

Table 5. Power Variations to Changing Wind Speed

Wind Speed Modification to Power Produced (AC kWh)			
	Grand Forks, ND	Tuscaloosa, AL	Blythe, CA
Baseline	17,233,000	16,782,000	24,856,000
0 m s^{-1}	16,314,000 (-5.3%)	16,055,000 (-4.3%)	23,450,000 (-5.7%)
3 m s^{-1}	17,024,000 (-1.2%)	16,770,000 (-0.1%)	24,769,000 (-0.4%)
6 m s^{-1}	17,399,000 (1.0%)	17,150,000 (2.2%)	25,471,000 (2.5%)
9 m s^{-1}	17,597,000 (2.1%)	17,352,000 (3.4%)	25,845,000 (4.0%)
12 m s^{-1}	17,701,000 (2.7%)	17,460,000 (4.0%)	26,043,000 (4.8%)

It is clear from figure 9 that wind is an important part of the power generation process, as it is integral for heat dissipation. The percentage change of power produced per incremental increase in wind speed consistently decreased with speed, showing that wind speed has the most impact within the first 3 m s^{-1}. The first incremental change in wind speed resulted in a larger percentage change in power production than the other three increments combined.

The impact of wind speed on heat dissipation was shown in the monthly data as well. Figure 10 shows the monthly percentage change in power produced for Blythe, Tuscaloosa and Grand Forks with both calm winds and winds of 6 m s^{-1}. The monthly data with 6 m s^{-1} winds tended to stay more consistent in terms of percentage change when compared to the curves with calm winds. This shows the effect wind had on the power change, as the runs with calm winds were not only more inconsistent month-to-month, but also saw a slightly higher percentage loss during the summer months, especially Grand Forks and Blythe. This would make sense, as the summer months are hotter at all three locations, causing increased module temperatures, and therefore, lowered efficiencies. Although Blythe still saw a decrease in power production during the summer months with winds of 6 m s^{-1}, the summertime loss was still less than that of the run with calm winds.

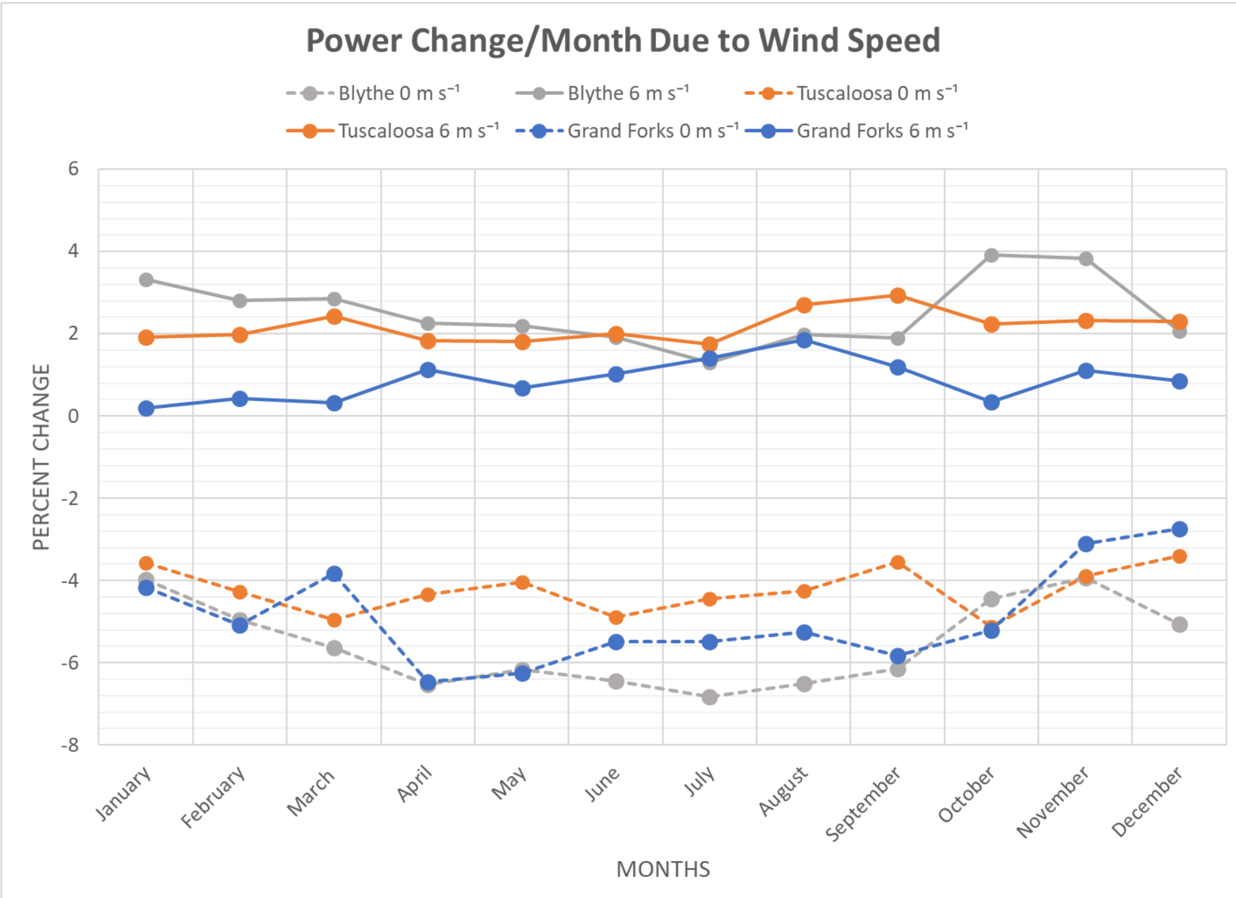

Figure 10. Percent changes in monthly power production at Blythe, Tuscaloosa and Grand Forks as a result of changing wind speed.

SAM Output for Modified Albedo Data

Albedo was the third variable that was explored for this study. As was done for both air temperature and wind speed, SAM was run with the baseline input meteorological conditions. In addition, four other simulations were run, increasing and decreasing the albedo by 3% and 6%. One of the results for the albedo parameter was that the annual power production deficit or excess was directly related to the decrease or increase, respectively, of the albedo of the surface upon which the plant was built. As the albedo increases, the overall power production numbers increase as well, and vice versa. The increases or decreases in albedo resulted in a linear relationship with the amount of power gained or lost at each power plant (Fig 11).

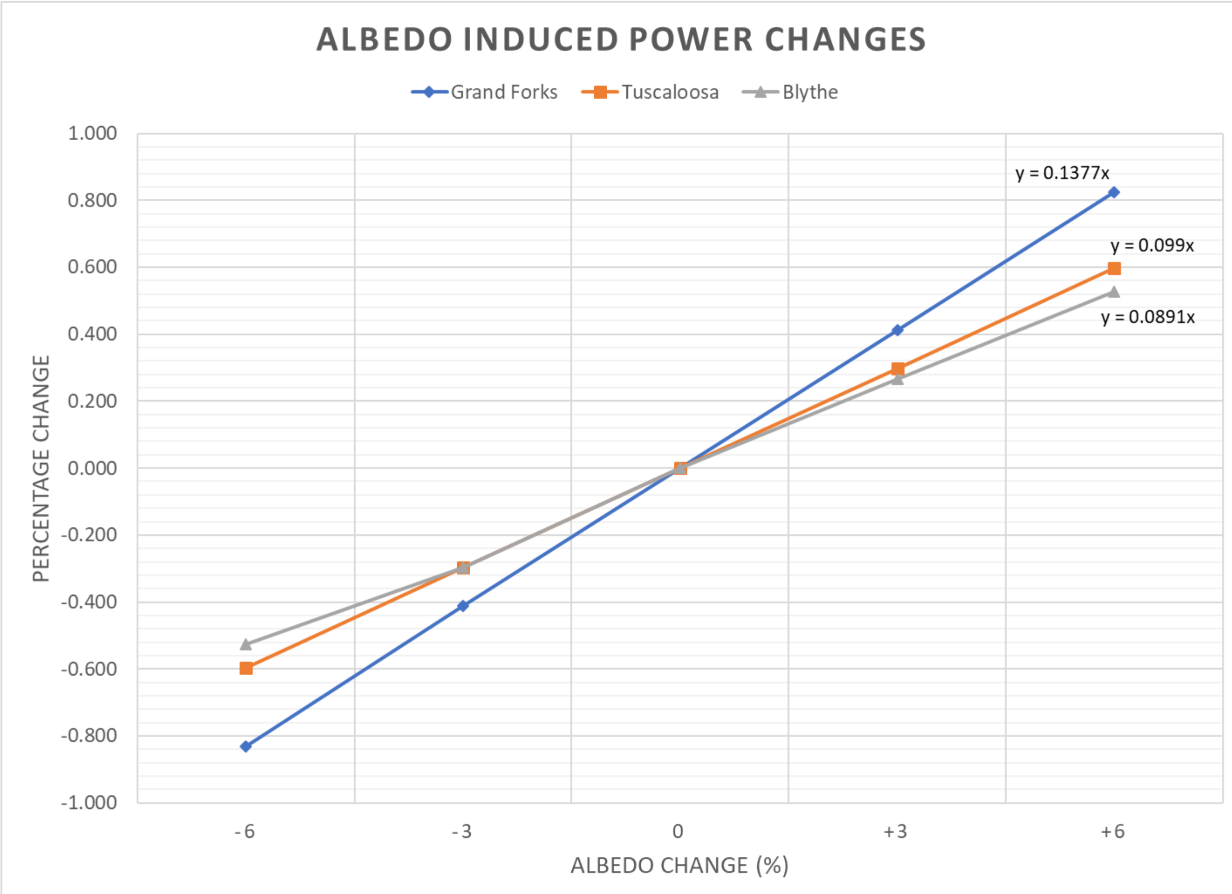

Figure 11. Percent changes in annual power production at Blythe, Tuscaloosa and Grand Forks as a result of changing albedo.

When the albedo was modified, the overall change noticed in power production was relatively small compared to the effects wind and temperature had on the production capabilities of a plant (Table 6).

Table 6. Power Variations to Changing Albedo

Albedo Modification to Power Produced (AC kWh)			
	Grand Forks, ND	Tuscaloosa, AL	Blythe, CA
Baseline	17233000	16782000	24856000
Decreased 6%	17,090,000 (-0.8%)	16,682,000 (-0.6%)	24,725,000 (-0.6%)
Decreased 3%	17,162,000 (-0.4%)	16,732,000 (-0.3%)	24,790,000 (-0.3%)
Increased 3%	17,304,000 (0.4%)	16,832,000 (0.3%)	24,922,000 (0.3%)
Increased 6%	17,375,000 (0.8%)	16,882,000 (0.6%)	24,987,000 (0.5%)

For all of the albedo simulations, Grand Forks (0.14% °C^{-1}) saw the largest changes in overall energy production from the baseline run. Even when the albedo was changed by the maximum 6%, the effect on overall power production was still less than 1% of the original simulation (Table 6). Blythe (0.09% °C^{-1}) saw the smallest changes in terms of percentage.

It is theorized that this is due to the relatively high latitude of Grand Forks. At 47.9° North, Grand Forks experiences lower sun angles than the other two locations throughout the year. This can be particularly important in the winter, as snow is a yearly occurrence in the area. In addition, at the passing of the winter solstice the sun never rises above 18.5° in the sky. This, in combination with the snow that accompanies the winter season in this region, which has a high albedo, could possibly lead to the reflection of large amounts of shortwave energy.

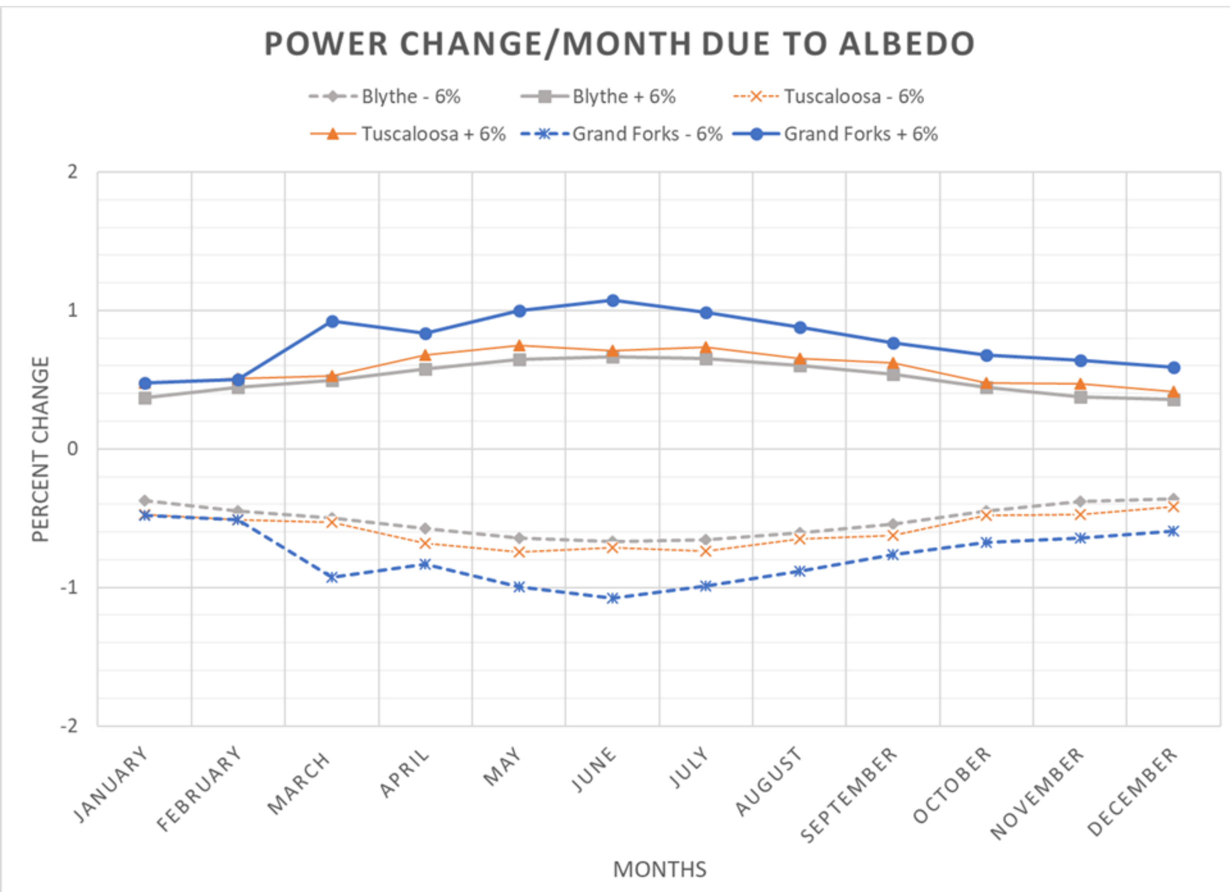

Figure 12. Percent change in monthly power production at Blythe, Tuscaloosa and Grand Forks as a result of changing albedo.

Ultimately, this could cause the solar plant to have a more noticeable change in the amount of energy that is produced. Snow, and a cold climate, are unique to Grand Forks, in that, the other two locations used for this research do not have the same sort of conditions for extended periods of time. This is why it is believed that Grand Forks experiences a higher change in the winter months than the other locations, despite the significantly lower sun angle (Fig. 12). In addition, both Blythe and Tuscaloosa have roughly the same latitude, which is much closer to the equator than that of Grand Forks. This will ultimately lead to higher sun angles, warmer climates, and lower albedo values than Grand Forks, particularly in the winter months, therefore lowering the change in percentage. It was found that the largest effects due to albedo occurred during the summer months and gradually decrease as the simulation moves towards the winter months. Grand Forks by far had the largest deviation from the baseline simulation during the summer months of the three locations, which could be due to the extended periods of daytime that Grand Forks experiences during these months. In addition, it is possible that the higher tilt angle of the modules at the Grand Forks site assisted in the collection of reflected surface radiation. The higher summer zenith angle at Grand Forks could also cause more light to be reflected off the surface of the Earth than at the other two locations, whose zenith angles are much lower and would result in more light being absorbed into the ground.

CHAPTER 5

DISCUSSION

Expectations as to how modifying each of the parameters would affect the overall power produced at each location were described in chapter one. These were as follows:

- Power output would vary inversely with temperature change
- Increased wind speed would result in increased power output
- Power output would increase with albedo.

In terms of the magnitude of importance for these parameters, it was anticipated that temperature changes would have the greatest effect, followed by wind speed, and only small but noticeable effects for albedo. For temperature and albedo, these expectations held true, although modifying the wind speed proved to have a larger impact than initially expected. Regardless of the amount each parameter was modified, there was still an impact on the amount of power produced. This is important, particularly on a utility scale, because power companies need to be able to produce enough power to supply all their customers, especially during times of high demand. If not enough power is being produced during peak times, then there exists the possibility of rolling brown-outs or black-outs, in which certain parts of the grid would see their power temporarily shut off. Modifying the atmospheric parameters in SAM gives an idea of some of the variability that can come from changing atmospheric conditions, and how companies would need to respond to best serve their customers, whether that is in the form of battery storage of power, or adding additional panels to compensate for the times that demand is exceedingly high.

The significant effect of temperature change on the amount of power produced was anticipated, as it is not uncommon for modules to lose efficiency due to heat above the reference temperature of 25°C. Kurnik et al. (2010) tested different mounting and operational conditions to determine the temperature and performance of their PV modules. In their study, they found the relative temperature coefficient of module efficiency to be -0.3% K^{-1}. This means for every degree Kelvin the temperature increased, the module would become roughly 0.3% less efficient when converting solar irradiance to DC power. In the simulations performed at the three locations across the United States, the Canadian Solar panels used have a manufacturer specified relative temperature coefficient of 0.477%/°C. This would seem to correlate well with the percent changes in power production at all three locations for the different values. The theoretical percentage loss when the temperature was increased 10°C was 4.77%. All three locations were within 0.4% of that value, with Grand Forks being the closest, at 4.69%. Blythe saw the largest discrepancy from that value, reporting a 0.37% larger decrease than the theoretical value. However, Blythe is continuously the warmest of the three locations, and constantly experiences temperatures well above the 25℃ reference temperature, which could have caused the larger percentage decrease in power production. The values SAM produced were also very close to what was expected with a 5°C increase in temperature, as well as when the temperatures were decreased by the same amounts. This leads to the conclusion that the model is accurate in modeling the effect of temperature on the power production at different geographical locations, as well as locations that see entirely different climates.

Wind speed was one of the more interesting parameters in the sensitivity testing as it had a greater effect than anticipated. What proved to be most intriguing about modeling the wind speed was seeing which speeds affected power the most. Since wind helps to dissipate heat from the solar panels, a wind speed of zero had a significant effect on power output, lowering it from baseline values by 5.1% on average. This correlates well with the dependence of power output on temperature found in this study. The baseline run used the observed mean wind speeds at the locations used for this study. Even a slight increase from zero in the amount of wind blowing through the panels caused a major increase in the amount of power produced. It is theorized that a majority of heat dissipation occurs within the lowest 6-9 m s^{-1}, as further increases in wind speed resulted in only minor increases in power.

The three individual locations were chosen because of their distinct geographical and climatological features. Grand Forks, in particular, was chosen because of the large changes in climate variation between the winter and summer months. It was assumed that the model would simulate less power here, due to the cold weather and snow during the winter months. However, when SAM completed the baseline simulations, it showed that Grand Forks was producing more power than Tuscaloosa, despite Tuscaloosa being warmer all year and having little to no snow. Tuscaloosa did see more significant variations in power production when the temperature and wind speed were changed. This was expected, as Tuscaloosa has a higher annual mean temperature and heat dissipation would be a bigger issue at this location than at Grand Forks. Albedo was the only variable of the three in which Grand Forks saw the largest variations in power production between changes in the input parameter values. It is speculated that this is due to the original input data already accounting for the high albedo from the snow during the winter months, which would cause a larger percentage of shortwave radiation to be reflected off of the surface and towards the solar panels, increasing the total diffuse light being directed towards the modules.

There are several steps that could be taken to improve upon this sensitivity study. Adding precipitation amounts to the model would be the first recommendation when looking at future work. Precipitation was not accounted for at any of the three locations when the simulations were performed for this study. Precipitation is a very important process that could affect the power production at these locations by cooling the panels when the precipitation is falling, as well as the more obvious blocking of solar radiation from the panel themselves. It is theorized that Grand Forks would see the greatest impact from adding precipitation. Due to the possible effects of snow. Snow can play an important role in power production, especially if it is accumulating on the faces of the solar modules. This would significantly decrease the amount of irradiance that reaches the cells within the module, thus generating less power. This could account for discrepancies between how much power the model predicts the solar farm would produce and how much it would actually produce.

Other future research for this project could include using multiple tilt angles when simulating power production. Changing the tilt angle of the panels would manipulate the angle at which the solar irradiance contacts the panel surface. This is known as the angle of incidence (AOI). Changing the AOI from anything but 90° normal to the panel surface could cause a decrease in power production as well. This is due to more solar irradiance being reflected off the panel glass and being returned back into the atmosphere. If there are multiple tilt angles used within SAM, a better understanding of how the model simulates AOI and its subsequent power production values can be obtained.

CHAPTER 6

CONCLUSION

Research for this project involved using SAM to determine the atmospheric parameters that had the largest effect on the ability for a solar farm to produce power. Three atmospheric parameters were chosen to be modified within the input data and ingested into SAM, including: temperature, wind speed and albedo. The parameters were individually modified through a range of values while the others were kept constant. The resulting data were then compared to the results of the model run with zero modifications made.

Of the parameters modified within the input data, it was determined that temperature and wind speed affect energy production the most. When constructing a new solar farm, temperature of the location has a large effect on the amount of energy produced and should be accounted for when making energy estimates. Areas that are consistently the highest above reference temperatures will see the efficiency of the panels decrease the most at maximum capacity, compared to locations whose temperatures are closer to the reference temperature at capacity. Wind is also a parameter that should be considered when deciding on solar farm locations. It was found with SAM that wind helped significantly with heat dissipation around the modules and increased the efficiency of the modules with each increasing increment of speed, whereas a significant decrease was noticed at all locations when the winds were consistently calm.

The last parameter modified was the albedo. This affected the model output significantly less than temperature and wind speed. Modifying the albedo showed that the locations with the most reflective environment (i.e. snow-covered surfaces) would see the most increased diffuse irradiance values and would therefore benefit from a slight increase in power production because of it. The effect in power production, however, is small compared to those of wind speed and ambient temperature. Therefore, this research shows that temperature and wind speed of a prospective location should be two of primary meteorological parameters taken into consideration when designing a new solar site, while albedo is much less significant in the decision process.

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