SOLAR PORTFOLIO WEATHER RISKS

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ABSTRACT

In this paper we investigate the weather risk associated with a portfolio of solar photovoltaic assets, with focus on correlations and their impact on portfolios of common solar contracts.

Portfolios of solar assets face a variety of risks including weather, equipment, operations and maintenance, installation quality, utility rates and credit risk. Some of these risks, like credit risk, are common to many asset classes. Others, like sunlight and weather risks, are less common risks for an asset class to have.

In this paper, the volatility of weather risk was analyzed across a number of different geographic regions in order to determine how well weather risk for a portfolio can be diversified away by geographically dispersing solar installations. It was found that both monthly and yearly correlations decrease with distance, though the trend for yearly correlation is less strong. This paper provides insight into the weather risks of solar asset portfolios and is relevant to all parties involved in sourcing, financing, or modeling the risk of PV portfolios.

1 INTRODUCTION

The US solar industry has experienced tremendous growth in recent years, including an estimated 70% increase in photovoltaic (PV) installations in 2012 [1]. While there are a variety of factors influencing the growth, falling costs and more financing options play a large role. As the solar market grows, the magnitude of financing demand is growing with it.

To support the expansion of the solar PV market, a large pool of capital has been deployed to fund installations to date, and an even larger pool of capital will be required to fund future growth. In light of the growth, some parties are amassing significant solar portfolios and there is increasing interest in securitization opportunities, which would expand the pool of capital available for new installations [2].

There are many risks associated with a portfolio of solar assets, such as customer default risk, operations and maintenance risks, utility rate risks, and weather risks [3] [4]. While many of these risks are common for other types of financial products, the risk associated with sunlight energy is fairly unique to solar assets and as such, makes for an important subject for investigation.

2 CHARACTERIZING SUNLIGHT EXPECTATIONS FOR INDIVIDUAL SITES AND AN OVERALL PORTFOLIO

The solar industry has adopted the use of Typical Meteorological Year (TMY) data files to characterize typical long-term sunlight expectations for a planned installation location. The TMY standard was created to represent typical meteorological years, not specifically typical solar years. While TMY files generally well-represent sunlight, there are cases where the TMY sunlight estimates for a location are larger or smaller than any actual year on record in the National Solar Radiation Database (NSRDB) for that location [5]. Additionally, the amount of sunlight energy in a given month or year can vary substantially, so it is important to account for the distribution of sunlight energy over many years, not just a single typical year [6].

While TMY files characterize typical sunlight expectations, there is also a need to characterize what lower-than-normal annual sunlight expectations could be for a location. This lower expectation can be important for various applications, including setting minimum energy generation promises to clients or sizing the reserve capital to help fund financing debt payments in low-production years.

Companies using TMY datasets generally employ fixed discounts from the expected production level to estimate the lower-than-normal production level, since TMY does not provide the type of information needed for variability analysis. Companies using a more complete historical data set may use P50, P90, P95, or P99 levels to assess a location's variability and estimate a low-production year. These levels refer to energy (kWh) production levels that the system will exceed the specified percent of the time. For example, P99 is the annual kWh level that the system will exceed 99% of the time (i.e., a 1% chance that yearly production will fall below this level). In commercial-scale PV projects, P50, P90, P95, and P99 levels are typically used to ensure projects have enough cash reserve to cover bad years, and these estimates are also used by financial institutions and rating agencies to assess the project risk [5].

While site-specific P50, P90, P95 and P99 analyses are important for assessing individual sites, portfolio-level analysis is relevant when a single entity is financially responsible for multiple solar production sites. Since the financial risk is shared across the sites, the weather risk metrics that characterize the risk are portfolio-level P50, P90, P95, and P99 analyses, which are different than the individual comprising sites. Therefore, when considering the risk that a solar asset portfolio owner faces (e.g., solar finance companies, securitized solar assets, etc.), understanding the portfolio-level risks is critical.

Aggregating a portfolio of solar production sites will result in a diversified, less risky portfolio, unless the weather at the sites is perfectly correlated. Equation 1 shows that the portfolio return is simply the weighted sum of the individual project returns.

(1) $$E(R_p) = \sum_i w_i E(R_i)$$

Equation 2 shows that the expected variance of the portfolio return is expressed as a function of individual site variability and the correlation of the sites' variability.

(2) $$\sigma_p^2 = \sum_i w_i^2 \sigma_i^2 + \sum_i \sum_{j \neq i} w_i w_j \sigma_i \sigma_j \rho_{ij}$$

Setting up a portfolio of lowly-correlated sites can therefore create a low volatility portfolio.

To illustrate the concept of solar diversification, consider Portfolio A with two solar PV assets, both in the San Jose, CA, area and both with the same expected energy output. If San Jose has an unusually low amount of sunlight one month (e.g., due to unusually large amounts of cloud cover), the entire portfolio will underperform. In contrast, consider Portfolio B with one solar PV asset installed in San Jose, and the other installed in Newark, NJ, both with the same expected energy output level. Portfolio B would need to have unusually low solar insolation occur in both San Jose and Newark in order for the portfolio to be at risk of serious underperformance, which intuitively seems less likely than having an unusually cloudy month in San Jose alone. In other words, the P90 output for Portfolio B will be higher than the P90 output for Portfolio A, because Portfolio B has better weather diversification.

The energy produced by solar power plants is converted into dollars based on a Power Purchase Agreement (PPA) or leasing contract. There are a variety of these contacts in the marketplace today, with different structures and terms. While the geographic diversification described above affects the risks associated with extremes in terms of energy output levels from a portfolio, the contract terms cover energy production at the individual site level and therefore add another layer of complexity to estimating the geographically-diversified portfolio's financial returns.

Modeling the financial impact at the portfolio level is required in order to accurately estimate the cash flows required to meet debt service payments for the portfolio and the level of reserve cash that should be held to maintain solvency through the expected volatility in the portfolio's return.

3 SUNLIGHT ENERGY ACROSS US LOCATIONS

Data from the National Solar Radiation Database (NSRDB) was used to conduct analyses of sunlight energy across a large number of locations. The NSRDB contains hourly data for 1,454 sites from 1991 to 2010, shown in Fig. 1 [7]. Class III sites were excluded from this analysis, as they are known to contain large gaps in measurement reporting. This leaves 860 sites with high-quality data for analysis.

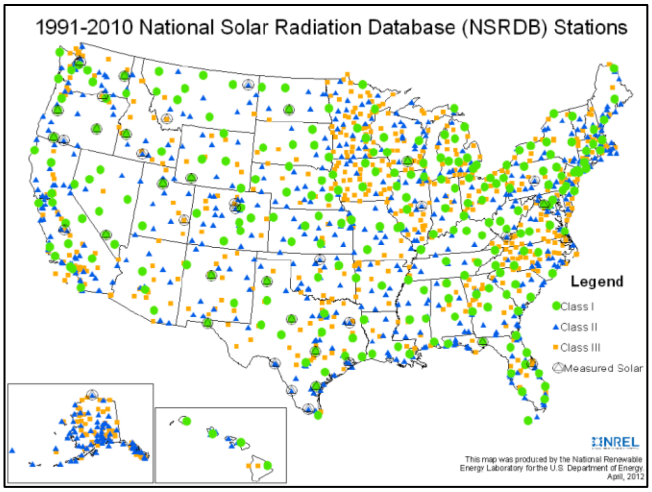

Fig. 1: NSRD Station Locations and Classes

Fig. 2 shows the mean annual sunlight insolation across the US. Some regions of the country are clearly sunnier than others. While the mean sunlight insolation drives the overall return from a solar portfolio (Equation 1), to model the variability of a solar portfolio it is necessary to understand both the variability of the installation locations and their correlations (Equation 2). Coefficient of variation (CV) is a useful metric in this context, since it describes standard deviation relative to the mean (Equation 3).

$$C_v = \frac{\sigma}{\mu} \tag{3}$$

This metric can help answer the question "What percent variation should I expect in sunlight energy?" As shown in Fig. 3, the yearly coefficient of variation varies significantly from location to location, but there appear to be some weak geographic trends (e.g., slightly more volatile in coastal regions).

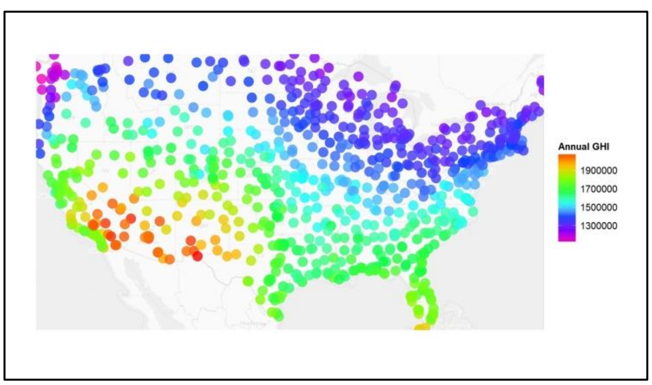

Fig. 2: Mean annual solar insolation

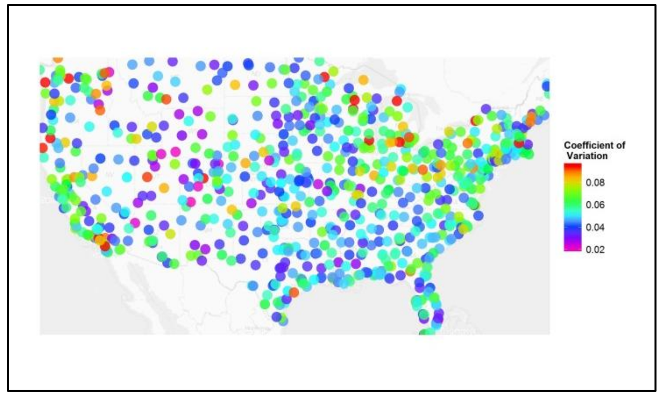

Fig. 3: Coefficient of variation for yearly solar insolation

Understanding sunlight correlations between locations is necessary to calculate expected variability of portfolios of solar assets, as shown in Equation 2. Earlier work has analyzed irradiance correlations across different sites, but generally at a short time scale (e.g., 1-second to a few hours) [8] [9]. For the case of solar portfolio performance, monthly or annual correlations are needed, since those are the time horizons at which debt service payments are typically made or energy generation contract minimums are set.

From an investment perspective, the sunlight correlations of interest are correlations in the difference from expectations at each site. Investments in solar sites, and their associated financial models, are based on the expected sunlight for the location. The under or over performance across sites should therefore be measured relative to the baseline expectations.

Using the twenty years of data from the NSRDB, correlations were calculated among the 860 Class I and Class II high-quality weather stations on monthly and annual time scales, using global horizontal irradiance data (GHI).

4 MONTHLY SUNLIGHT CORRELATION

For this analysis, monthly NSRDB insolation data was converted into percent over or under the typical insolation for each location for each month of the year, allowing comparison of difference from expectations and removing seasonality. Correlations of these values were calculated between all possible pairings of locations.

Figures 4 through 6 illustrate how these correlations in insolation patterns vary with the geographic location of the pair under consideration. Each figure fixes one member of the pair (Newark, Denver, or San Francisco), while mapping the location of the other member, with warmer colors indicating a higher correlation between that pair. For purposes of these color maps, negative correlations were plotted as zero (few negative correlations were observed).

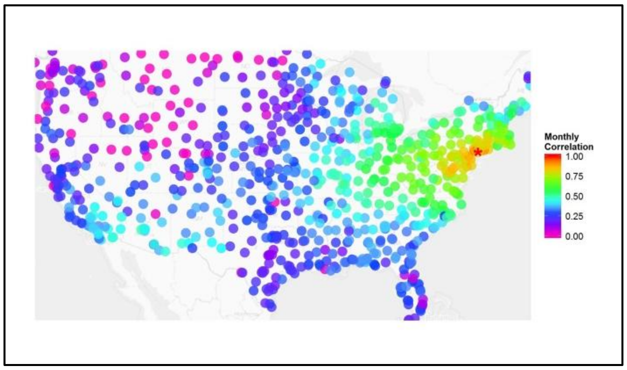

Fig. 4: Monthly insolation correlation to Newark, NJ insolation

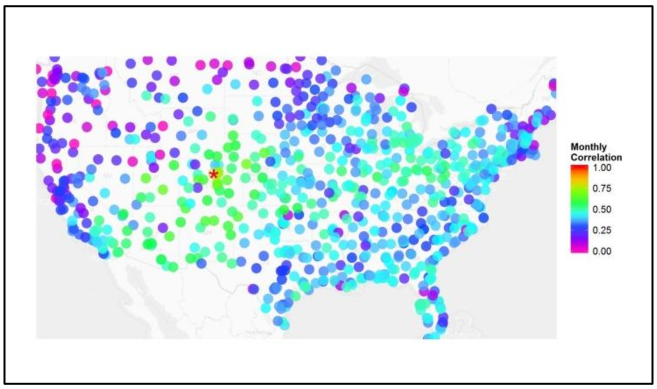

Fig. 5: Monthly insolation correlation to Denver, CO insolation

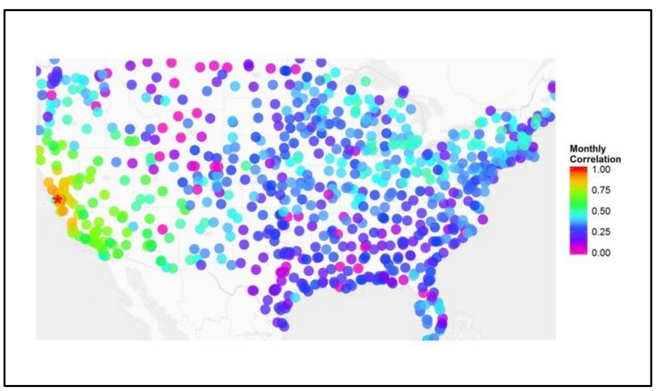

Fig. 6: Monthly insolation correlation to San Francisco, CA insolation

While correlation drops with distance, there is clearly some dispersion around the general trend. To better understand the trend with respect to distance, correlations were calculated for all station pairs and plotted versus distance. Fig. 7 shows a straight plot of the correlations, along with lines indicating the median, 25th, and 75th percentiles at each distance.

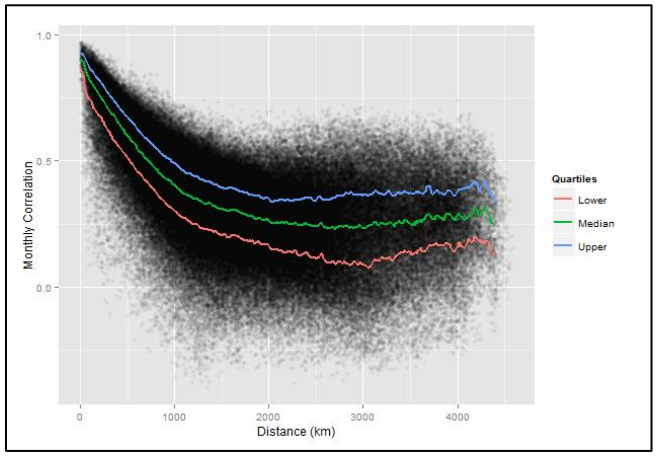

Fig. 7: Monthly correlation between NSRDB locations as a function of distance

While there is significant dispersion in the results, there is generally a steep decrease in correlation with distance up to about 1500 km, with a median correlation of about 0.31 at that distance. Beyond 1500 km, increasing distance does not appear to significantly reduce correlation. A linear fit for the correlation of locations less than 1500 km apart yields an R2 of 0.45, indicating a fairly strong relationship between correlation and distance.

5   ANNUAL SUNLIGHT CORRELATION

Twelve-month rolling sums of insolation data were created from the monthly data, to simulate typical annual solar contract periods, and this data was converted into percent over or under the typical yearly insolation for each location.

Figures 8 through 10 illustrate how patterns in this annual measurement of insolation vary with the geographic location of the pair under consideration. Yearly correlations were also calculated for all station pairs and plotted versus distance. Fig. 11 shows a straight plot of the correlations, along with lines indicating the median, 25th, and 75th percentiles at each distance.

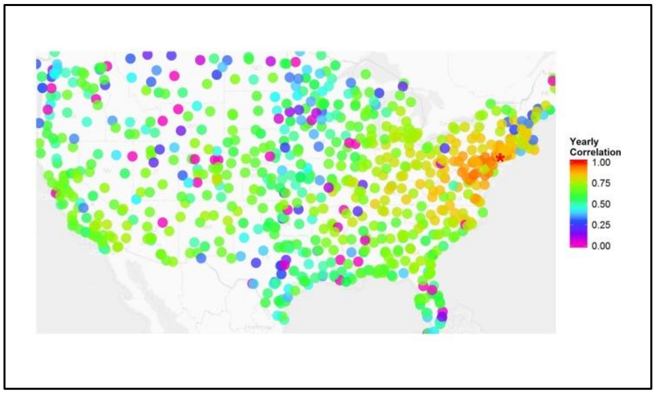

Fig. 8: Yearly insolation correlation to Newark, NJ insolation

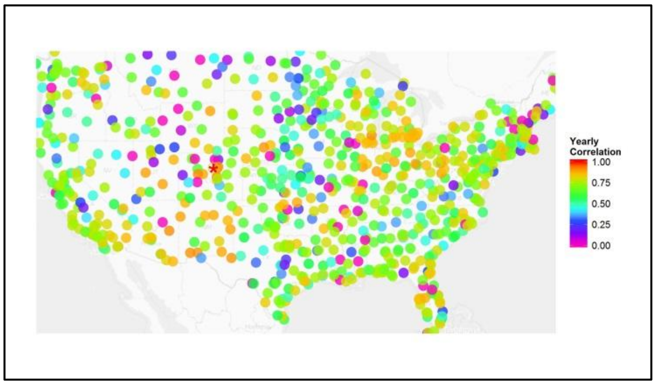

Fig. 9: Yearly insolation correlation to Denver, CO insolation

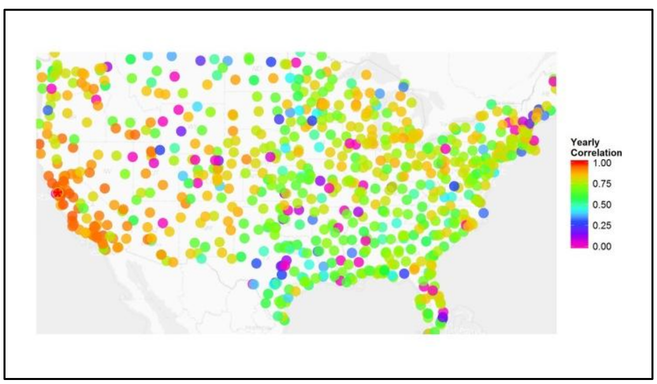

Fig. 10: Yearly insolation correlation to San Francisco, CA insolation

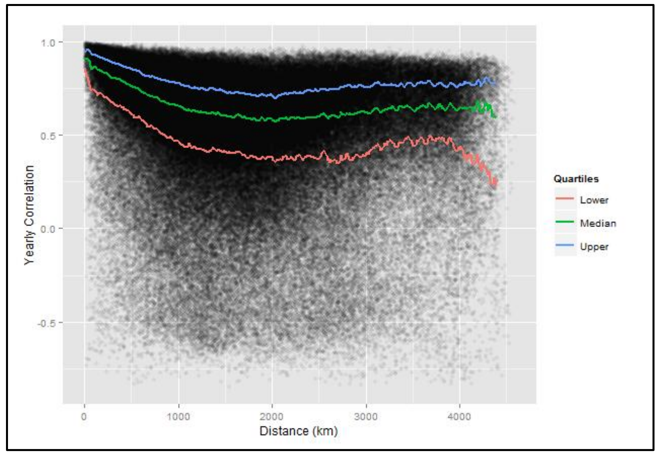

Fig. 11: Yearly correlation between NSRDB locations as a function of distance

As shown in Fig. 11, annual correlations are generally higher than monthly correlations. While annual correlation decreases with distance, the decrease in correlation is not as steep as for monthly, and the relationship with distance is not as strong as is seen with monthly correlations.

The higher annual correlations could be due to global effects that have a long-term impact not as visible in the monthly correlations. One example of an effect is the impact of the 1991 Mount Pinatubo eruption. The aerosols from this eruption affected sunlight though 1994, and had a negative impact on insolation across US locations during this time [5]. Fig. 12 shows frequency plots of site pair correlations using the full 1991-2010 data set and a 1995-2010 subset of the data. The chart indicates that the volcano-affected time period increases the overall yearly correlations, i.e., if not for the high correlation across the US during these years, correlations between the site pairs would have been lower (though still generally higher than monthly correlations). Insolation measurements showed a global upward trend over the 1991-1994 period as aerosols were slowly dissipating after the eruption. The monthly correlations were not substantially affected by the volcano eruption, however.

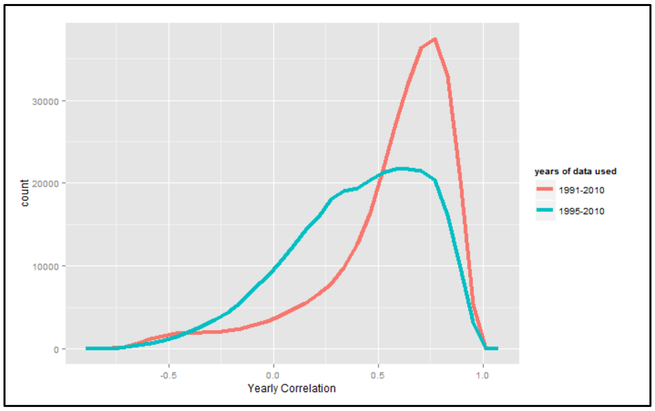

Fig. 12: Yearly correlations between NSRDB sites, calculated with and without Mount Pinatubo-affected years

6 CONNECTING INSOLATION DATA TO FINANCIAL IMPACT FOR A SOLAR SITE

Energy produced by a solar asset is converted into a financial value according to a contract between the asset owner and an entity that agrees to pay for the energy production. For commercial scale projects, the buyer is typically a utility or other business. For residential scale projects, the buyer is typically a homeowner.

Contracts for the purchase of produced energy typically have some of the following features:

1. **Price for energy produced:** The price may be a fixed price regardless of energy output (e.g., as in a leasing agreement), or a $/kWh rate
2. **Expected production amount:** The amount of energy that the asset owner expects to be produced by the solar asset
3. **Minimum guarantee amount:** A minimum guarantee level for the energy to be produced, below which the asset owner will compensate the buyer for the below-expectations production
4. **Penalty for below-minimum production:** Typically a $/kWh rate for the amount of energy below expectations
5. **Roll-over clause:** A roll-over clause defines whether or not excess production in one year (i.e., production above the minimum guarantee level) accumulates to count against minimum production requirements in future years.
6. **Term:** Length of the agreement
7. **Weather adjustment:** Some contracts include weather adjustments (e.g., irradiance adjustment) for energy expectations

Fig. 13 illustrates the payout from a contract with a fixed $/kWh rate and no penalty clause. Since sunlight insolation translates fairly directly into kWh energy production for a solar asset, the sunlight energy translates fairly directly into financial impact according to the $/kWh conversion rate.

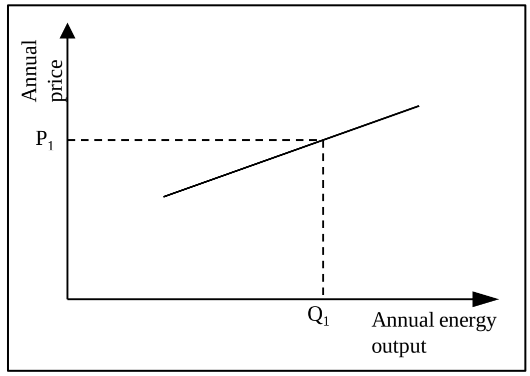

Fig. 13: Payout profile for a contract with a fixed $/kWh rate and no minimum production penalty

Fig. 14 shows a $/kWh contract with expected production level of Q_1 and minimum guarantee level of Q_2, below which penalties reduce the amount paid for energy production. For a given site, the smaller the difference is between Q_1 and Q_2, the higher the risk. The risk of reaching the Q_2 minimum guarantee level is dependent on the volatility of the insolation for the site. As shown in Fig. 3, the insolation volatility can vary significantly across different locations. Across the full NSRDB Class I and Class II data set, twelve-month insolation coefficients of variation were observed between 2% and 12%, indicating a wide range of potential insolation variability levels. Therefore, to maintain similar risk levels across sites, a firm would need to contract the penalty clause at a probability-based level of hitting the minimum guarantee level (e.g., P90 assessment) that takes into account site-specific insolation volatility levels, rather than using a fixed discount rate on the expected production level.

Fig. 15 shows a fixed price contract with expected production levels of Q_1 and penalty levels of Q_2, below which penalties reduce the amount paid for energy production. The financial model for this contract structure is similar to what was described above for Fig. 14, but because of the flat pricing above the minimum production level, either a larger spread is required between Q1 and Q2, or the P1 pricing level needs to be set higher than in the Fig. 14 example in order to achieve equivalent expected value.

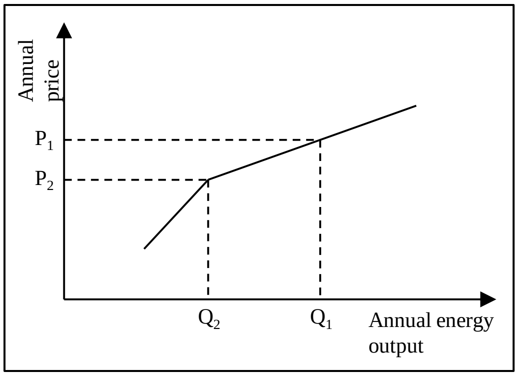

Fig. 14: Payout profile for a contract with a fixed $/kWh rate and a minimum production penalty level

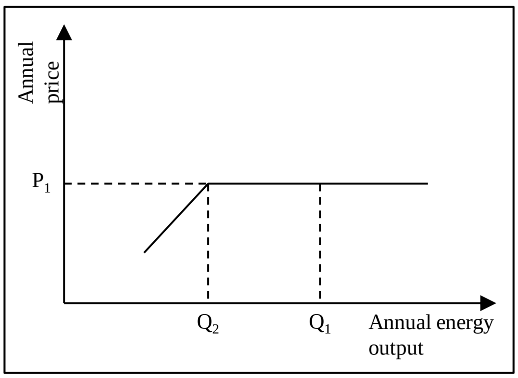

Fig. 15: Payout profile for a contract with a fixed price and a minimum production penalty level

When contracts with production minimums are involved, an important element of the contract is whether or not any excess over and above the minimum is banked from year to year. When banked, the minimum becomes less of a risk each year, because the expected production is substantially above the minimum production level (i.e., if expectations are set properly, the bankable rollover amount should quickly become a large buffer). Conversely, contracts with minimums and rollover clauses are much more risky when they are less seasoned and therefore lack an accumulated rollover buffer. Two approaches to reduce the risks of unseasoned contracts are to set a lower minimum in the early years of the contract, or to define the minimum level for penalties as a multi-year period early in the contract (e.g., penalties only apply if below the accumulated minimum at the end of the second year of the contract).

Weather-adjusted contract terms can be applied to the minimum production levels. This type of contract shifts solar asset weather risk from the asset owner to the entity contracting for the energy off take, while keeping energy production risks due to other reasons (e.g., operations and maintenance issues) with the asset owner. For asset owners with fixed rate contracts with minimums (i.e., Fig. 14), the owner still has some weather risk remaining. The weather adjustment only removes the downside penalty by effectively converting the payout profile to be a plain fixed-rate contract (Fig. 13) from a weather risk perspective, since lower energy production will still result in lower revenue. For asset owners with fixed price contracts (i.e., Fig. 15), a weather adjustment clause can shift the weather risk entirely to the entity contracting for energy off take, because only non-weather-related energy production losses will trigger the penalty.

7 CONNECTING INSOLATION DATA AND CONTRACTS TO FINANCIAL IMPACT FOR A SOLAR PORTFOLIO

The site-level contract models can be aggregated into overall portfolio models. In the case of a portfolio consisting of fixed $/kWh contracts as shown in Fig. 13, all at the same rate, the overall portfolio's financial performance can be estimated from the portfolio's insolation characteristics (i.e., Equation 1 and Equation 2, multiplied by the $/kWh rate).

If the portfolio contains additional complexity from different $/kWh rates or minimum production penalties, individual sites within the portfolio will need to be modeled individually and aggregated into the overall portfolio model.

Despite the need to model portfolios by modeling the discrete assets and aggregating results, some general observations can be made:

1. Examining monthly insolation correlations reveals there is significant opportunity for diversification with respect to managing monthly volatility in a portfolio of solar assets. Since solar asset owners often are paid monthly for energy generated, and also need to make debt service payments for financing on a monthly basis, the ability to diversify and reduce monthly cash flow mismatches is important.
2. Examining yearly insolation correlations reveals that there is an opportunity to diversify the overall portfolio, though it is less significant than on the monthly level. The yearly correlations have implications for the design of cash reserves to support a portfolio through a bad year or years affecting all locations (e.g., as followed the Mount Pinatubo eruption).

3. Portfolios with contracts containing minimum production penalties benefit significantly from geographic diversification, since if concentrated geographically the asymmetric downside risk in these contracts could lead to steep decreases in revenue in outlier years. This is particularly true for fixed-price contracts as shown in Fig. 15, since these contracts do not benefit from kWh outperformance vs. expectations, and geographic diversification is important to reduce the downside risk.

8 CONCLUSIONS

Owners of solar assets should manage their portfolio in the same way as any conventional asset portfolio. To do so, asset owners should consider sunlight and other weather data volatility and correlation as part of their overall investment decision-making process.

The intuitive idea that solar installations farther apart should be less correlated does in fact hold. Reduction in monthly volatility is very achievable through geographic diversification, since correlations drop steeply out to about 1500 km. Geographic diversification also reduces annual volatility, but the strict relationship between distance and correlation is not as strong.

With respect to contract design, if minimum guarantee levels are specified it would be best to set them according to consistent risk levels (e.g., P90), to achieve even risk allocation across contracts. In the early years of a contract with minimum production levels and roll-over accumulation, contracts with lower minimum kWh thresholds or multi-year initial evaluation levels could reduce the risks of failing to meet the contract.

The concepts described in this paper can be combined with standard portfolio calculations (Equations 1 and 2) to estimate the risks associated with a planned or current solar asset portfolio, as well as evaluate the potential impact on a solar portfolio of adding new solar assets in different locations.

9 FUTURE WORK

A better understanding of global effects at play in yearly correlations could support modeling yearly correlations across geographies outside the sample set used in this paper (i.e., extending the model results outside the United States). Here, we examined one known global mechanism that was at play (aerosols blocking sunlight after a 1991 volcano eruption), but there are inevitably other factors to consider. Given the importance of yearly correlations for solar prospecting activities, and the difficulty associated with collecting long time-histories of site-specific data, a more sophisticated yearly correlation model could be quite valuable to asset owners modeling a global portfolio.

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