National Renewable Energy Laboratory
Innovation for Our Energy Future

JMP Applications in Photovoltaic Reliability

JMP Discovery Summit 2011
Denver, CO

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NREL is a national laboratory of the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy operated by the Alliance for Sustainable Energy, LLC

Outline

- Photovoltaics history and application
- Importance of degradation (power decline over time)
- Literature degradation rates, analysis and trends.
- Impact on warranty risk.
- Time series modeling can help reduce time & uncertainty
- Impact of climate on PV performance
- Bubble plot as diagnostics tool
- Non-linear Modeling

Modern Photovoltaics History

Bell Labs - 1954

A New Silicon *p-n* Junction Photocell for Converting Solar Radiation into Electrical Power

D. M. Chapin, C. S. Fuller, and G. L. Pearson
Bell Telephone Laboratories, Inc., Murray Hill, New Jersey
(Received January 11, 1954)

↓

1st major application: Satellites

Vanguard I
1958

Photo credit: NASA

- Solar efficiency not as high as today
- Satellites required modest amount of power
- Lightweight → important for launch
- Not affected by cold space temperatures

1st terrestrial application – stand-alone

Ogami Lighthouse, Japan – 1st solar powered lighthouse 1963

Photo credit: Sharp

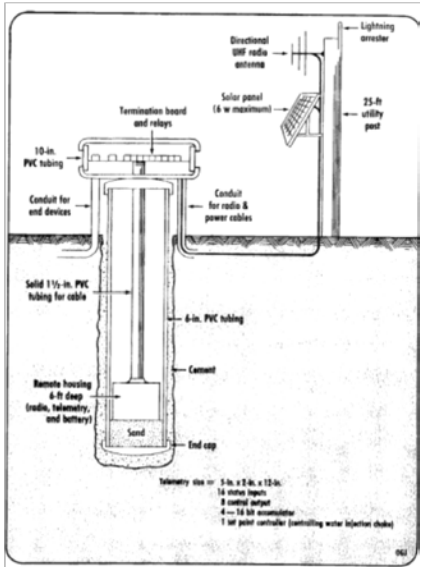
John Perlin, From space to Earth, 1999.

1st major solar applications

Modern Photovoltaics History

Stand-alone application in remote locations

Cathodic Well Protection



Nolan D., The Oil and Gas Journal, 1978.

Signal & foghorn on oil platform

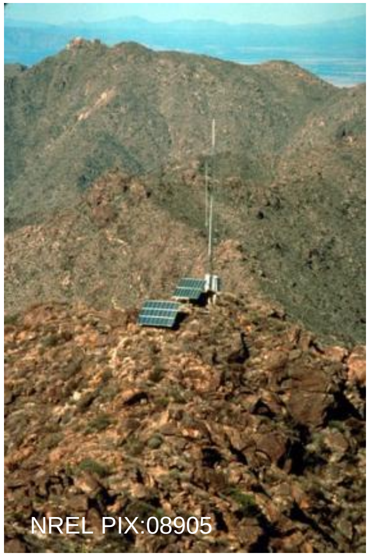
Photo credit: Solarex

Railroad Signals

Photo credit: Kyocera

Telecommunications

NREL PIX: 07586



NREL PIX:08905

Terrestrial application after 1970s oil crisis

Today

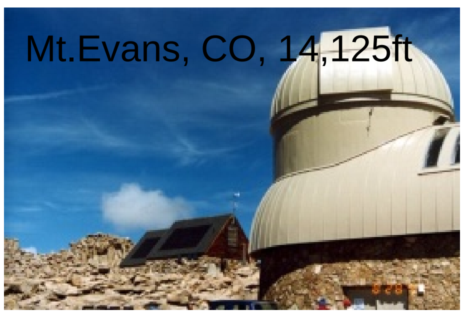
Space

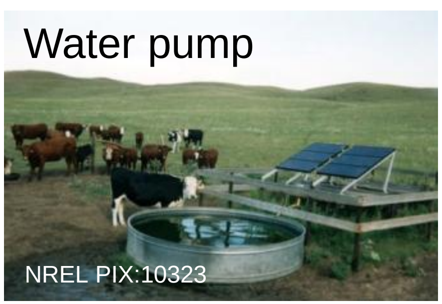
Transportation

Utility

Consumer Products

Stand-alone





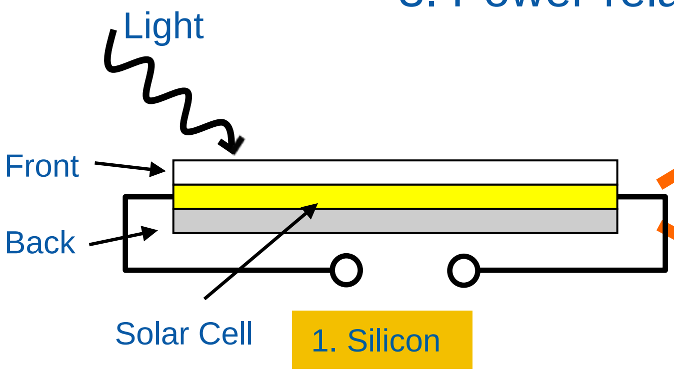
Lighting

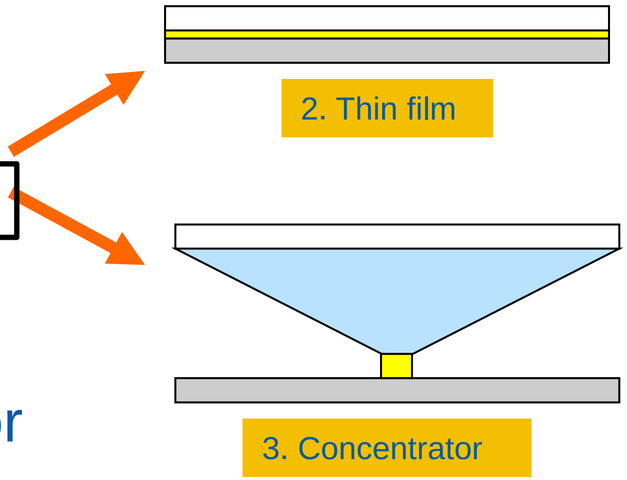
Building Integrated PV

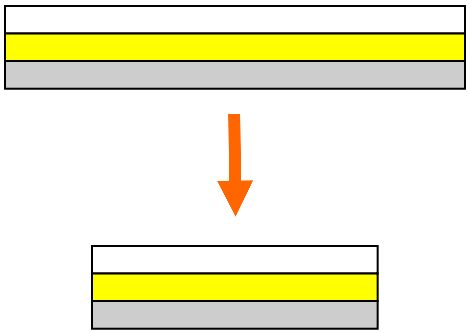
Residential

Cost reduction in PV

Upfront costs:
1. Semiconductor material
2. Area-related costs (glass, installation, real estate, wiring)
3. Power-related costs (inverter)

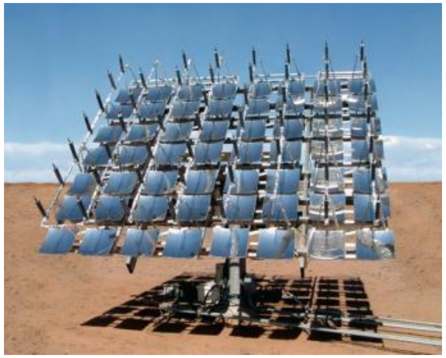


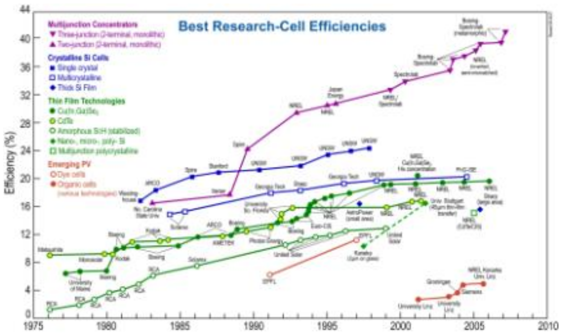




Reduce semiconductor material

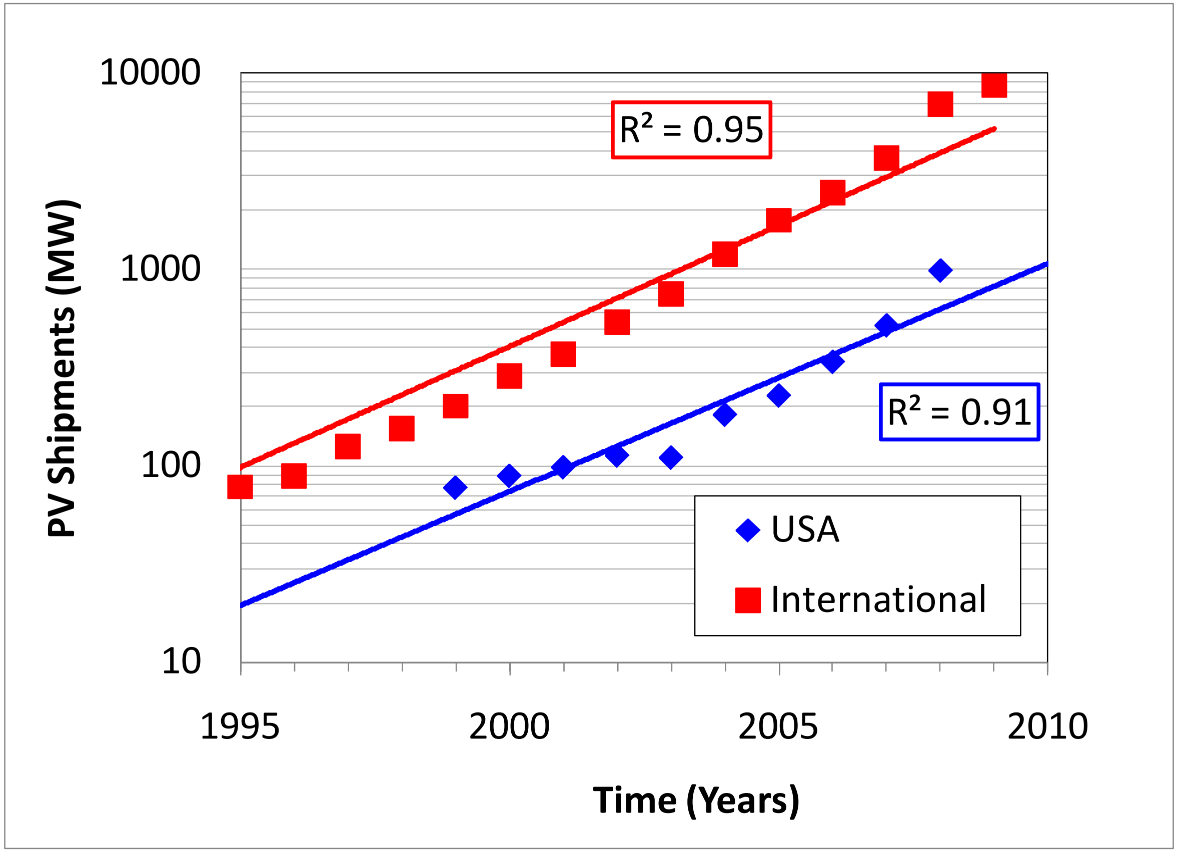
Reduce area by increasing efficiency





Cost reduction approaches leads to different technologies

Growth of PV Industry

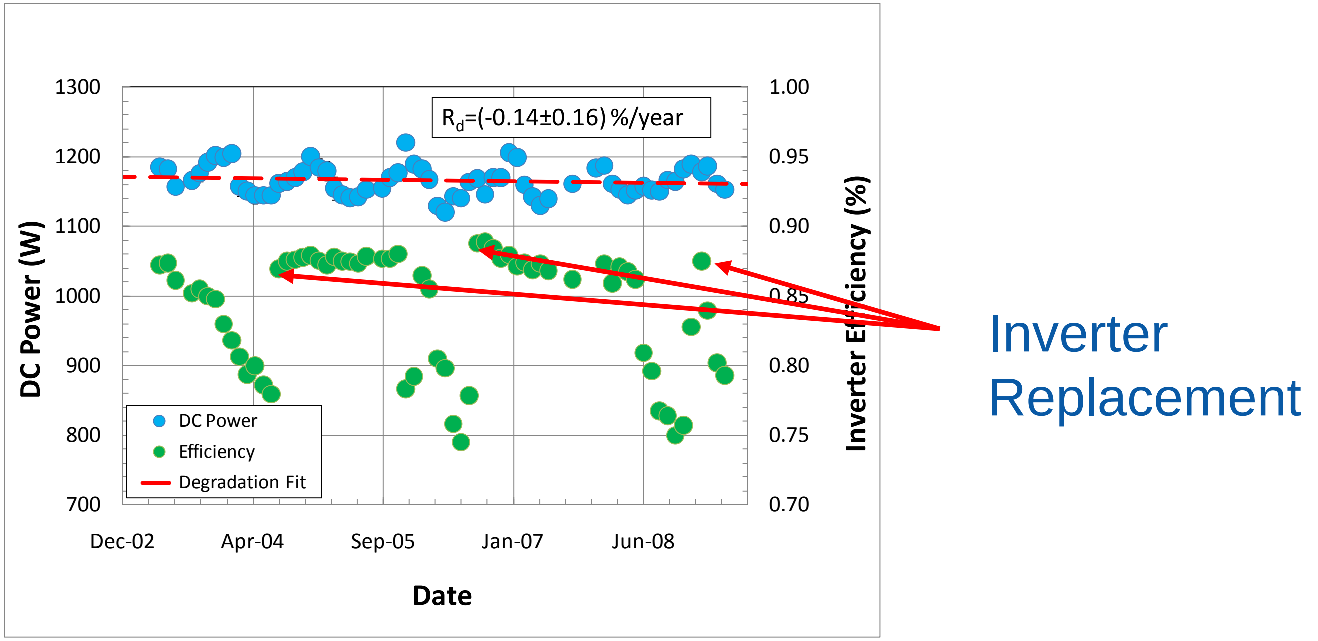


Sources:International: PV News, April 2009
USA: http://www.eia.doe.gov/emeu/international/contents.html

Reliability required to sustain exponential growth of industry

Reliability & Durability

- **Reliability:** Ability to perform designed task without failure → discrete, disruptive events
- **Durability:** Ability to perform task without significant deterioration → continuous, gradual decline



Both important for cost of electricity

Photovoltaic Financial Considerations

Levelized Cost of Energy (LCOE)

$$\text{LCOE} = \frac{\text{Total Life Cycle Cost}}{\text{Total Lifetime Energy Production}}$$

$$= \frac{\text{Initial Investment} - \sum_{n=1}^{N} \frac{\text{Depreciation}^{n}}{(1+\text{Discount Rate})^{n}} \times (\text{Tax Rate}) + \sum_{n=1}^{N} \frac{\text{Annual Costs}^{n}}{(1+\text{Discount Rate})^{n}} \times (1-\text{Tax Rate}) - \frac{\text{Residual Value}}{(1+\text{Discount Rate})^{n}}}{\sum_{n=1}^{N} \frac{\text{Initial kWh/kWp} \times (1 - \text{System Degradation Rate})^{n}}{(1 + \text{Discount Rate})^{n}}}$$

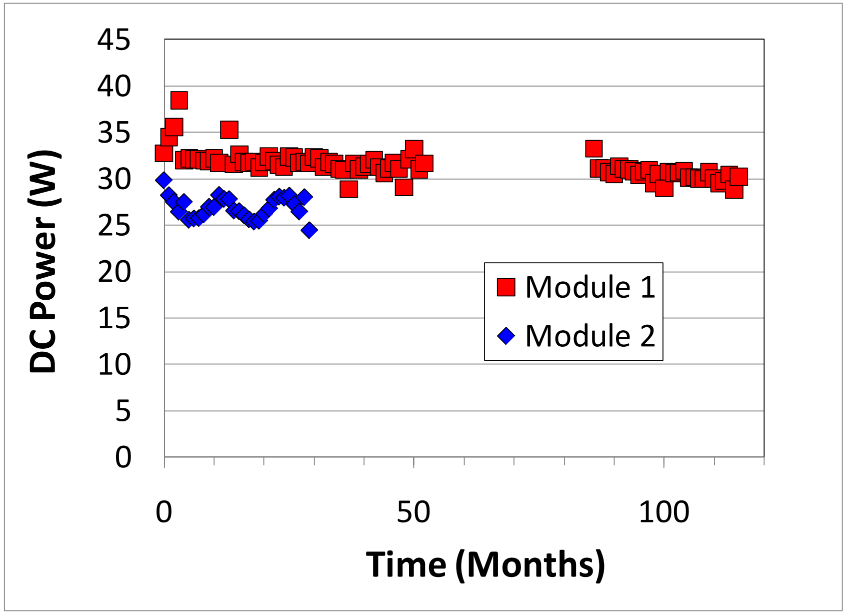
How efficiently convert sunlight into power

How this efficiency evolves over time

Efficiency & Degradation important to cost

Motivation

Uncertainty is very important too.



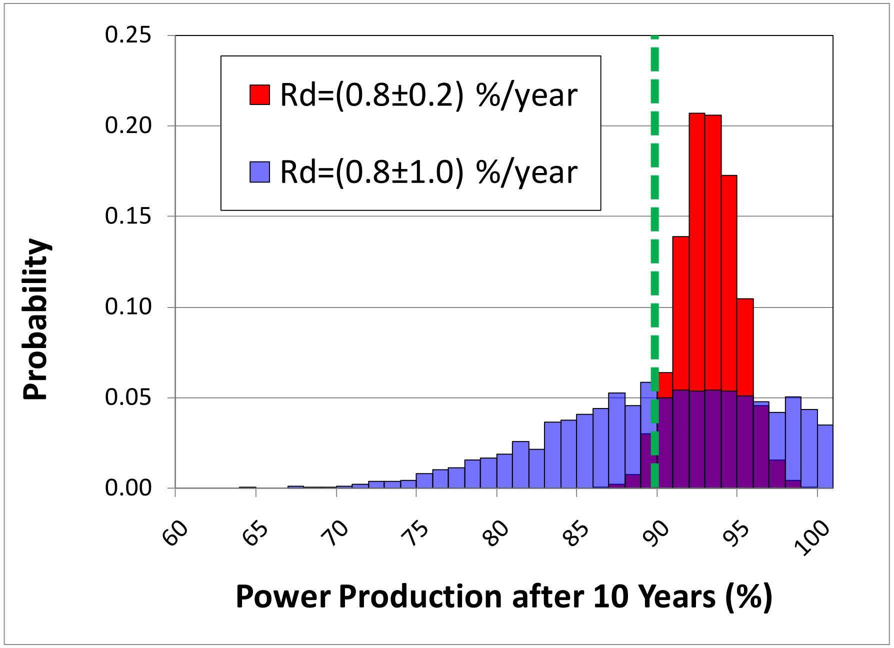
2 examples from NREL:
Different observation lengths, seasonality etc. → Leads to different uncertainties

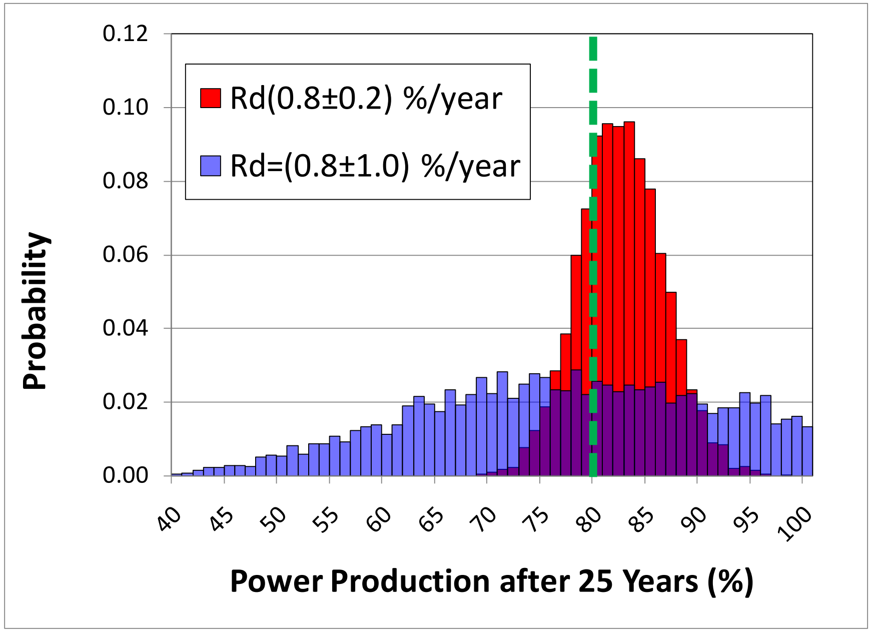
R_d (Module 1) = (0.8 ±0.2) %/year
R_d (Module 2) = (0.8 ±1.0) %/year

Same R_d but very different uncertainty

R_d Uncertainty Impact on Warranty

Manufacturer Warranty often twofold: 90% after 10 years, 80% after 25 years





$$Energy(Year_N) = \sum_{n=1}^{N} \frac{Energy(Year_1) \cdot (1 - R_d)^n}{(1 + r)^n}$$

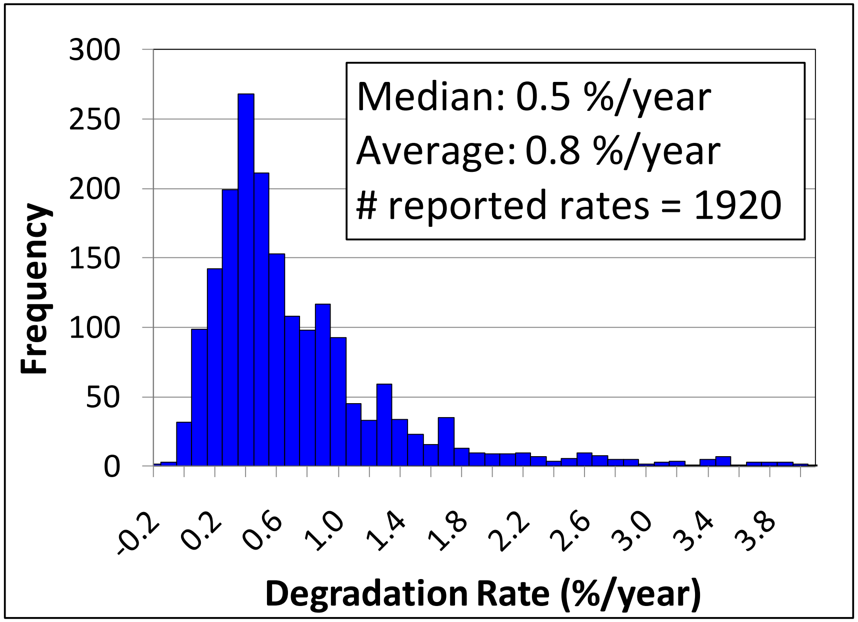
Probability to default warranty:
1.0 %/year uncertainty = 46%
0.2 %/year uncertainty = 4%

Probability to default warranty:
1.0 %/year uncertainty = 57%
0.2 %/year uncertainty = 24%

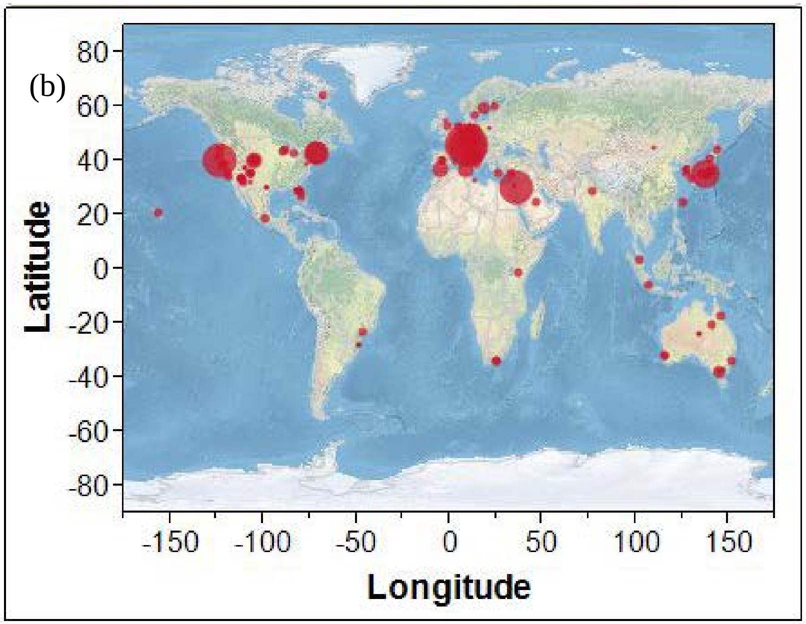
Higher R_d uncertainty significantly increases warranty risk

Degradation Rates – Literature Survey

Number of Degradation rates (R_d) from literature: 1920



ca. 100 publications



Technology, age, packaging, geographic location

ca. 80% below 1%/year

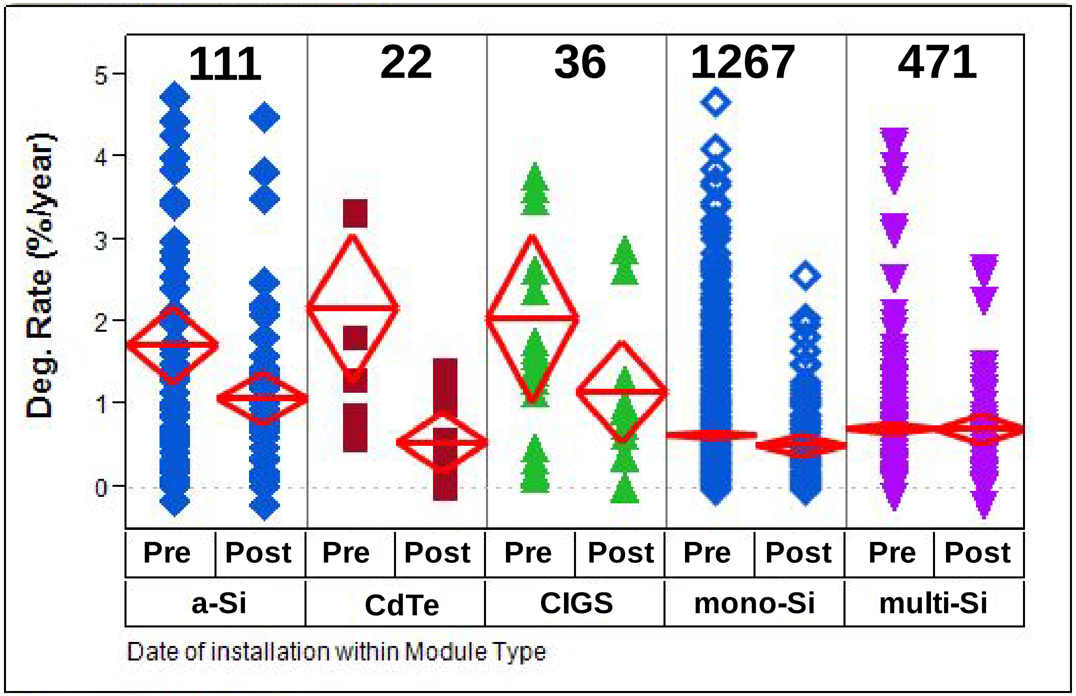
Circle size = number of data points from a given location.

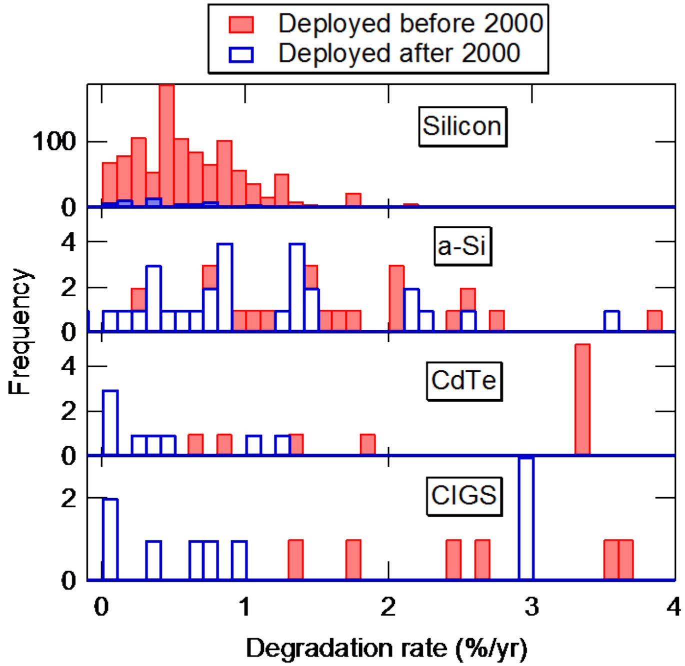
Most modules degrade by ca. 0.5 %/year

Jordan et al., "Degradation Rates – An Analytical Review", submitted to Progress in PV

Literature Degradation Rates

Variability chart of literature results





Partitioned by date of installation: Pre- & Post-2000
Red diamonds: mean & 95% confidence interval

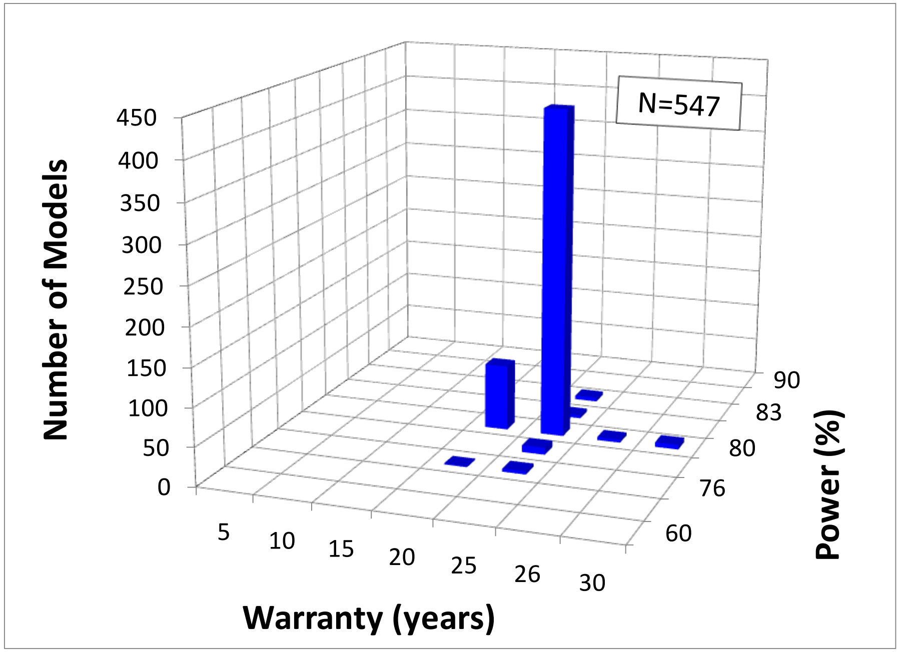
Crystalline Si technologies appear to be the same

Thin-film technologies appear to decrease in R_d in last 10 years

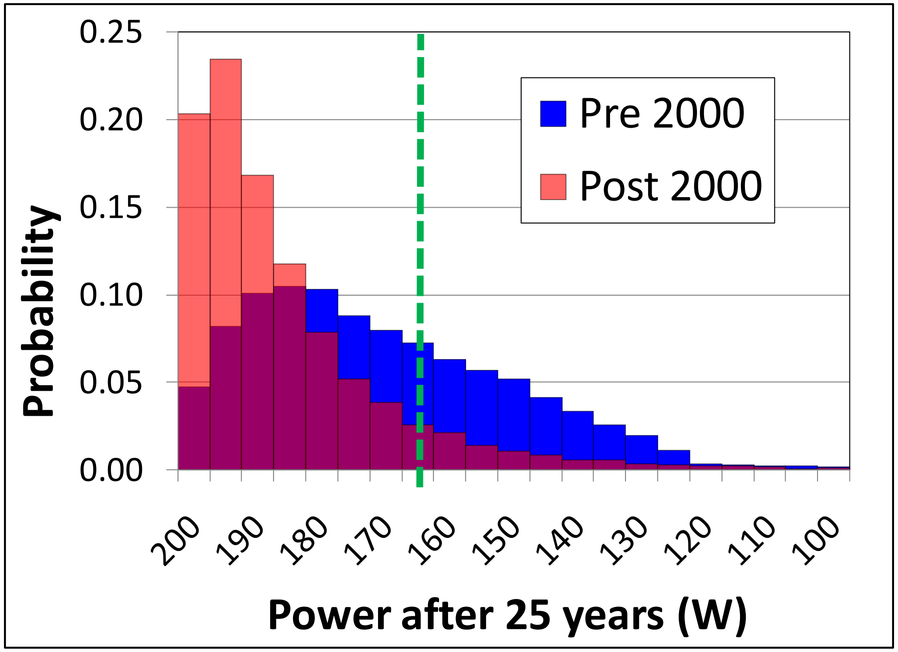
Musikowski et al., “Analysis of the Operational Behavior and Long-Term Performance of a CIS PV System,” Proc. PVSEC, 2010, 3942.

Warranty Risk

Manufacturer Warranty



Monte Carlo Simulation



Source: Photon International, Feb 2010.

Most common: 80% after 25 years

Procedure: Take random degradation rate from literature distribution
Calculate power output after 25 years

Default risk : below dashed green line
Decreased from 26% to 6% in last decade

Warranty default risk substantially decreased in last decade

PV for Utility Scale Application (PVUSA)

The plant was originally constructed by the Atlantic Richfield oil company (ARCO) in 1983.

Provided electricity, data & experience in the 1980s and 1990s. Plant was dismantled in the late 1990s.

PVUSA Rating Methodology

Improved PVUSA models include Sandia & BEW model**

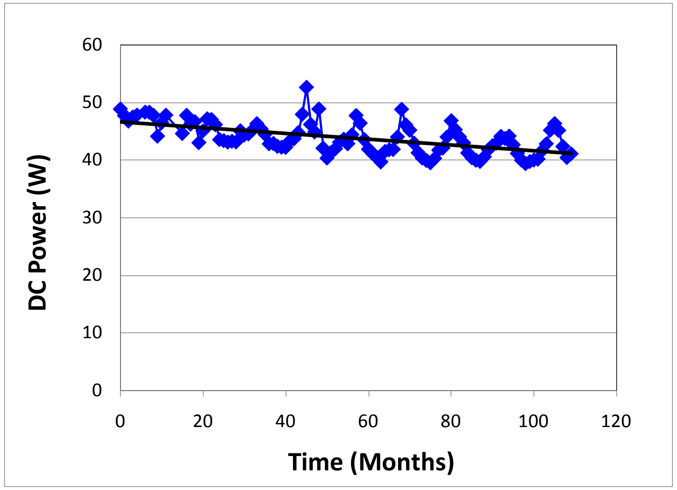
1. Step: Translation to reference conditions (use a multiple regression approach)

$$P = H \cdot \left(a_1 + a_2 \cdot H + a_3 \cdot T_{ambient} + a_4 \cdot ws\right)$$

H= Plane-of-array irradiance
$T_{ambient}$=ambient temperature
ws= wind speed
a_1, a_2, a_3, a_4= regression coefficients

Reference conditions:
PVUSA Test Conditions (PTC): E=1000 W/m^2, $T_{ambient}$=20ºC, wind speed=1 m/s

2. Step: Time series to determine degradation rate



Need basic weather station to collect $T_{ambient}$ and wind speed on top of irradiance

Seasonality leads to required observation times of 3-5 years* → long time in today's market

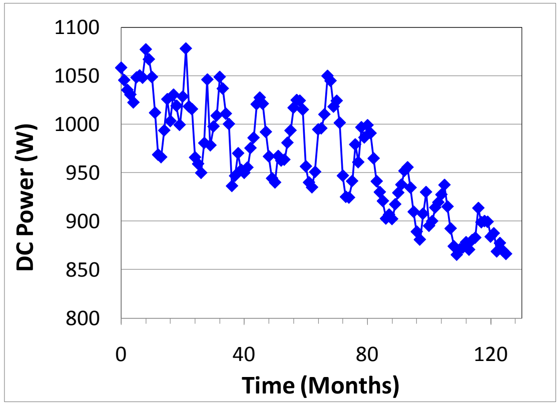
Long time required for accurate R_d

*Osterwald CR et al., Proc. of the 4th IEEE World Conference on Photovoltaic Energy Conversion, Hawaii, 2006.
**Kimber A. et al., Improved Test Method to Verify the Power Rating of a PV Project. Proceedings of the 34th PVSC, Philadelphia, 2009.

Classical Decomposition

Signal = Trend + Seasonality + Irregular

Original Data



Classical Decomposition

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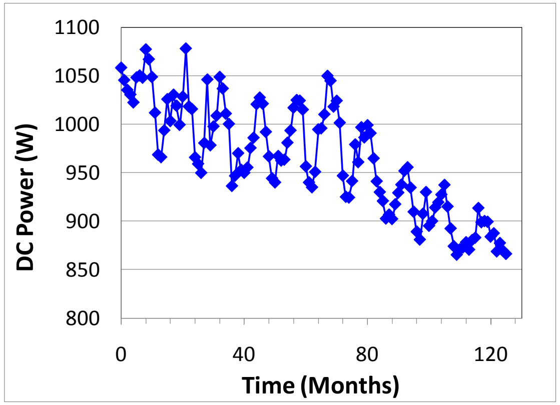
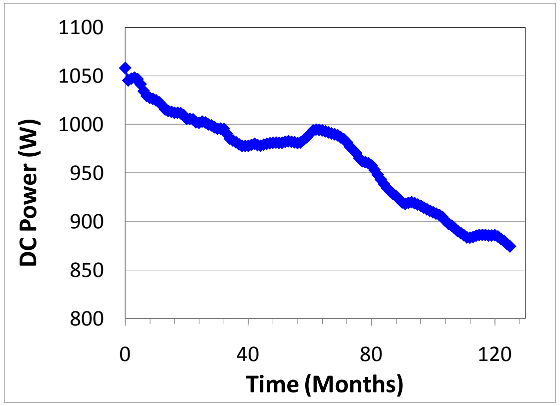




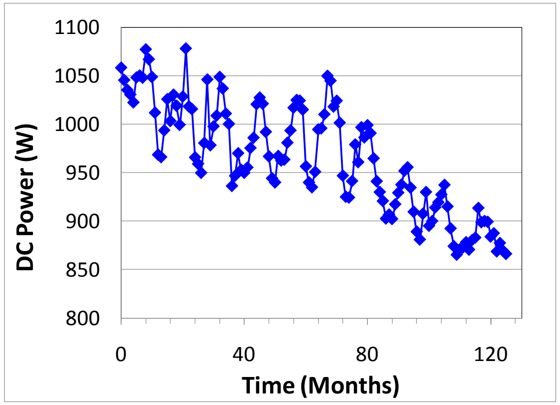
Trend

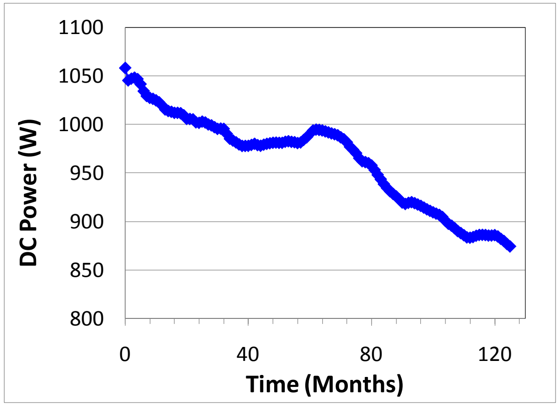
12-month centered-Moving Average

Classical Decomposition

Signal = Trend + Seasonality + Irregular

Original Data



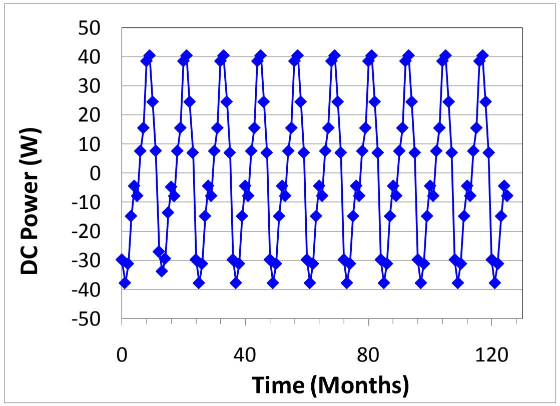


Trend

12-month centered-Moving Average

Seasonality

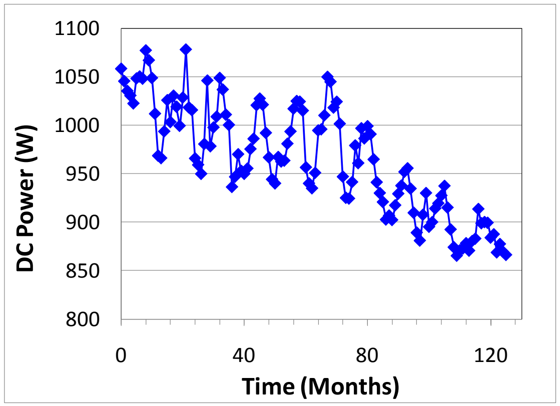
Average of each month for all years of observation



Classical Decomposition

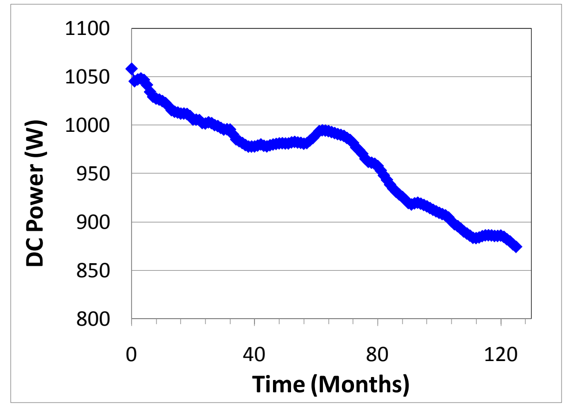
Signal = Trend + Seasonality + Irregular

Original Data



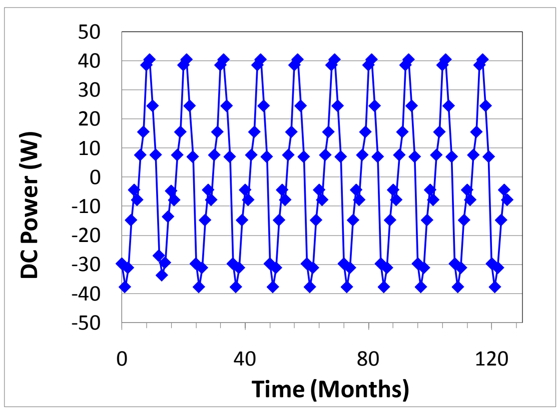
Trend

12-month centered-Moving Average

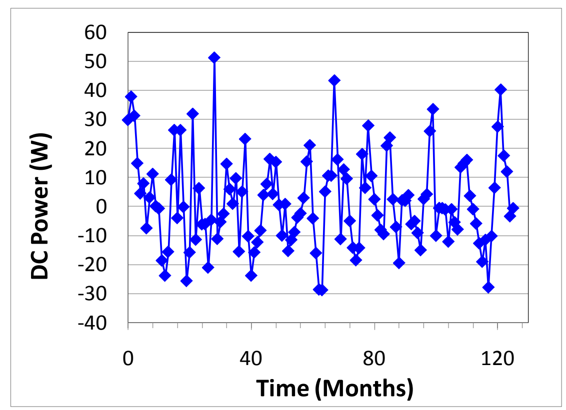


Seasonality

Average of each month for all years of observation



Irregular



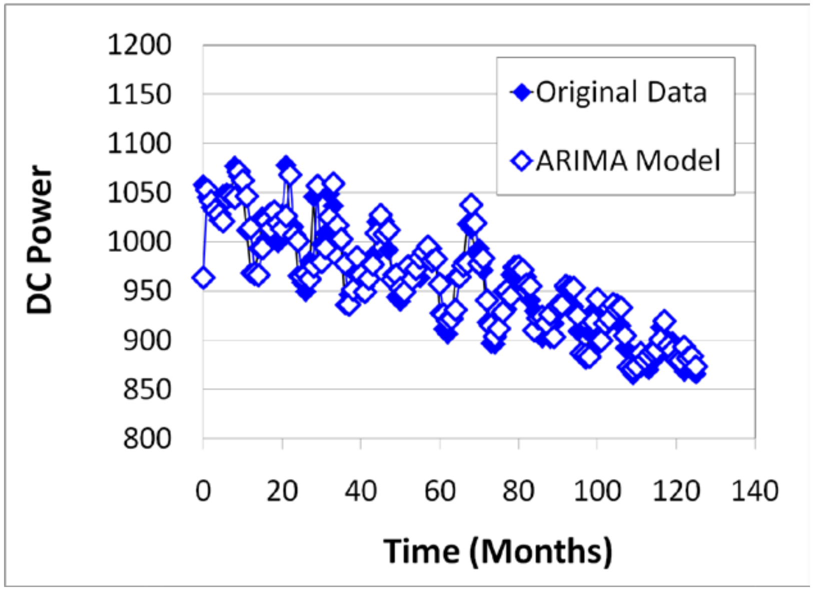
Determine R_d from Trend graph for higher accuracy

S.G. Makridakis et al., “Forecasting”, New York, John Wiley & Sons 1997.

ARIMA

Auto**R**egressive **I**ntegrated **M**oving **A**verage (ARIMA)

Model trend & seasonality component w/ linear combination of weighted differences & averages



$$\boxed{P_t - P_{t-12} - \phi \cdot P_{t-1} + \phi \cdot P_{t-13} = \delta + \varepsilon_t - \theta \cdot \varepsilon_{t-12}}$$

ARIMA(100)(011)

P=Power
c, δ, ϕ, θ =constant
ε=noise

1. Built several Models → minimize noise component
2. Chose parsimonious model w/ aid of several selection criteria

Many statistical software packages include time series analysis (JMP, Minitab, R etc) Developed script to make model selection less sensitive to outliers.

Use ARIMA to model data, then decompose

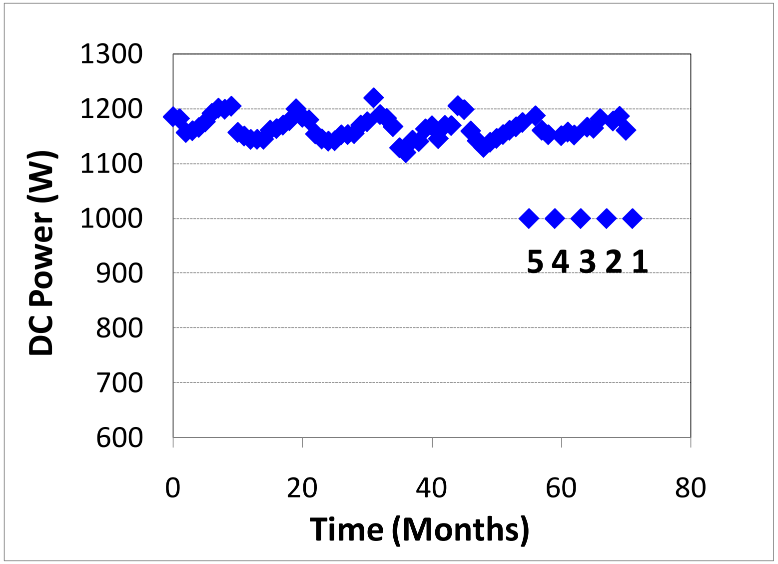
Box, GPP and Jenkins, G: Time series analysis: Forecasting and Control, San Francisco: Holden-Day, 1970.

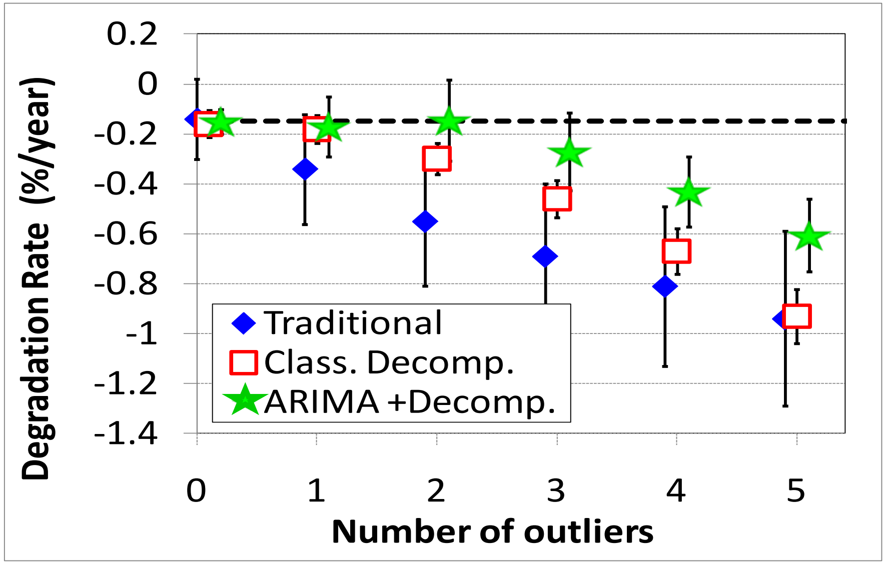
Outliers

Compare sensitivity of 3 methods to outliers

Procedure:

1. Dataset from NREL
2. Introduce outliers sequentially
3. Calculate R_d & study effect on all 3 methodologies





ARIMA most robust against outliers

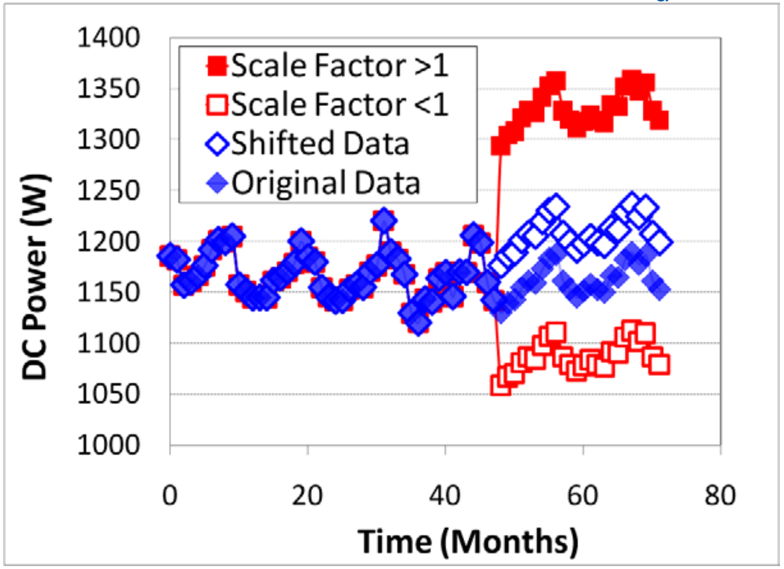
Data Shifts

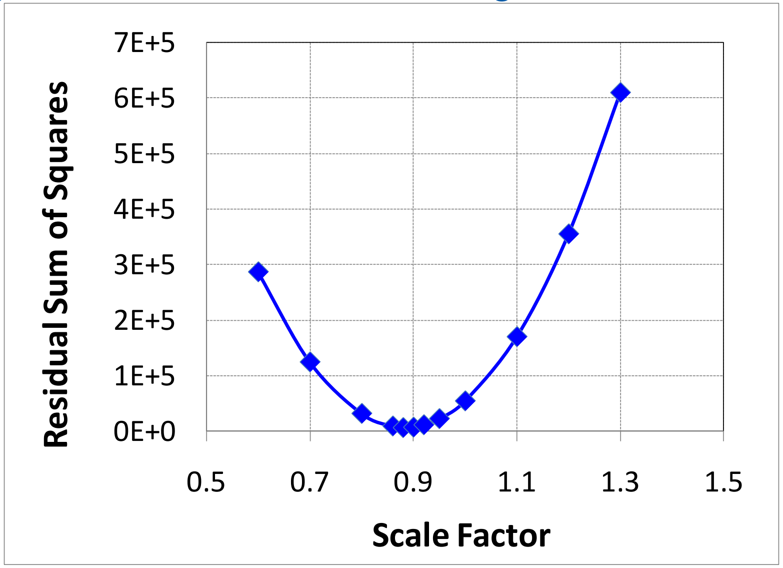
Compare sensitivity of 3 methods to data shifts

Example: inverter change

Procedure:

1. Dataset from NREL
2. Introduce a data shift deliberately
3. Multiply shifted section with a scaling factor
4. Calculate R_d & study effect on all 3 methodologies

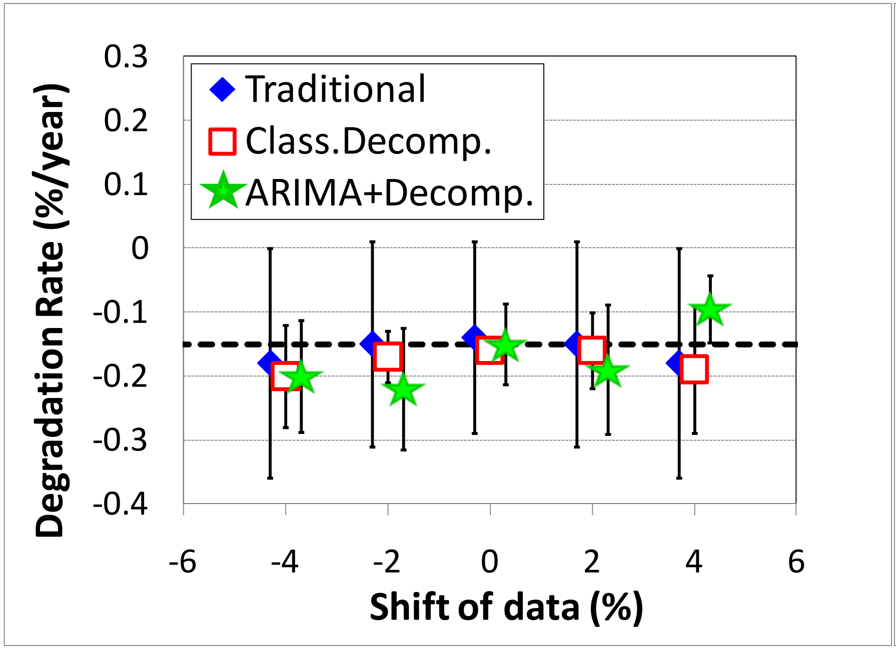




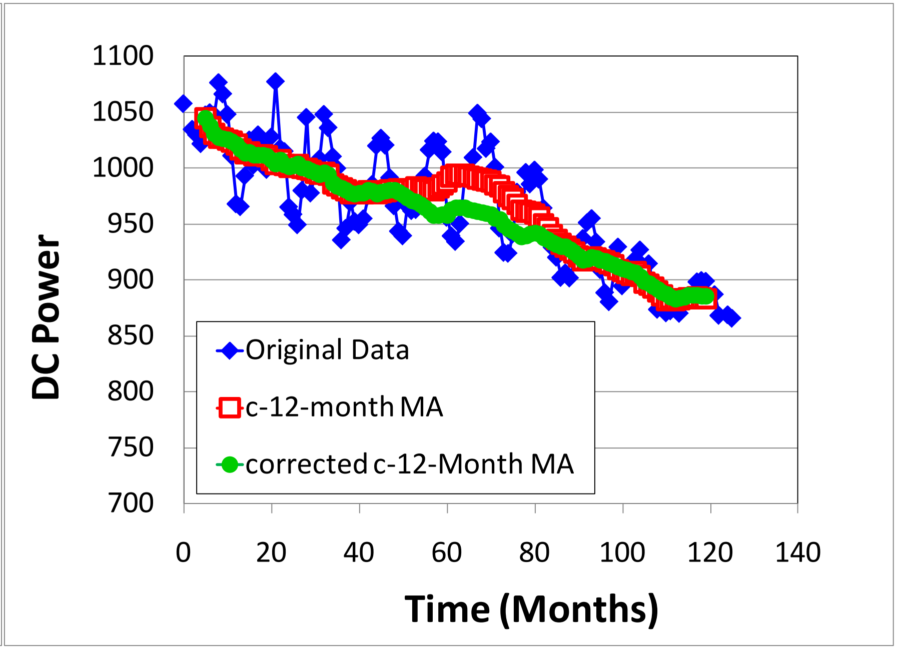
Correct data shifts by minimizing residual sum of squares

Data Shift Results

Results from induced shift



Real Shift – Blind test



Data shift correction procedure is successful for all 3 approaches.

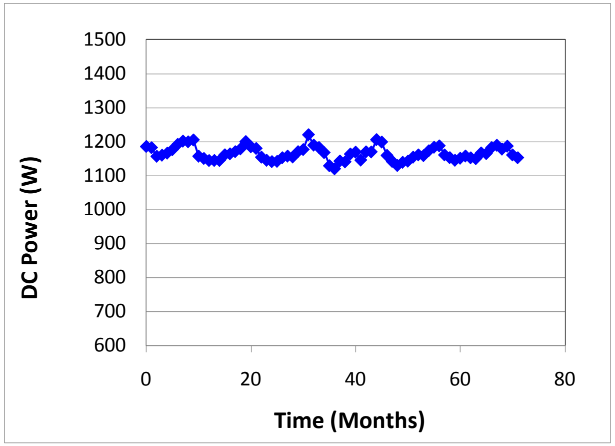
Data shift cause: Erratic ambient Temp sensor.
Misleading degradation rate if R_d calculated after shift.

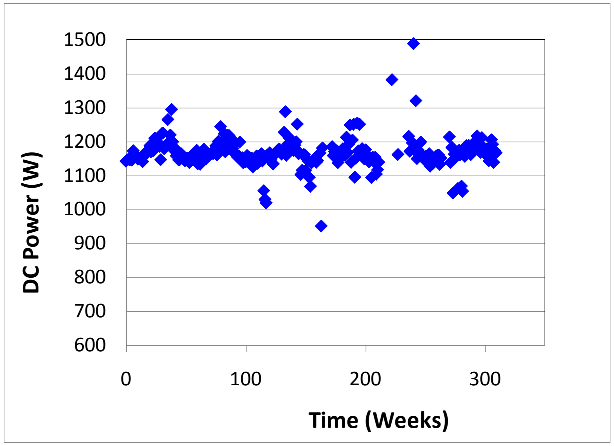
Residual minimization technique works on real shifts

PVUSA – Weekly Intervals

Multi-crystalline module

Monthly Intervals



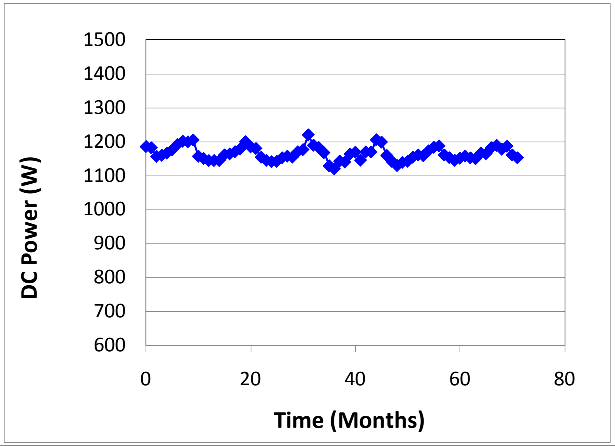


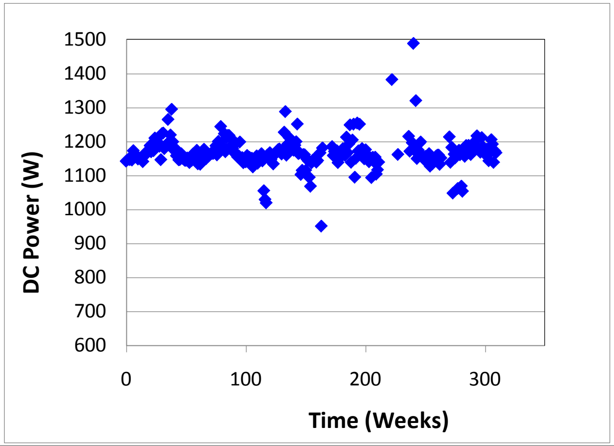
Weekly Intervals

PVUSA – Weekly Intervals

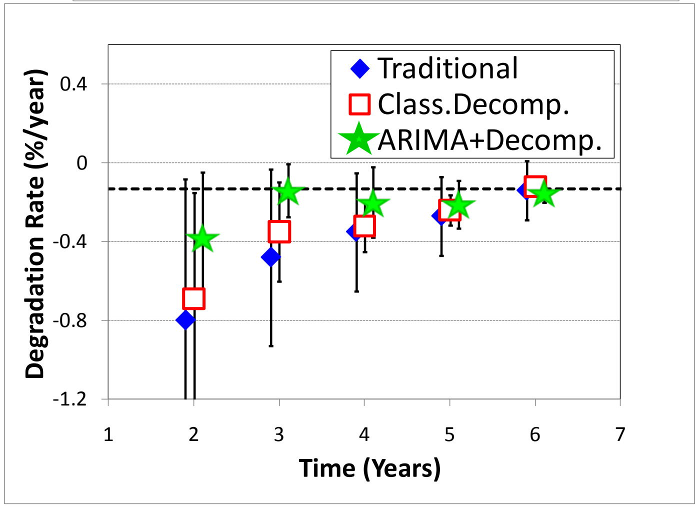
Multi-crystalline module

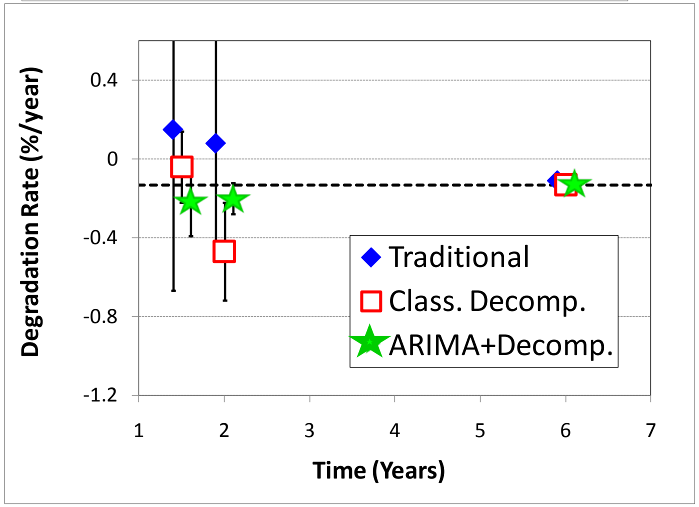
Monthly Intervals





Weekly Intervals

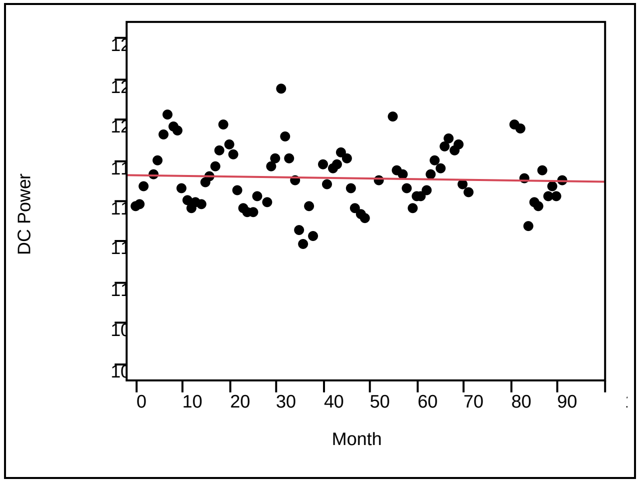




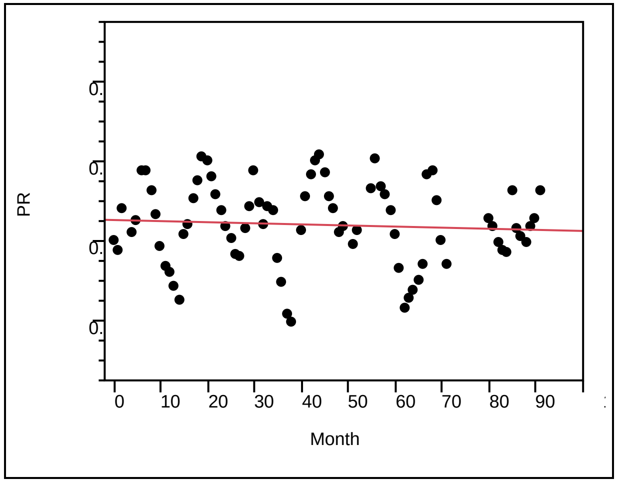
Weekly intervals → converges in less time

Performance Ratio

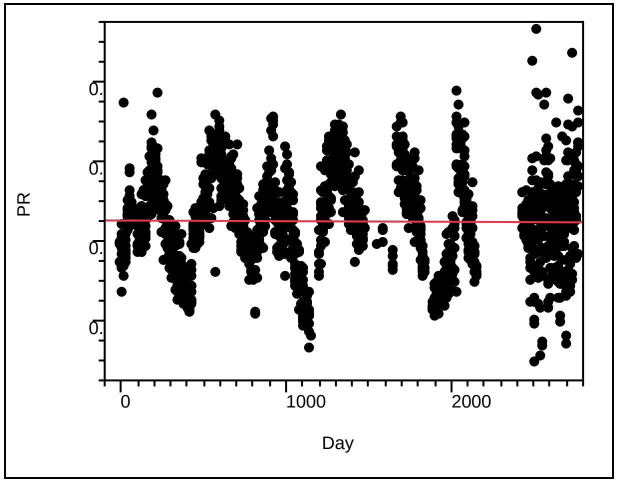
PVUSA



Monthly PR



Daily PR



Multi-crystalline Si system

$$Y_f = \frac{E}{P_0}$$

Y_f=Final Yield
E=Net Energy output
P_0=Nameplate DC rating

$$Y_r = \frac{H}{G}$$

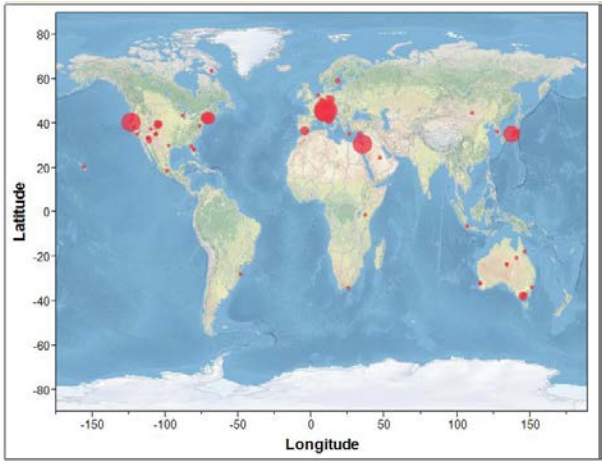
Y_r=ReferenceYield
H=In-plane Irradiance
G=Reference Irradiation

$$PR = \frac{Y_f}{Y_r}^{*}$$

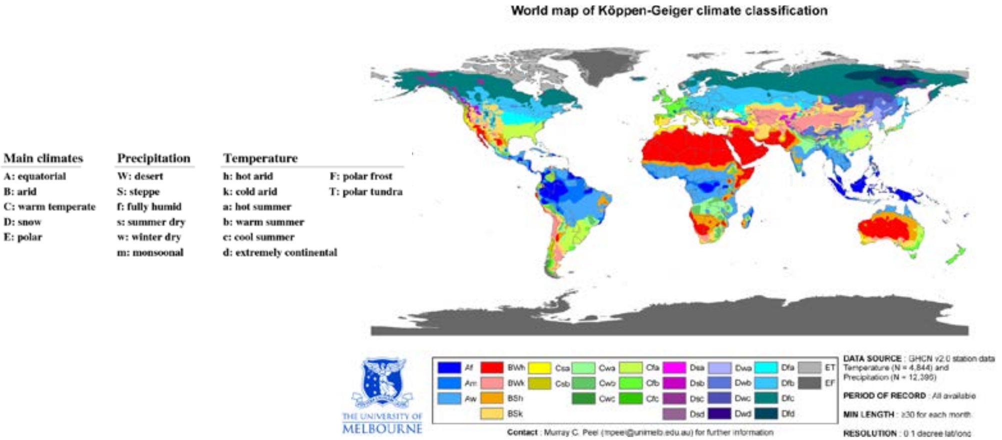
Can apply same modeling approaches to minimize seasonality

*B.Marion et al., “Performance Parameters for Grid-Connected PV Systems”, Proc. 31st PVSC, Orlando, FL 2005.

Impact of Climate – JMP Maps

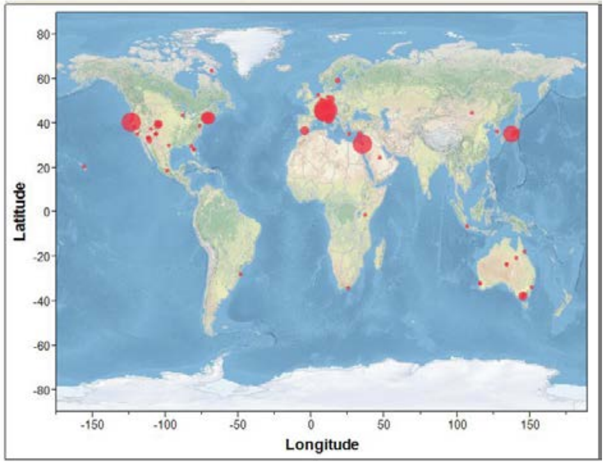


Köppen-Geiger climate map of the world (2007)

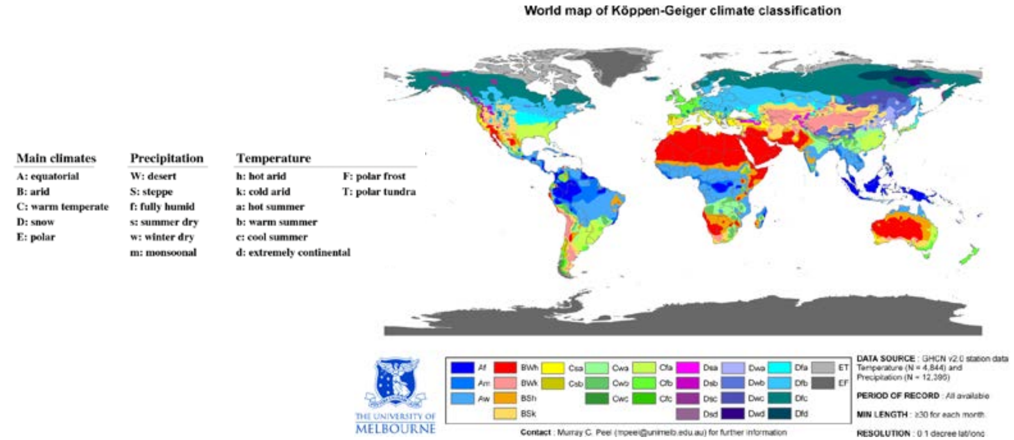


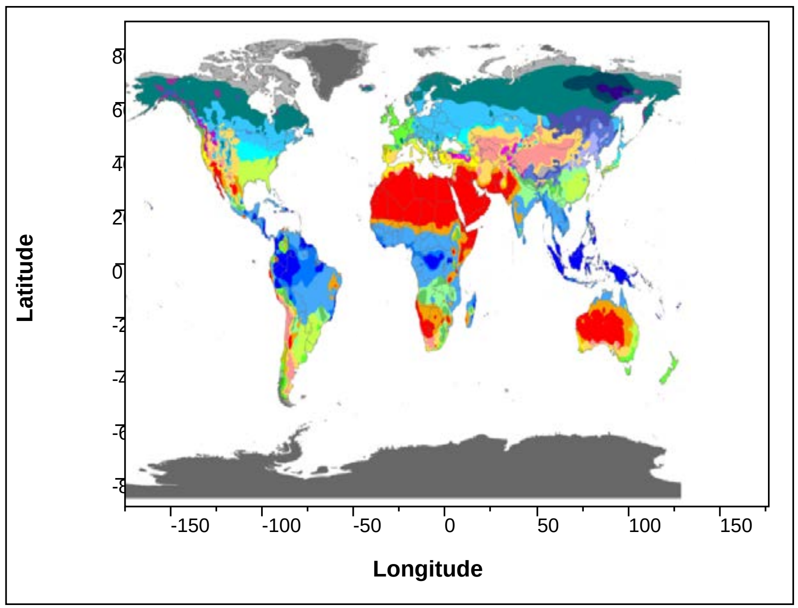
No reported degradation rates in many climate zones

Impact of Climate – JMP Maps



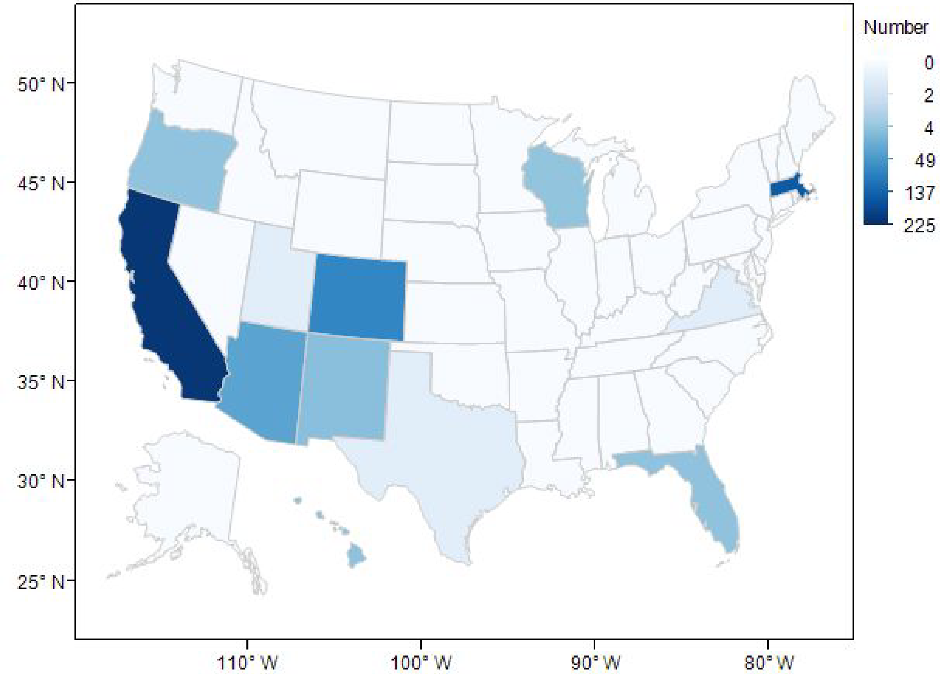
Köppen-Geiger climate map of the world (2007)



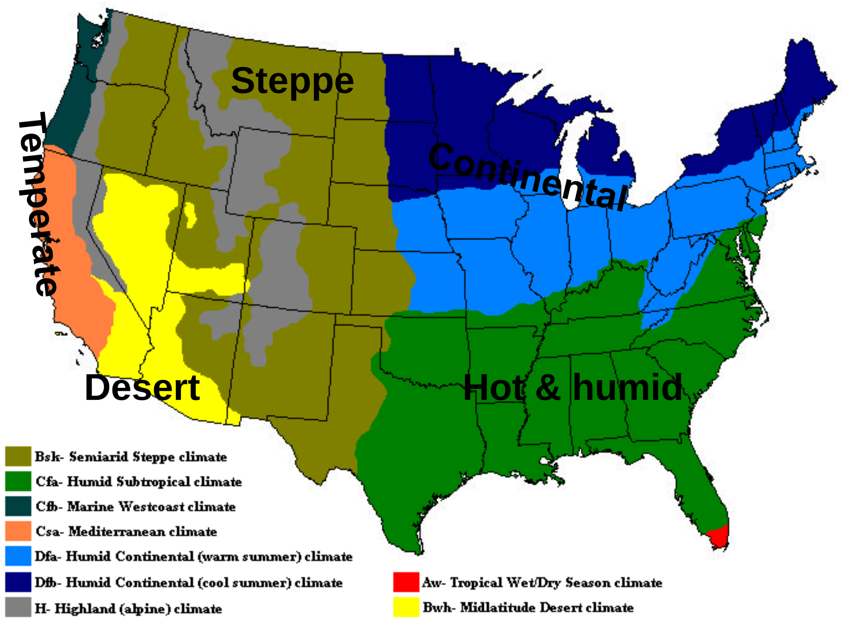


No reported degradation rates in many climate zones

Degradation Rates around the USA



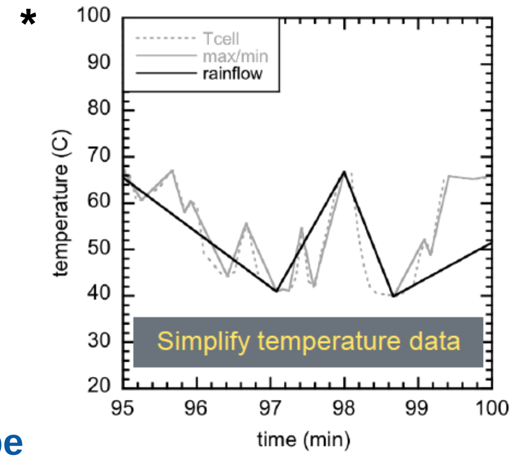
Climate Zones of the USA

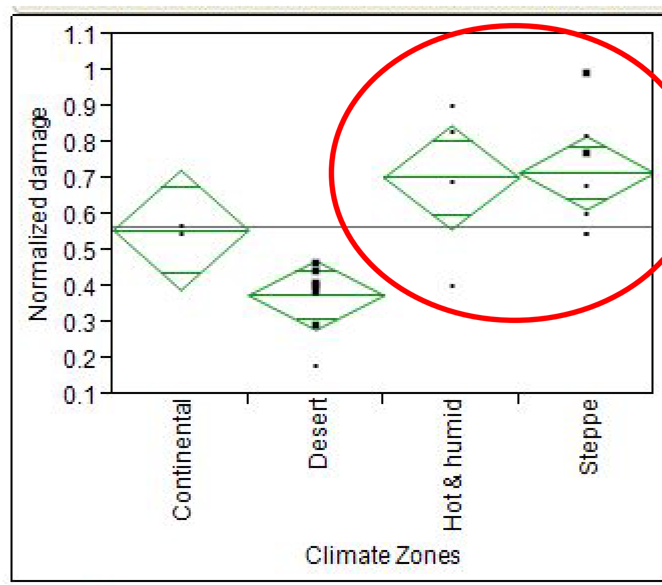


Similar picture as from around the world → some climate zones have not been investigated

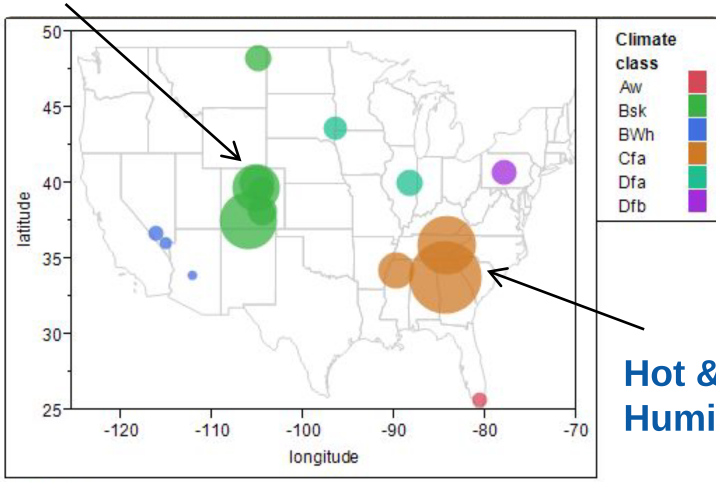
No reported degradation rates in some climate zones

Rainflow Calculations





Steppe



Hot & Humid

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Clim.code2	3	0.57996071	0.193320	10.1472	0.0003*
Error	20	0.38103308	0.019052		
C. Total	23	0.96099379			

Steppe, Hot & humid show significantly higher damage than Desert & Continental climate.

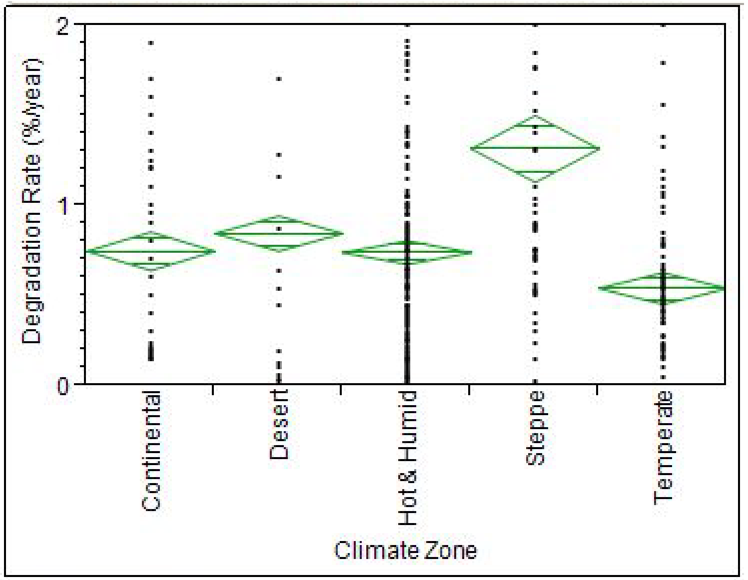
Steppe Climate has high damage due to thermal cycling

*Quantifying the Thermal Fatigue of CPV Modules_Bosco__NREL_International Conference on Concentrating Photovoltaics_2010

Analysis of all R_d by climate

All Technologies

Pre 2000

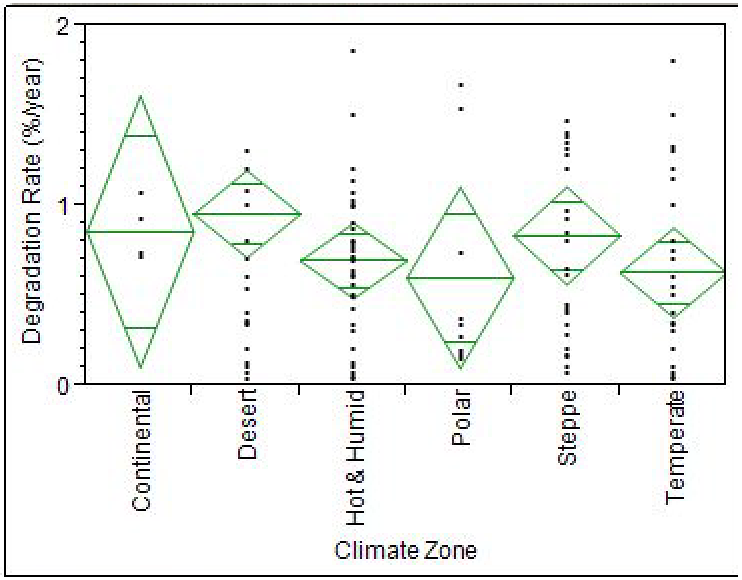


Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Climate Code3	4	32.32	8.08	15.50	<.0001*
Error	1186	618.26	0.52		
C. Total	1190	650.58			

Steppe climate significantly higher.

Post 2000



Analysis of Variance

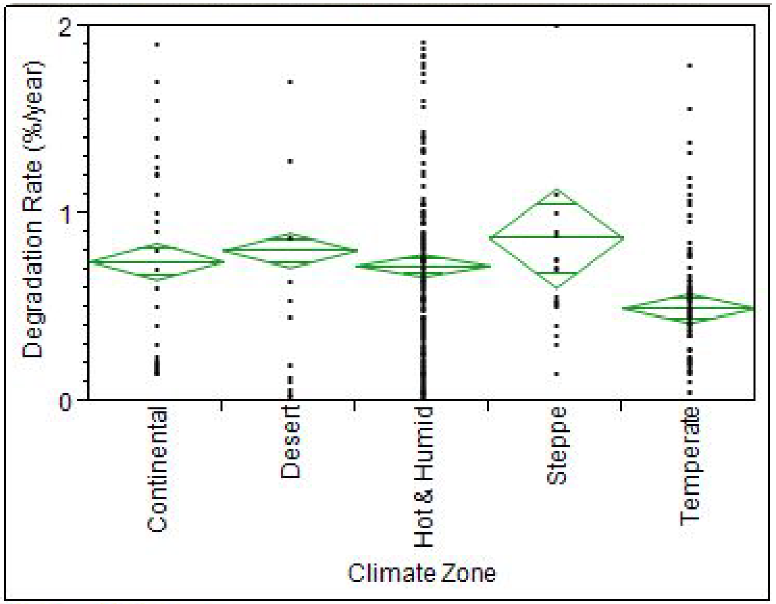
Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Climate Code3	5	2.78	0.56	0.95	0.4514
Error	166	97.25	0.59		
C. Total	171	100.03			

No significant difference.

Steppe Climate shows significantly higher R_d before 2000

Analysis of R_d by climate – c-Si

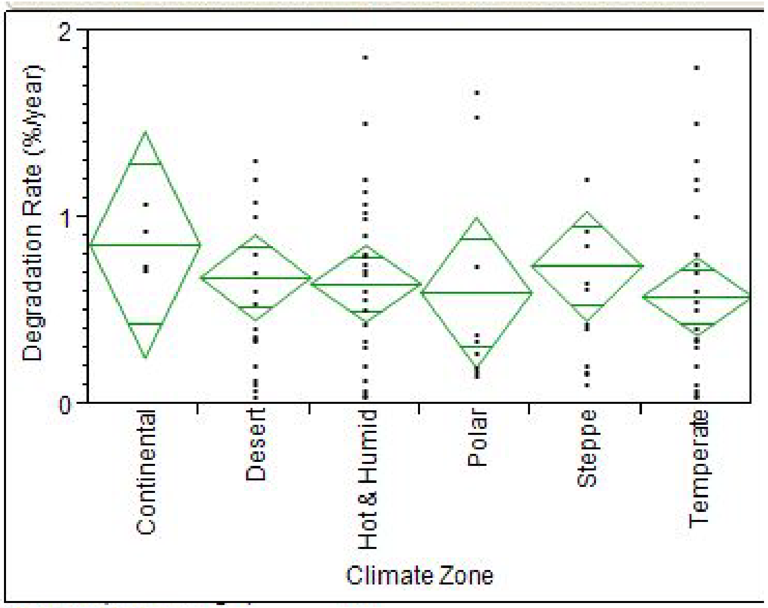
Pre 2000



Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Climate Code3	4	14.53	3.63	8.28	<.0001*
Error	1138	499.39	0.44		
C. Total	1142	513.92			

Post 2000



Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Climate Code3	5	0.53	0.11	0.29	0.9197
Error	121	45.15	0.37		
C. Total	126	45.69			

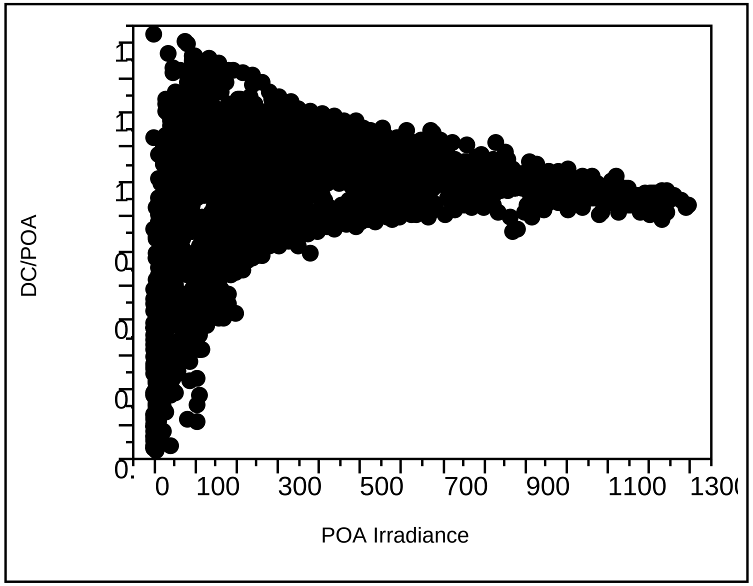
Similar but not as distinct trend for c-Si

Use of automated equipment, low stress ribbon effect visible…?

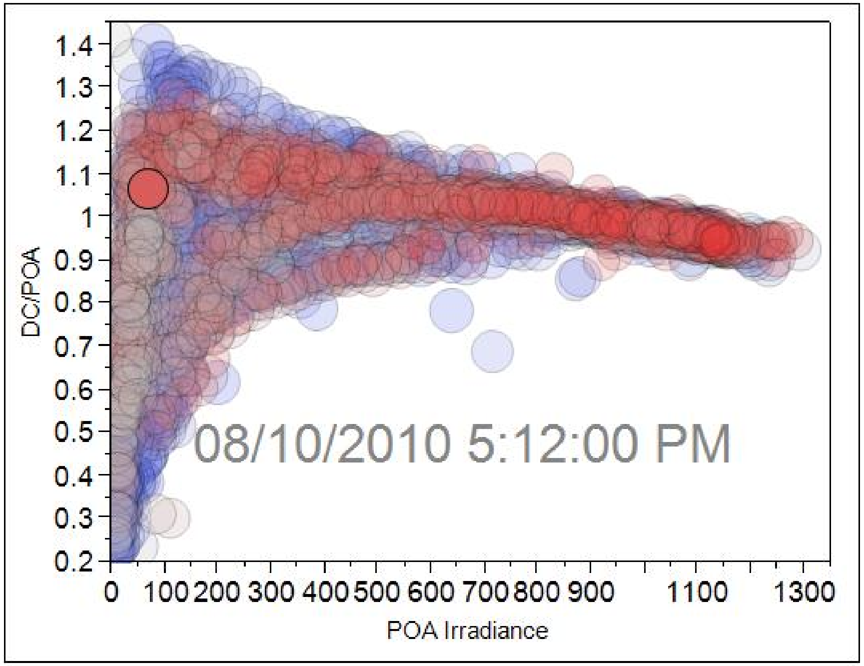
Steppe Climate shows significantly higher R_d before 2000

Animated Bubble Plot

Scatter plot: static version



Power output normalized by Irradiance



measdatetime
Speed
Circle Size

Graph is smeared out at Low Light:

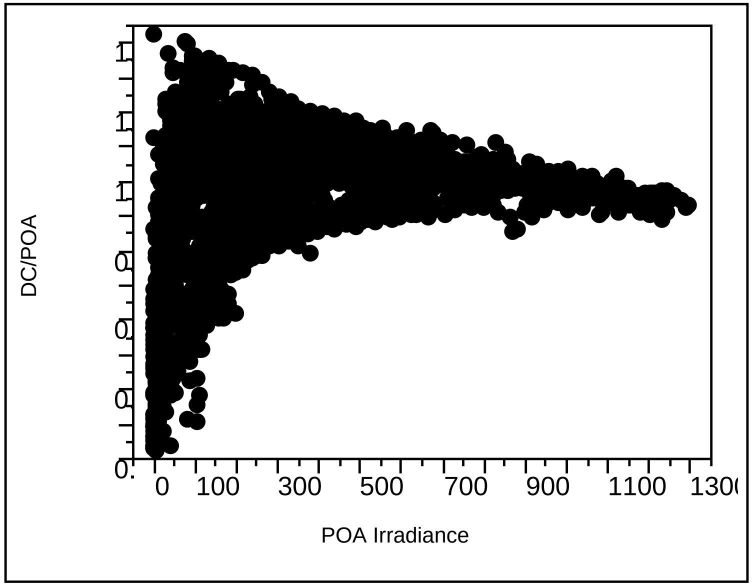
1. Clear, sun is close to horizon
2. Cloudy, midday

Bubble size: Angle of incidence of sunlight onto system
Bubble color: Temperature

Light level the same but not the spectrum
Photovoltaics depend on light level and spectrum → different performance

Movie Slide

Scatter plot: static version



Power output normalized by Irradiance

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Bubble size: Angle of incidence of sunlight onto system
Bubble color: Temperature

Light level the same but not the spectrum
Photovoltaics depend on light level and spectrum → different performance

Animated bubble plot can reveal details difficult to find in static plots

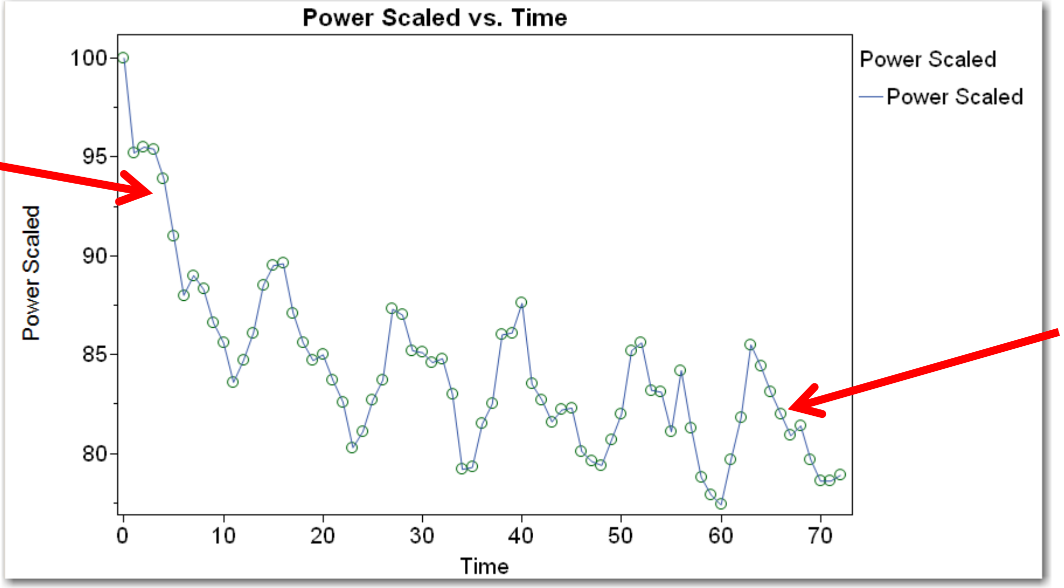
Non-Linear Modeling

Thin-film technologies:

1. Initial light-induced degradation linked to hydrogen content in film
2. Long-term degradation

light-induced degradation

(Staebler-Wronski Effect)



Long-term degradation

1. Wait until stabilization → model linearly
2. Model as non-linear

Data appear to have a general nonlinear degradation over time

Seasonality is also obviously present

Seasonal component has an apparent ‘knee’

PV Power Data Model

Degradation component is exponential decay with asymptote – and a power parameter

Seasonal component is a two term Fourier approximation

$$
\begin{aligned}
P(t) &= D(t) + S(t) \\
D(t) &= \beta_0 + \beta_1 e^{-\beta_2 t^{\lambda}} \\
S(t) &= a_1 \sin\left(\frac{\pi}{6}(t-\phi)\right) + a_2 \sin\left(\frac{\pi}{3}(t-\phi))\right)
\end{aligned}
$$

Model Assessment

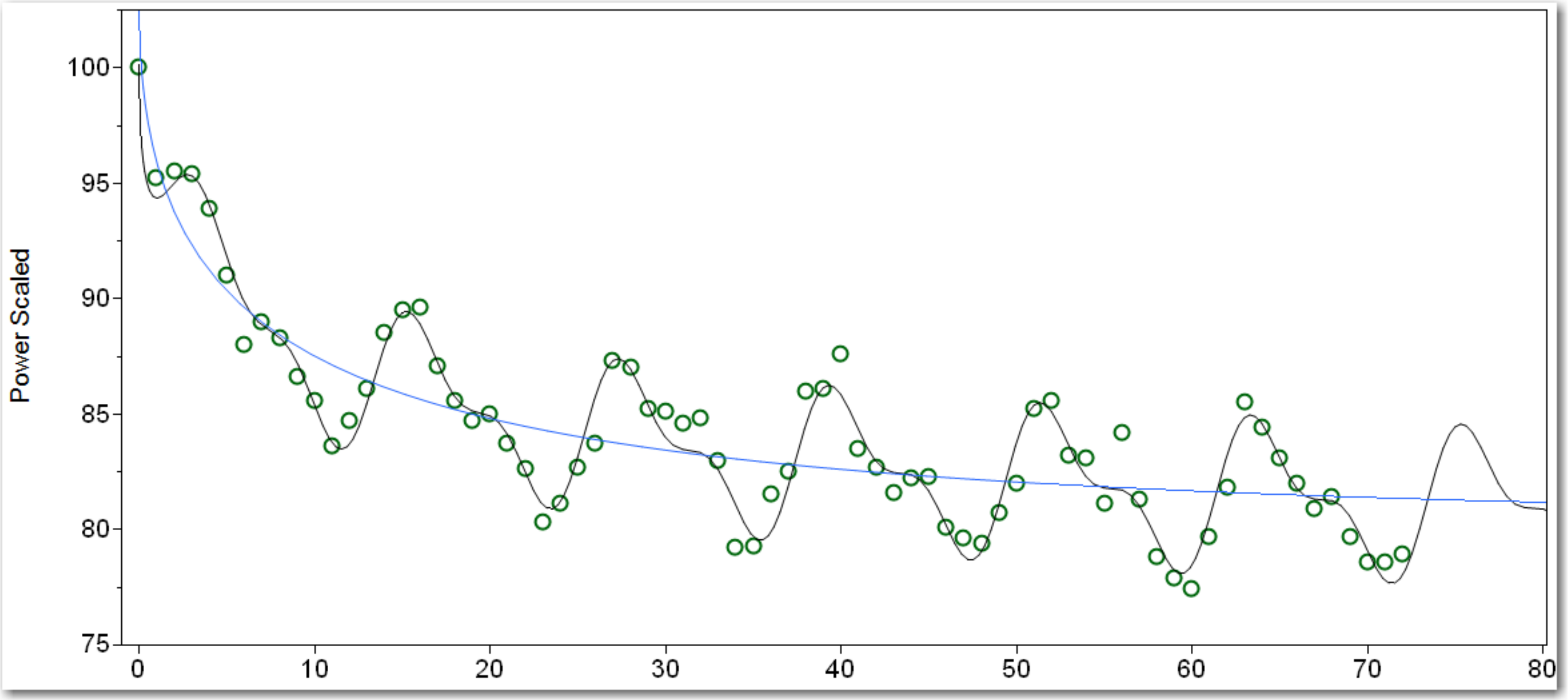
The lambda estimate is .42, and the data are consistent with lambda=.5, *but not* lambda=1!

A single sine term also degrades the fit.

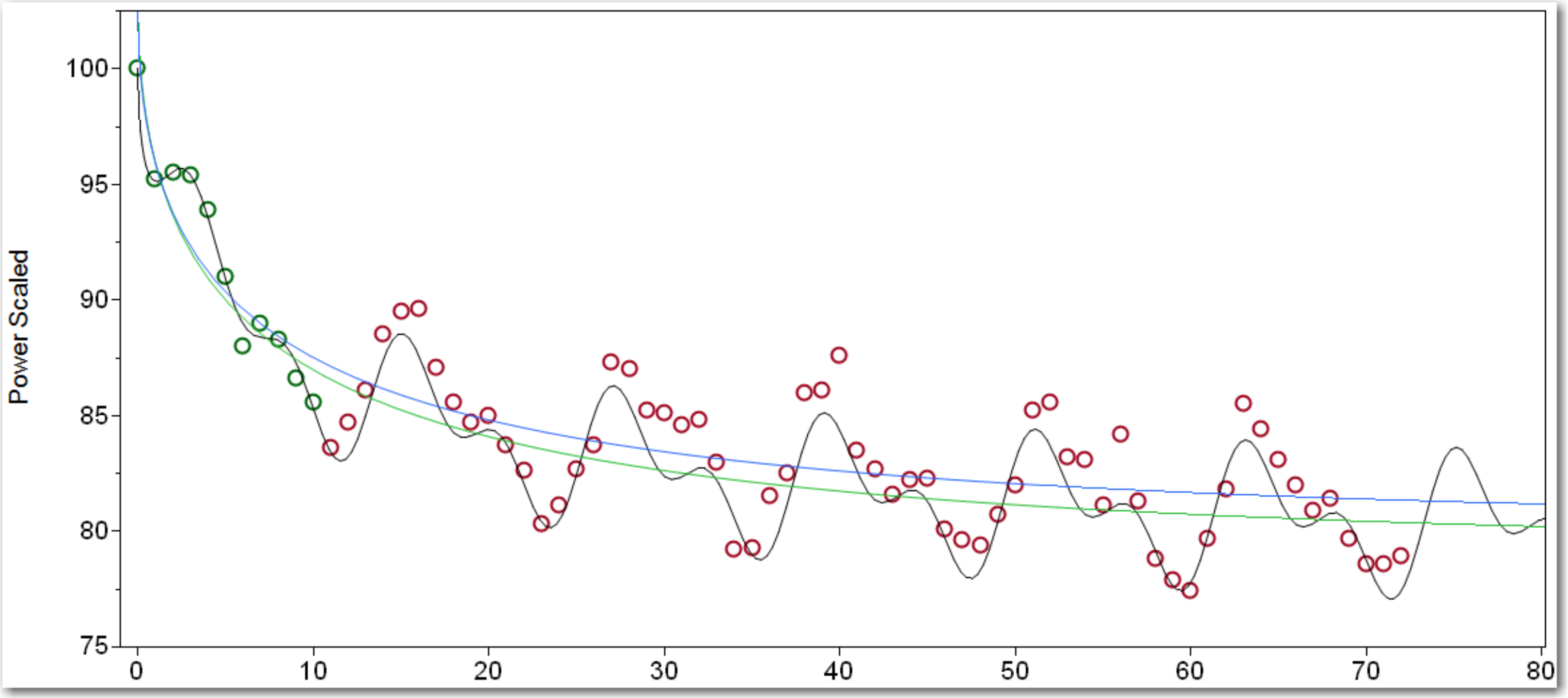
Hypothesized	Alternative	Denominator	SS	NDF	DDF	F Ratio	Prob > F
Lambda=1	Lambda Optimal	Lambda Optimal	68.073823	1	66	87.790	<.0001*
Lambda=.5	Lambda Optimal	Lambda Optimal	2.2268144	1	66	2.872	0.0949
Single Seasonal Term	Lambda Optimal	Lambda Optimal	67.500688	1	66	87.051	<.0001*

$$
\begin{aligned}
P(t) &= D(t) + S(t) \\
D(t) &= 80.2 + 22.2e^{-.35\sqrt{t}} \\
S(t) &= 2.7\sin\left(\frac{\pi}{6}(t-1.3)\right) + 1.3\sin\left(\frac{\pi}{3}(t-1.3)\right)
\end{aligned}
$$

Model Fit to 72 Months of Data



Model Fit to 12 Months of Data



Conclusions

- Two component degradation + seasonal model fits data well
- Fitting only the first 12 months of data leads to good predictions on the remaining 60 months
- Promising start, but this is only one dataset, and the sqrt power would need to be justified

Conclusions

- Showed importance of degradation (power decline over time) and impact on warranty risk
- Time series modeling can help reduce time & uncertainty
- Non-linear Modeling Two component degradation + seasonal model fits data well. Promising start, but this is only one dataset, and the sqrt power would need to be justified
- Impact of climate on PV performance
- Bubble plot as diagnostics tool

Acknowledgments

Thank you for your attention!

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