Real-world and Accelerated Degradation of PV Module Backsheets

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Acknowledgements

Work from this talk:
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Devin Gordon, PhD (3M)
Addison Klinke, MS (data science consultant)

Lifetime Prediction of Materials with Data Science: PV Module Focus

Accelerated Exposures are "standard" for material durability

Companies don't want to wait 3+ years to see if their material lasts

- Multiple real-world stressors
- History of failures

Utilize Data Science to move beyond "acceleration factor"

- Assumes reciprocity
- Misses combination of stressors
- Often assumes materials behave similarly

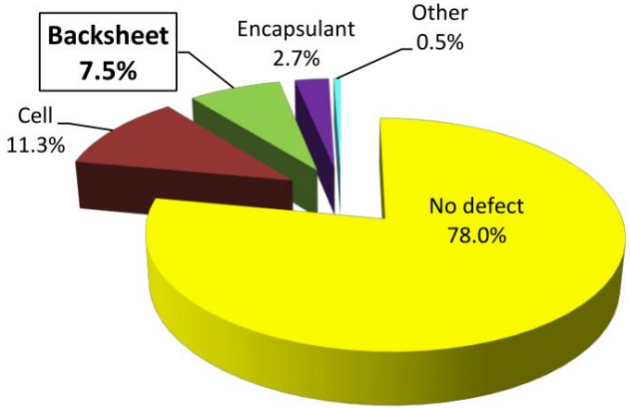
Need to build predictive models that relate

- Data driven models (Stress|Response)
- network Models (Stress|Mechanism|Response)

Combine accelerated with real-world data

Common Degradation Response

- Delamination
- Cracking
- Discoloration
- Hot spot
- Bubbling



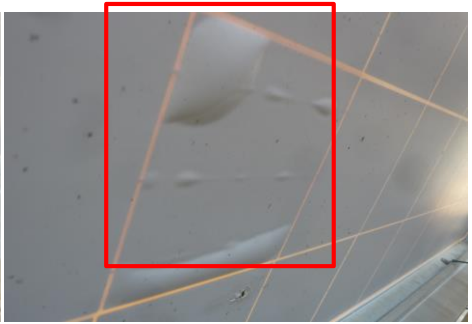
22% global modules show visual defects (> 1.9 million modules)

Backsheet defects = 7.5% [1]

Delamination

Cracking

Hot Spot



Bubbling

Hu, H., Gambogi, W., Felder, T., Macmaster, S., Choudhury, K. R., Wang, W., . "Study of PV Backsheet Early Degradation Signs in Field and Relevance with Lab Accelerated Aging Tests", Oral presentation, 11th SNEC, Shanghai,China, Apr 19th, (2017).

Open Data Science Tool Chain

Using Open-source tools

Reproducible Research

- Using Rmarkdown reports
- Python Jupyter Notebooks
- Add new data
- Recompile your report
- All new figures and report!
- Well Documented Code/Reports

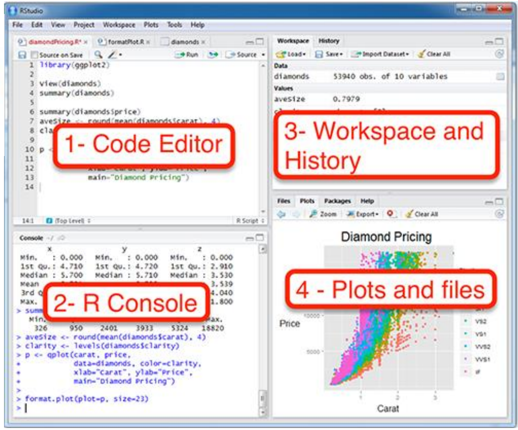
High Level Scripting Languages: R, Python

Rstudio Integrated Development Environment

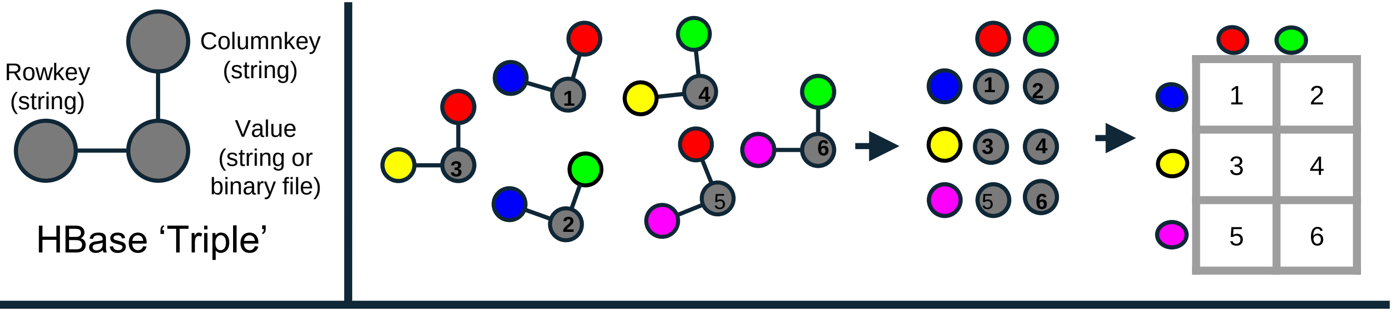
- Commercially Supported

Git Repositories for Code Version Control

- Share code scripts with colleagues
- Share project data and reports with others



Data Storage: NoSQL DB Abstraction of Hadoop/Hbase



Combines Lab data (Spectra, Images etc.) With Time-series Data (PV Power Plant Data)

High Performance PV Data Analytics: Petabyte Data Warehouse In A Petaflop HPC Environment

- In-place Analytics: Distributed R-analytics in Hadoop/HDFS
- In-memory Data Extraction: To Separate HPC Compute Nodes

IEEE JPV

A non-relational data warehouse for the analysis of field and laboratory data from multiple heterogeneous photovoltaic test sites

Yang Hu, *Member, IEEE*, Venkat Yashwanth Gunapati, Pei Zhao, Devin Gordon, Nicholas R. Wheeler, Mohammad A. Hossain, *Member, IEEE*, Timothy J. Peshek, *Member, IEEE*, Laura S. Bruckman, Guo-Qiang Zhang, *Member, IEEE*, and Roger H. French, *Member, IEEE*

Hu, Y., V. Y. Gunapati, P. Zhao, D. Gordon, N. R. Wheeler, M. A. Hossain, T. J. Peshek, L. S. Bruckman, G. Q. Zhang, R. H. French. "A Nonrelational Data Warehouse for the Analysis of Field and Laboratory Data From Multiple Heterogeneous Photovoltaic Test Sites." IEEE Journal of Photovoltaics 7, no. 1 (January 2017): 230–36. doi:10.1109/JPHOTOV.2016.2626919.

Field Surveys of Backsheets

CWRU: Yu Wang, Addison Klinke, Roger French, Laura Bruckman
UL: Liang Ji, Kent Whitfield, Ken Boyce,
NREL: Michael Kempe
Arkema: Camille Loyer, Adam Hauser, Gregory O`Brien
NIST: Andrew Fairbrother, Xiaohong Gu
NEU: Scott Julien , KT Wan

SOLAR ENERGY TECHNOLOGIES OFFICE
U.S. Department Of Energy

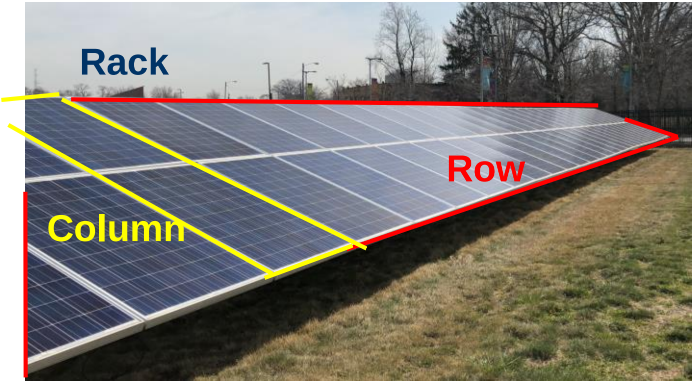
Field Survey Procedure

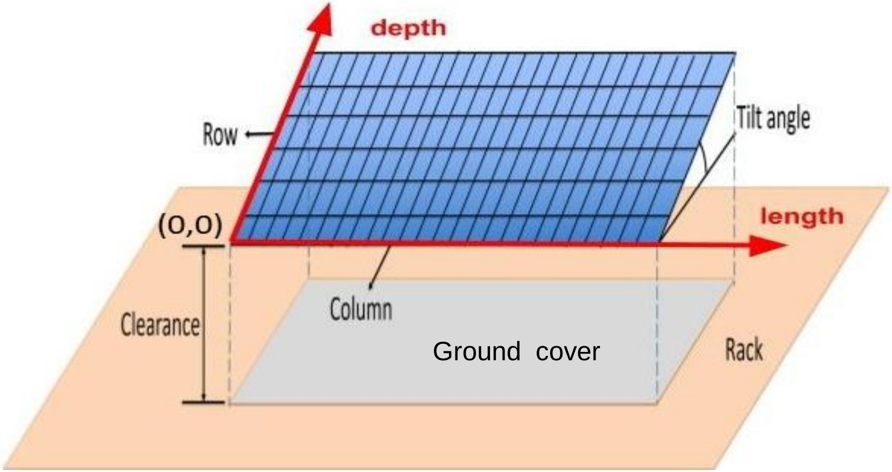
Field description

- Rack: a section of PV modules
- Column (length): horizontal direction
- Row (depth): vertical height and tilt angle

Field Survey:

- Measured 1300 + modules
- ~9 measurements each module
  - center, edges, junction box

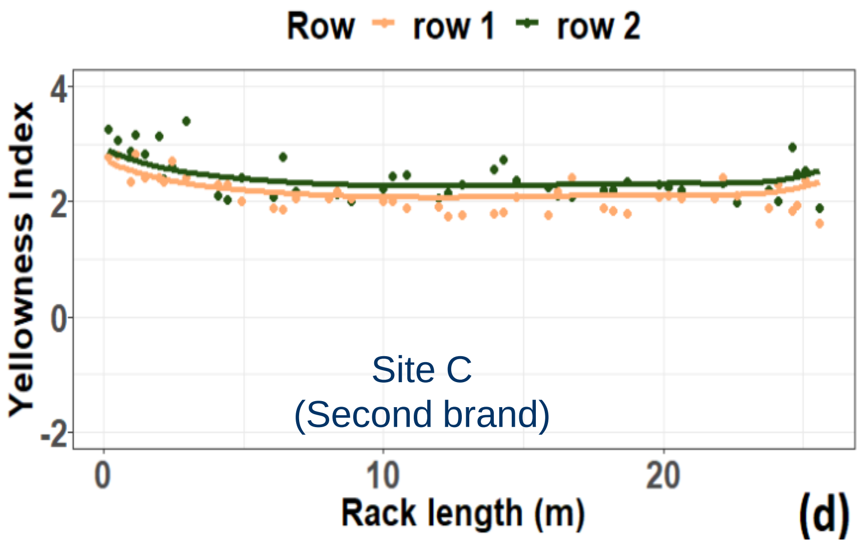


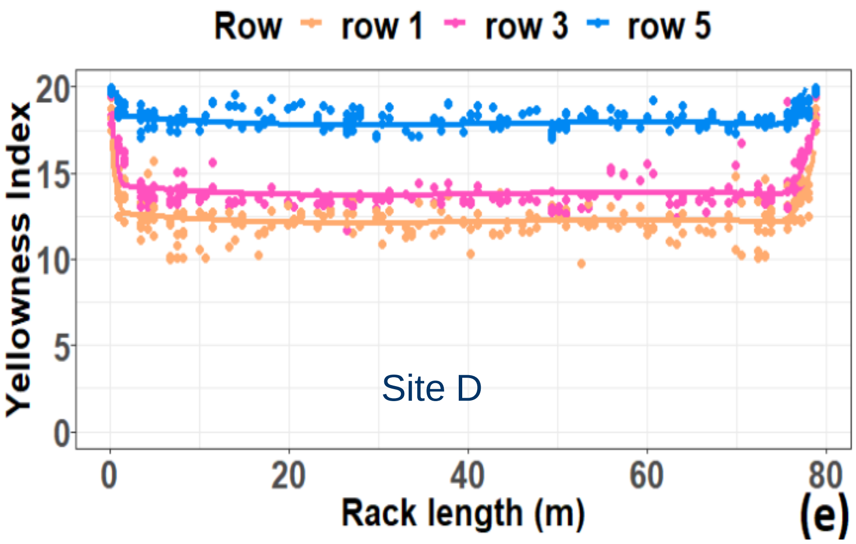


Field Information

Site	A	B	C	D
Climatic Zone	Dfb: humid continental climate		Cfa: humid subtropical climate	
Brand & Model	r0t0akg	untww6o	t4lqg3w, qathm7f	a5uyujm
Air-side Material	PVDF	PA	PET, PET	PEN
Ground Cover	Grass	Grass	Grass	Gray rock
Installation Year	Nov, 2013	Feb, 2012	Sep, 2014	Aug, 2012
Field Survey Year	2017	2017	2016-2018; 2017-2018	2016
Column Number	82	80	26	48
Row Number	4	5	2	5

Field Survey Results





Non-uniform degradation

- gives insight into unique degradation stressors
- same climate zone

Need to understand relationship

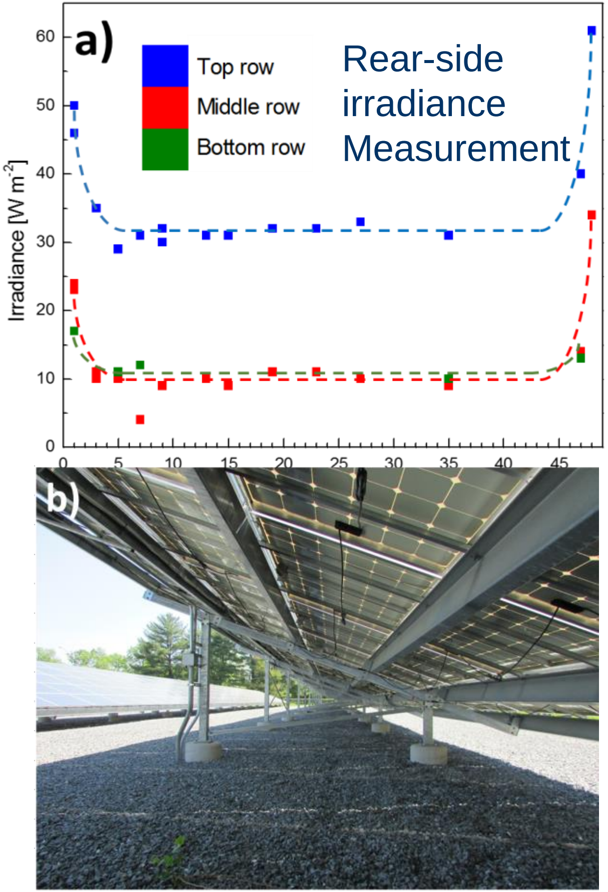
- between the increased stress and the time

$$Y = \beta_0 + \beta_1 L + \beta_2 L^2 + \beta_3 L^3 + \beta_4 (L - a_1)^3_+$$

$$+ \beta_5 (L - a_2)^3_+ + \beta_6 D + \beta_7 D^2 + \beta_8 t + \epsilon,$$

Wang, Y., Huang, W. H., Fairbrother, A., Fridman, L. S., Curran, A. J., Wheeler, N. R., ... & Bruckman, LS (2019). Generalized Spatio-Temporal Model of Backsheet Degradation From Field Surveys of Photovoltaic Modules. *IEEE Journal of Photovoltaics*, 9(5), 1374-1381.

Non-uniform Irradiance



Similar rear-side irradiance distribution with YI pattern

- Measurement: rear-side irradiance measured in site D
- Simulation: physical model for ordinary PV rack[1]

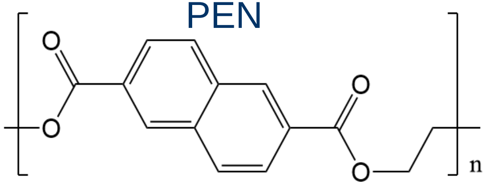
Different temperature distribution YI pattern

- Measurement: no significant difference of temperature in siteD
- Simulation: Higher temperature at center of rack[2]

Inhomogeneous rear-side irradiance

- May cause non-uniform backsheet degradation
- Within one rack in the PV site

PEN



[1] Yusufoglu, U. A., Lee, T. H., Pletzer, T. M., Halm, A., Koduvelikulathu, L. J., Comparotto, C., ... & Kurz, H. (2014). Simulation of energy production by bifacial modules with revision of ground reflection. Energy Procedia, 55, 389-395.
[2] Elwood, T., & Simmons-Potter, K. (2017, August). Comparison of modeled and experimental PV array temperature profiles for accurate interpretation of module performance and degradation. In Reliability of Photovoltaic Cells, Modules, Components, and Systems X (Vol. 10370, p. 1037006). International Society for Optics and Photonics.

Conclusion

Generalized spatio-temporal model

- Adjusted R^2 range: 0.31-0.89
    - Low adjusted R^2 due to noise in measurement and minimal degradation
- Identify the backsheets with a higher degradation rate

Non-uniform backsheet degradation

- For columns and rows in a rack
- **Inhomogeneity of rear-side irradiance**
    - May lead to non-uniform backsheet degradation
- **Ground cover and air-side material**
    - Affect the non-uniform backsheet degradation

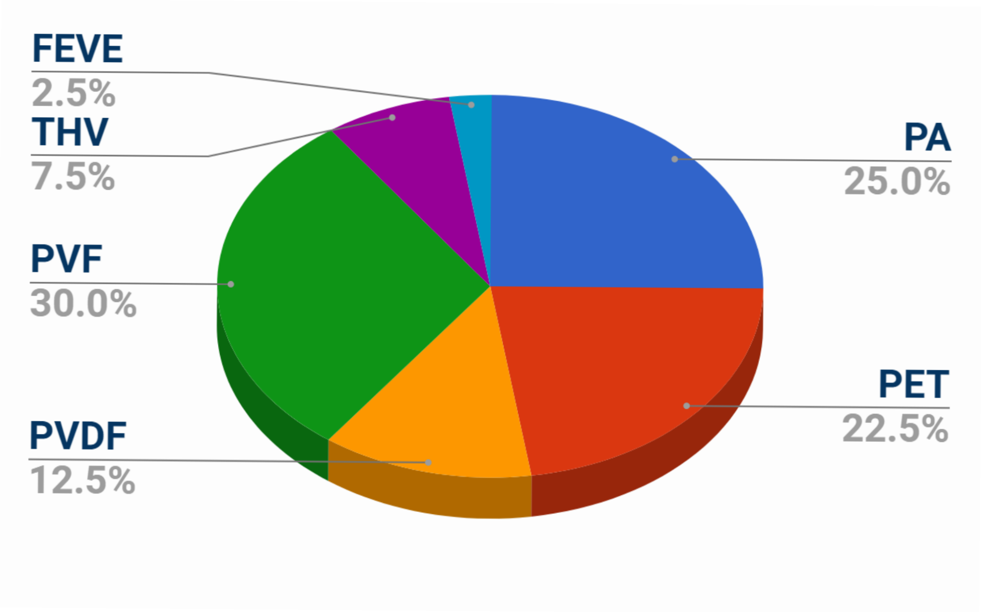
Current Research is expanding these field survey data

- Increase dataset and model

Retrieved Modules & Accelerated Exposures

Retrieved Backsheets

40 modules of 19 brands
6 outer layer materials



PVDF

- Crystalline phases (coupons phase)
- Acrylic additives (5 of 6)
- Wide range of YI values (< 6 years)

PVF

- Minimal changes in YI (< 28 years)

PET

- Discoloration (< 18 years)
- Wide variety of YI values, cracking delmaniation
- Coupons had microcracking

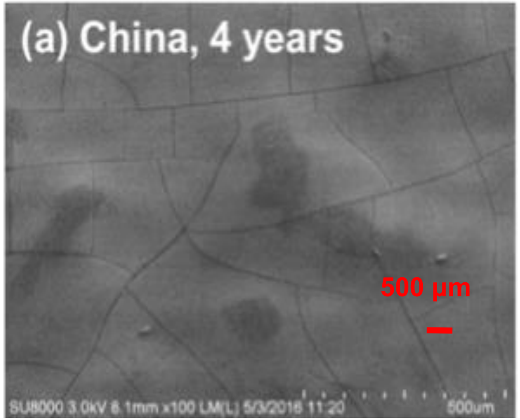
PA

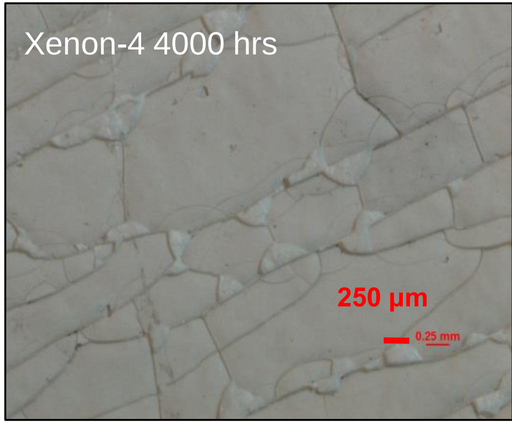
- Micro and Macro cracking, delamination
- Pollution impact on YI
- < 6 years
- Cracking in coupons, not films

Accelerated Exposures on Coupons

Exposure	Irradiation ($W/m^2/nm$ at 340 nm)	Chamber Temperature	Relative humidity	Comments
DH	0	85°C	85%	Damp Heat
Xenon-1	0.8	65°C	20%	102 minutes light, 18 min water spray in the light
Xenon-2	0.8	65°C	20%	100% light, no water spray
Xenon-3	0.8	80°C	20%	102 minutes light, 18 min water spray in the light
Xenon-4	0.8	80°C	20%	100% light, no water spray
Xenon-5	0.25	80°C	20%	102 minutes light, 18 min water spray in the light
Xenon-6	0.8	65°C	50%	102 minutes light, 18 min water spray in the light
Xenon-7	0.5	65°C	20%	102 minutes light, 18 min water spray in the light
Xenon-8	0.8	65°C	50%	100% light, no water spray

Cracks of Polyamide(PA/PA/PA): Retrieved and Films





Xenon-3: High Irra, High T, Low RH, Water spray

Xenon-4: High Irra, High T, Low RH, No water spray

PA/PA/PA cracking in accelerated exposures

- Xenon-3: Removal of air-side layer, degradation and crack of core layer
- Xenon-4: Micro cracks Degradation of sun-side and core layer between cells
- No Cracking in films
- Chromatography confirmed molecular weight loss

Stress or core layer degradation: key to cracks on PA/PA/PA

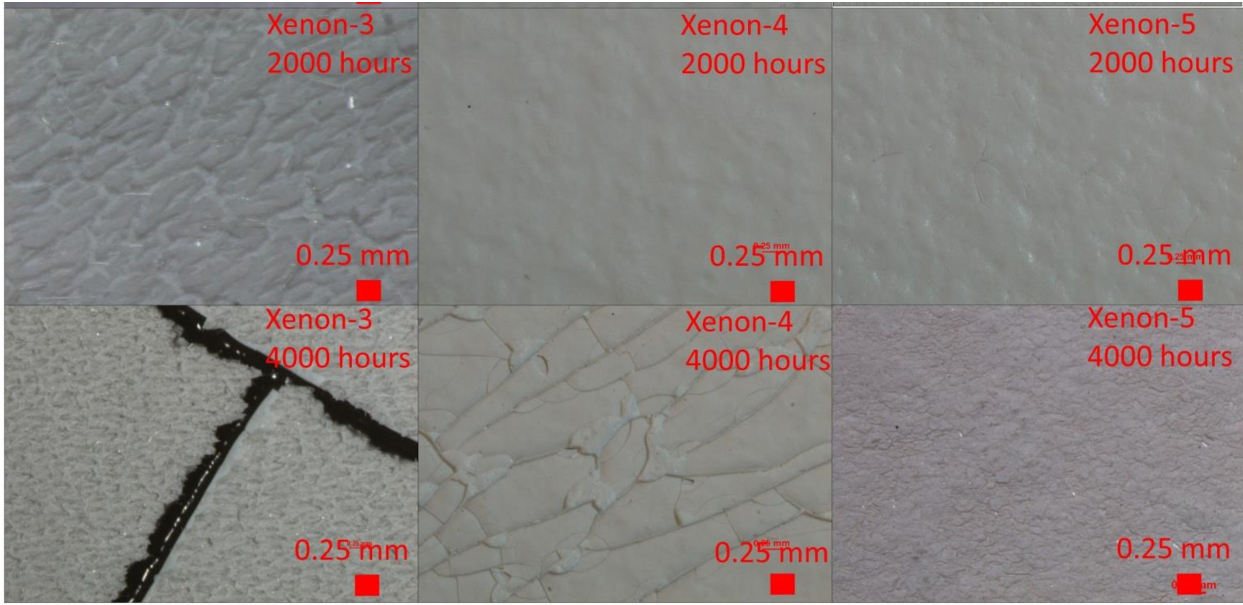
PA/PA/PA Surface Images under Accelerated Exposures

Xenon-3
- high irradiance & water spray
- 2000 hrs (Surface erosion)
- 4000 hrs (Crack formation)

Xenon-4
- high irradiance & no spray
- 4000 hrs (Micro cracks)

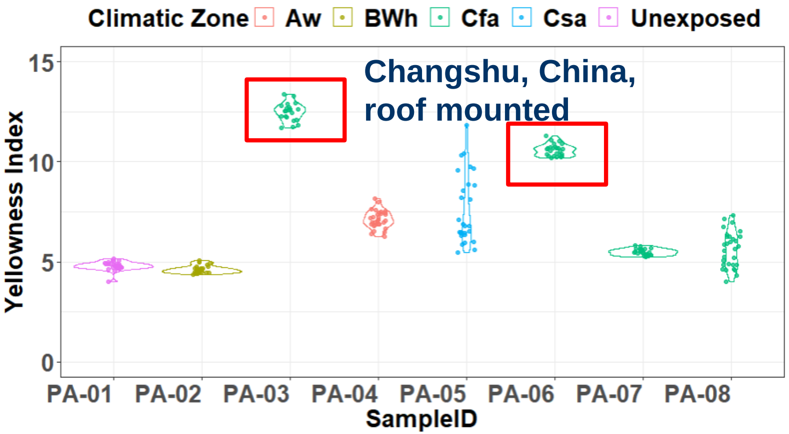
Xenon-5
- low irradiance & water spray
- No Cracking

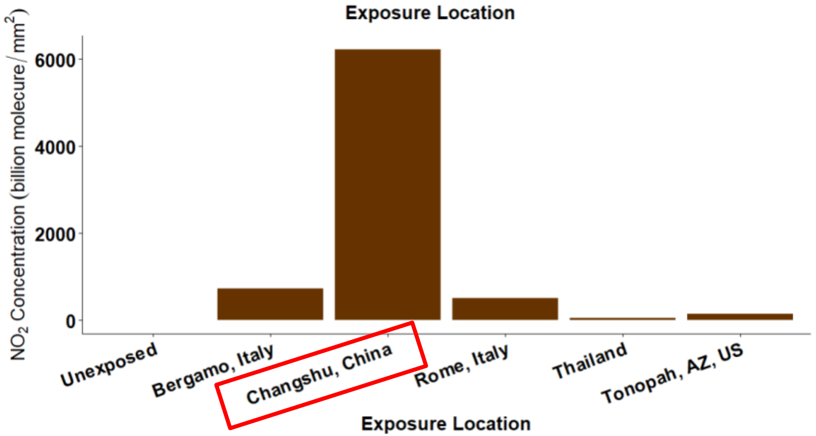
Size Exclusion Chromatography
- Show MW decrease



Wang, Yu et. al"Predictive Models for Backsheet Degradation in Indoor Accelerated Exposures.", in prep, 2019

Pollution Effect on Backsheet



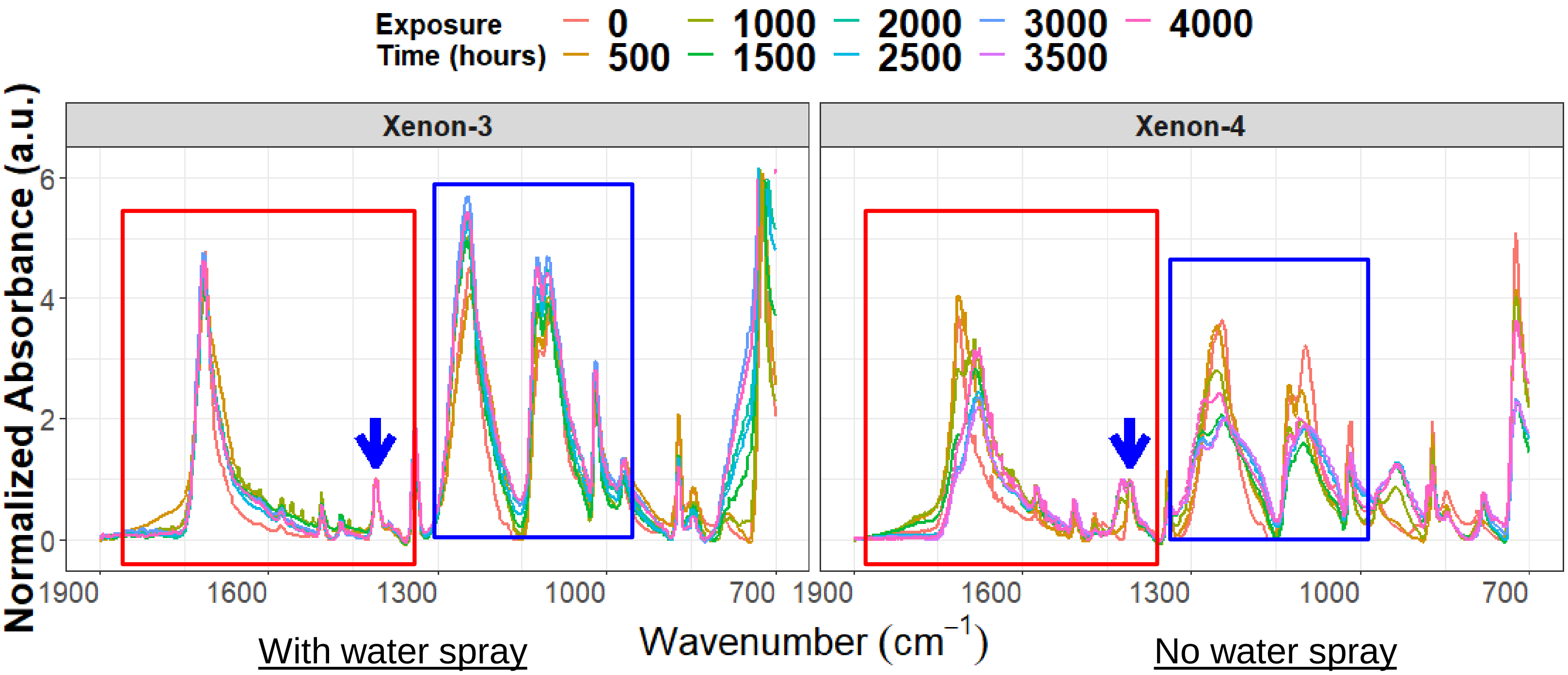


Air pollutant

- NO_2 causes yellowing of polyamide[1]
- More prominent effect of NO_2:
  - Roof mounted modules
  - Potentially higher irradiance & temperature
- Lower yellowness index value
  - With grass ground cover

[1] Pokholok, T. V., Gaponova, I. S., Davydov, E. Y., & Pariiskii, G. B. (2006). Mechanism of stable radical generation in aromatic polyamides on exposure to nitrogen dioxide. Polymer degradation and stability, 91(10), 2423-2428.

Effect of Water Spray on PET Backsheets

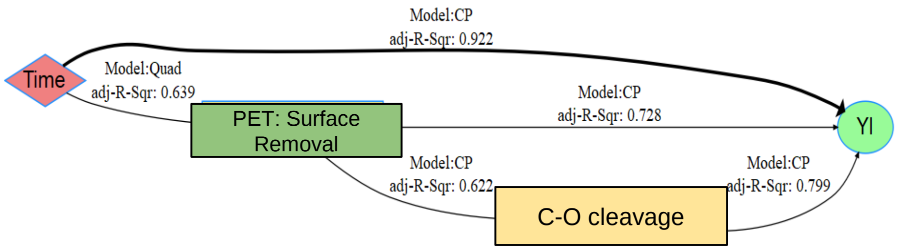


Water spray removes degraded materials for PET

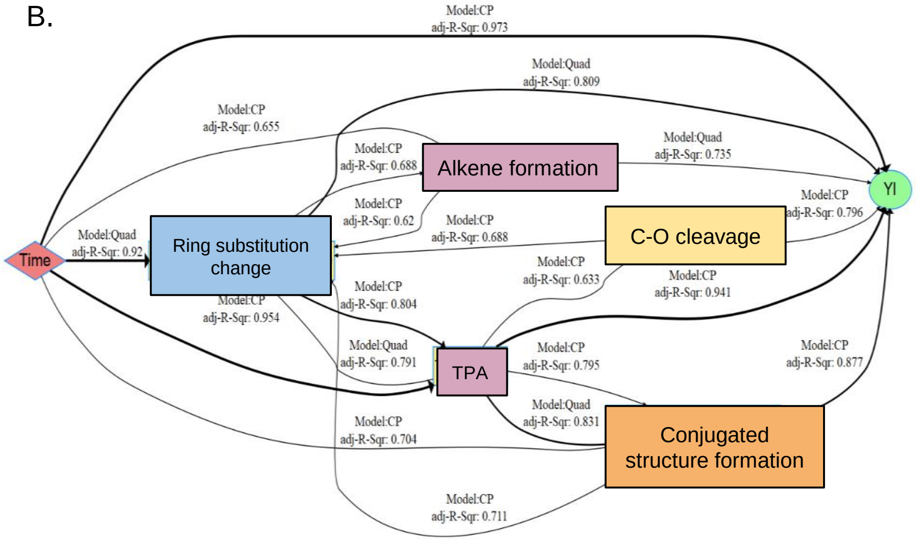
- No observable degradation product peaks observed in Xenon-3 FTIR
- Small decrease of PET peaks

netSEM modeling of PET: Network Structural Equation Modeling

A.



B.



netSEM is modified Structural Equation Modeling

- sociology
- adds nonlinear relationships between variables (semi-supervised)

PET exposed to 0.8 w/m²/nm at 340 nm, 80℃

- with water spray (A)
- without water spray (B)

ATR-FTIR indicated

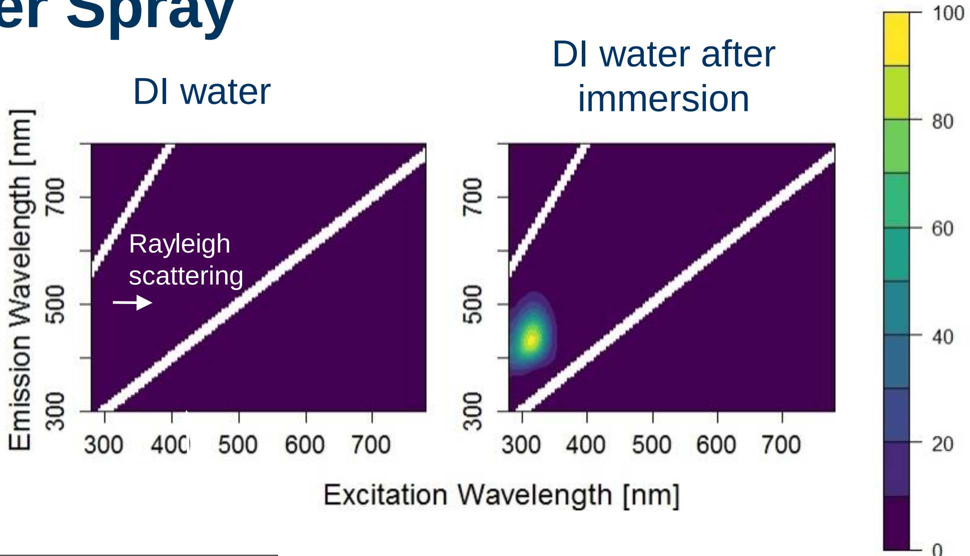
- Surface removal of degraded products with water spray
- Identify degradation products without water spray

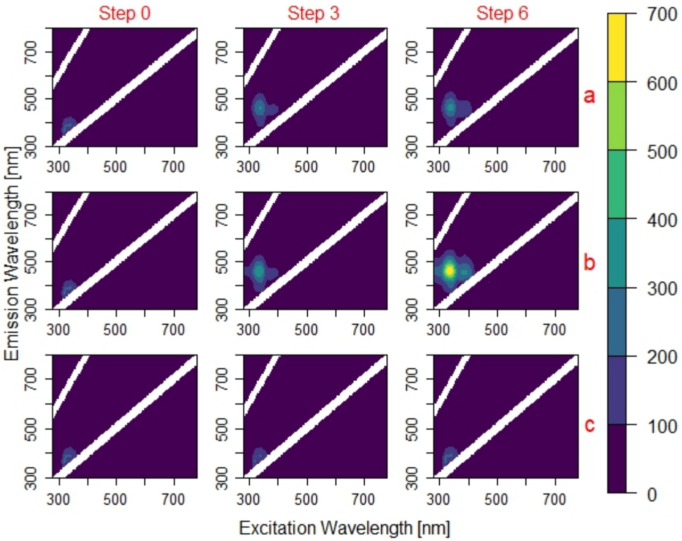
Bruckman, Laura, et al. *Backsheets: Correlation of Long-Term Field Reliability with Accelerated Laboratory Testing*, No. DOE-UL-0007143. Renewable Energy, Underwriter's Laboratories, Northbrook, IL 60062, 2019.

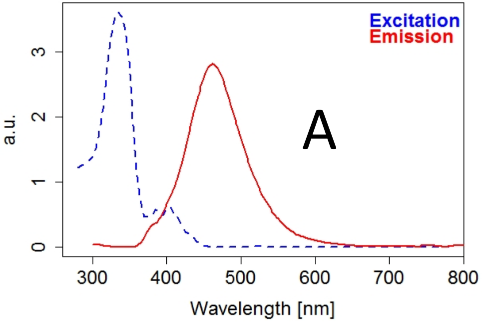
Degraded Surface Loss: Water Spray

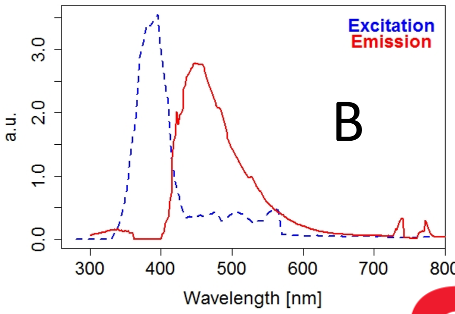
Degradation product observed in DI water

- Parallel Factor Analysis
- Excitation/Emission Fluorescence
- Relative concentrations of
    - Mono- (A) or di-hydroxy (B) species









Devin A. Gordon, Zhonghao Zhan, and Laura S. Bruckman. Characterizing the weathering induced degradation of Poly(ethylene-terephthalate) using PARAFAC modeling of fluorescence spectra. Polymer Degradation and Stability, January 2019.

Conclusion

Mismatch between field data and accelerated exposures in some cases

- Duplication of PA/PA/PA crack in Xenon-3 successfully
- Severe bond cleavage observed in PVF/PET/EVA in Xenon-3

Effect of Water: delivery method and water amount is key to accelerated tests

- Parallel factor analysis identified degradation products

Compare accelerated exposures to real-world exposures

Semi-Supervised Machine Learning Extraction of Crack Parameters

Quantitative Comparison of Accelerated and Real-World Behavior

Graduate Student
Addison Klinke

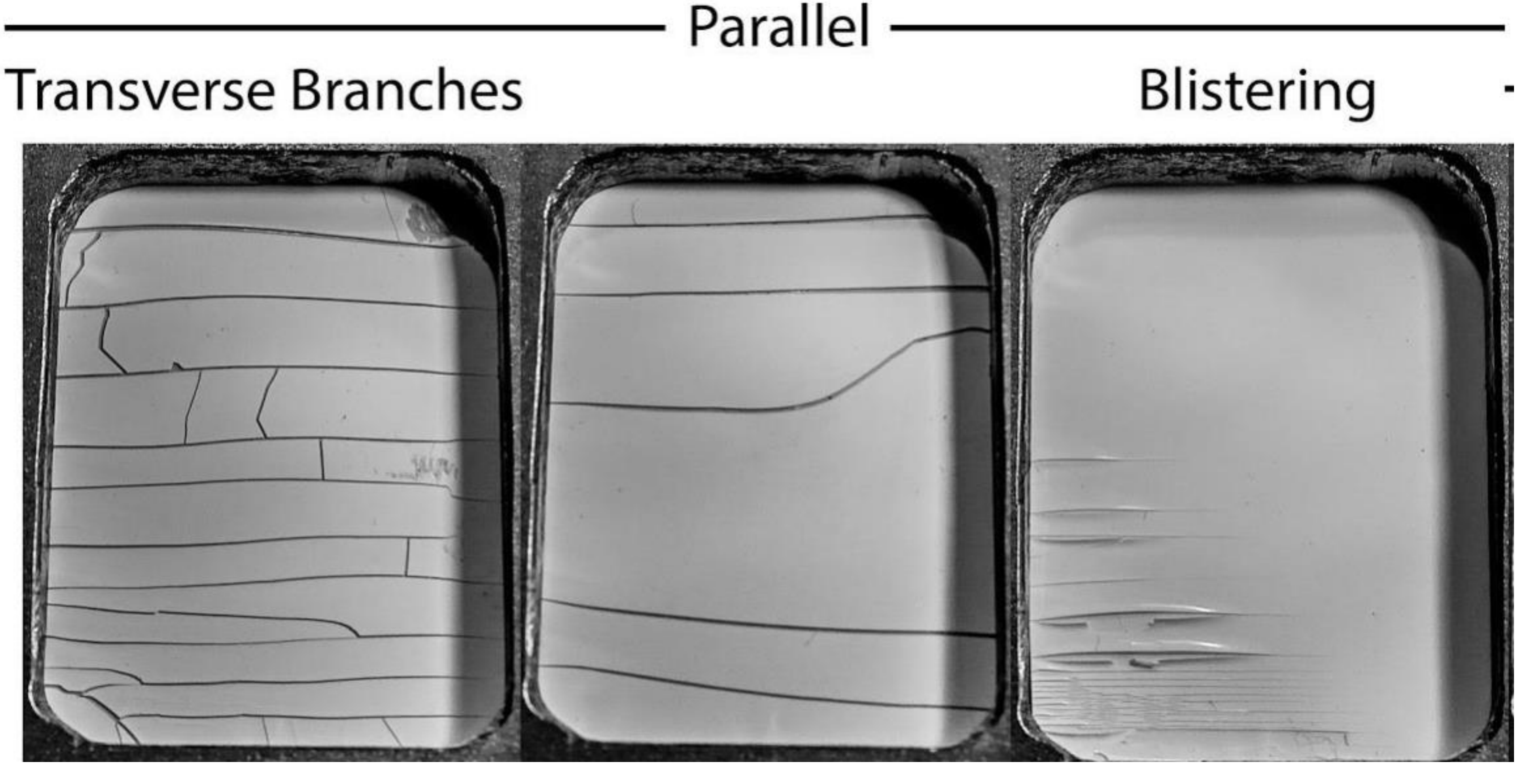
Yu Wang (Backsheets)

Types of Cracking Observed

23 different backsheet types

> 900 samples

Accelerated
Real-world
Exposures



Klinke, A. G., Gok, A., Ifeanyi, S. I., & Bruckman, L. S. (2018). A non-destructive method for crack quantification in photovoltaic backsheets under accelerated and real-world exposures. *Polymer degradation and stability*, *153*, 244-254.

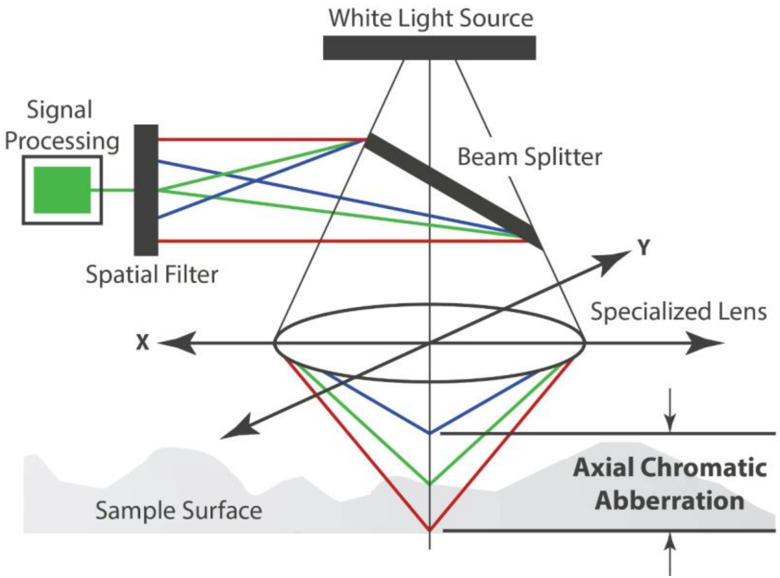
Data Collection Using Nanovea ST400

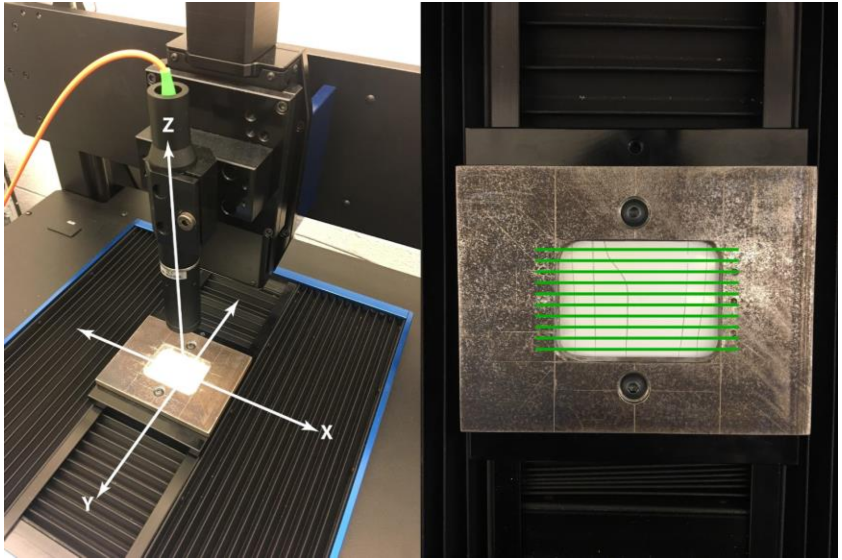
Optical Profilometry Theory

- Axial chromatic aberration: focuses wavelengths at different depths
- Reflected light passes through spatial filter
- Only the in-focus wavelength passes through with high efficiency
- Non-destructive and non-contact

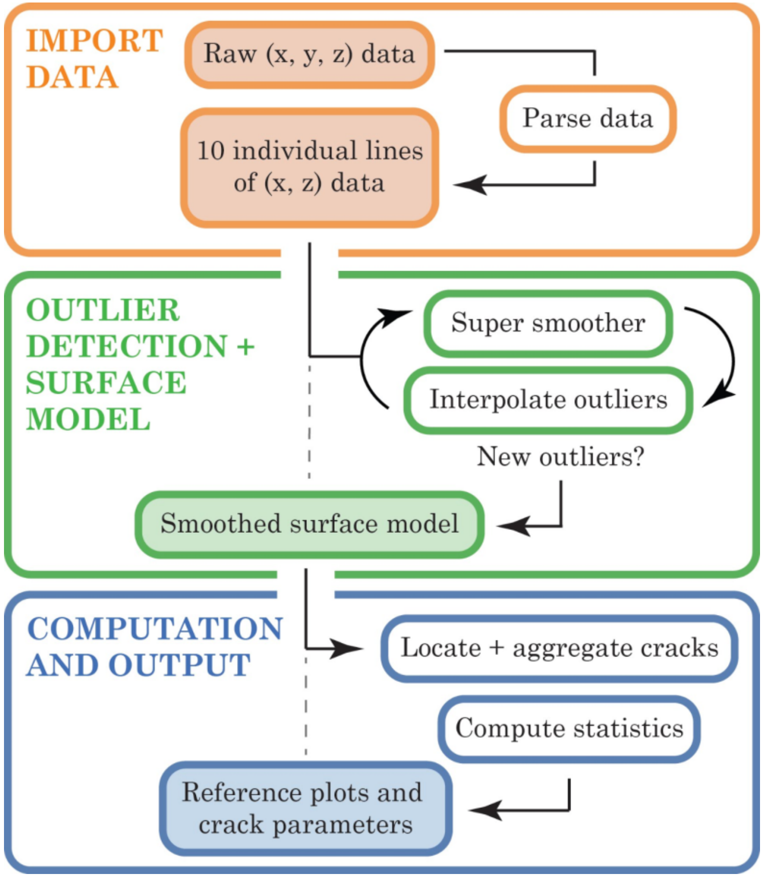
Measurement Methodology

- Measure height (z-axis) every 1.0 µm in x-direction
- Repeat for 10 equally spaced "lines" in the y-direction
- Time-efficient yet robust to local variations in cracking
- Ideal for parallel cracks with minimal deadhesion





Crack Quantification Algorithm and Extraction of Parameters: R



Localized Regression

- Non-parametric statistical technique that weights model at each point towards the closest data
- Friedman's Super Smoother optimizes the span parameter for each x-value (sample width)
- Iterative application allows simultaneous outlier detection to decrease computational time (average 2.7 iterations)

Computation

- Fleets of parallel Slurm jobs run in about 6 minutes on CWRU's High Performance Computing Cluster
- **Over 52,000 cracks measured (at a rate of 17.3 cracks/minute)**

Measured Crack Features / Parameters

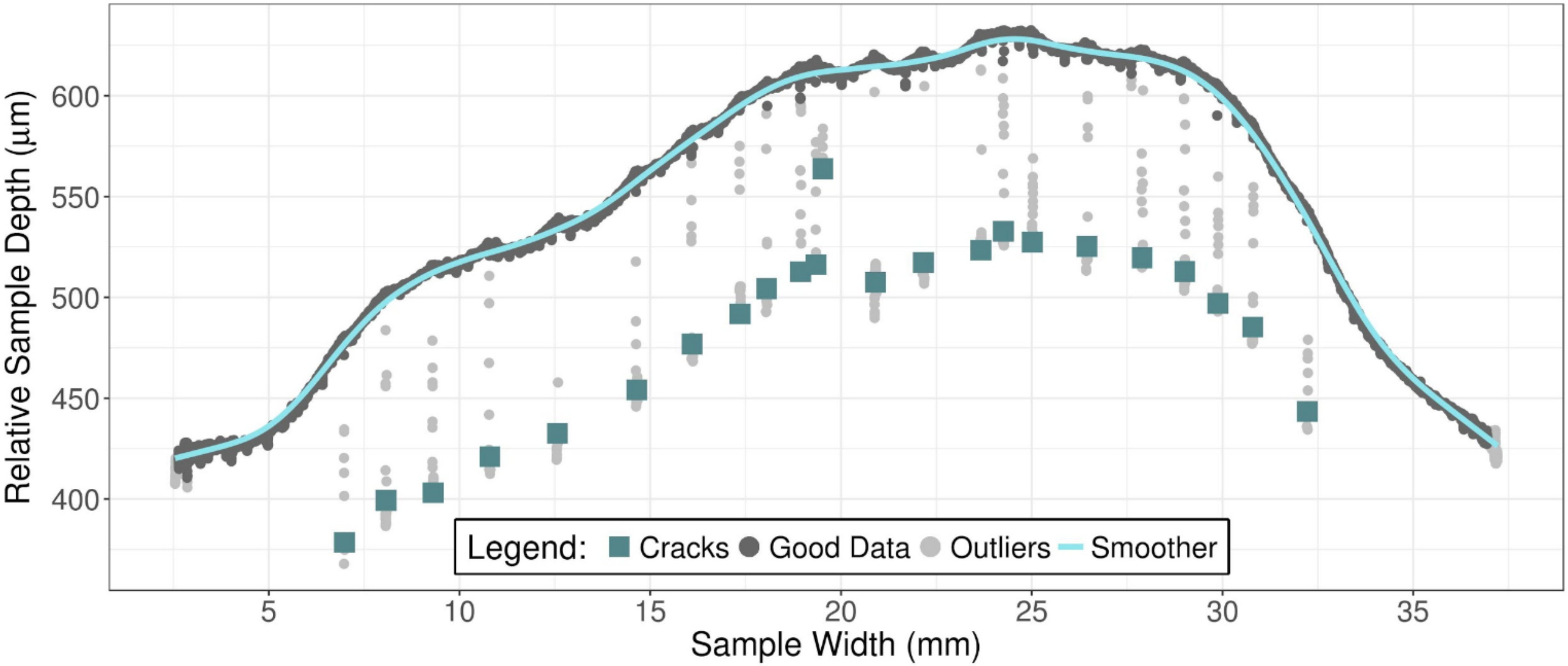
- Average depth, width, and area
- Min, max, and average spacing
- Number of cracks
- Normalized depth and number of cracks

$$D_n = \frac{d_{avg}}{d_L UVA_{<360}}$$

$$C_n = \frac{c_{avg}}{UVA_{<360}}$$

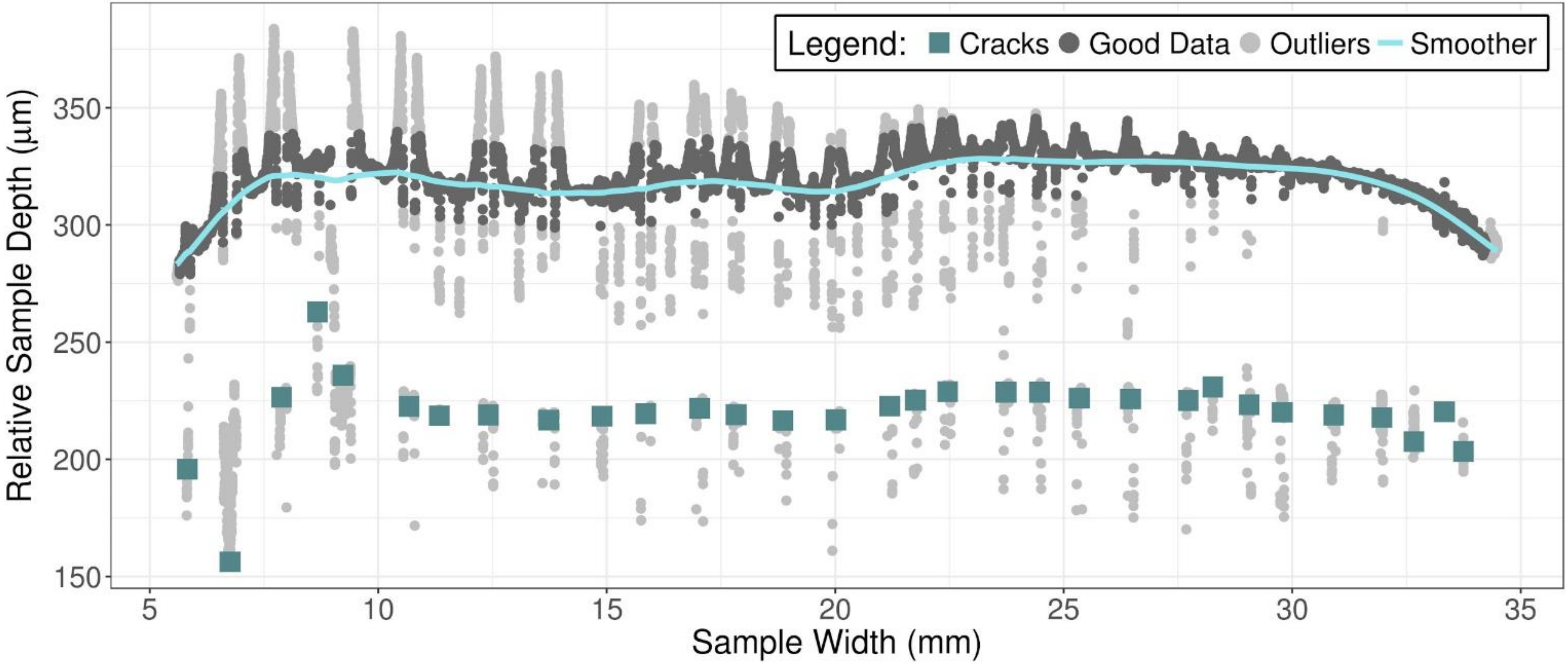
Automatically Generated Reference Plots - Parallel Cracks (FPE2)

- Parallel cracks and consistent surface (no deadhesion) are easily handled by the algorithm
- Most samples had these characteristics



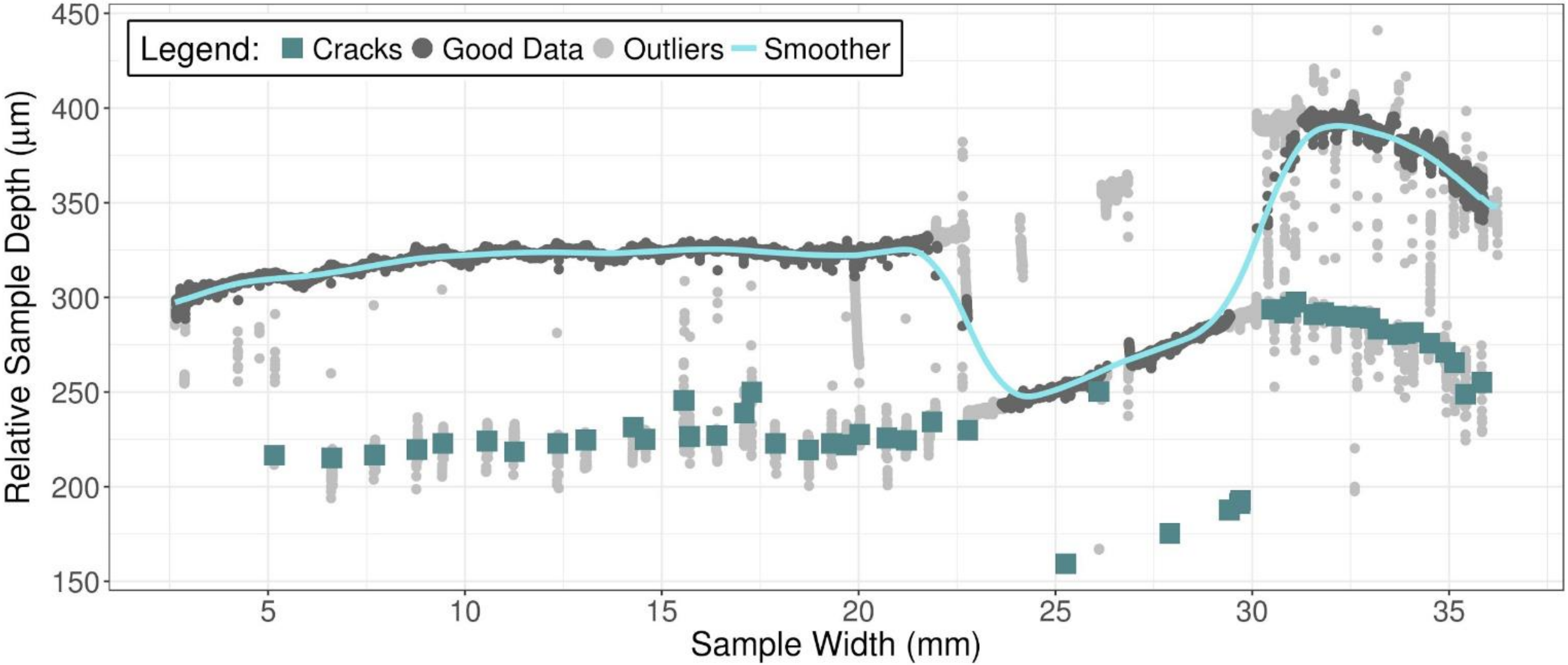
Automatically Generated Reference Plots - Blistering (FPE2)

- Data points associated with blistering are successfully detected as outliers
- Super Smoother follows the expected surface



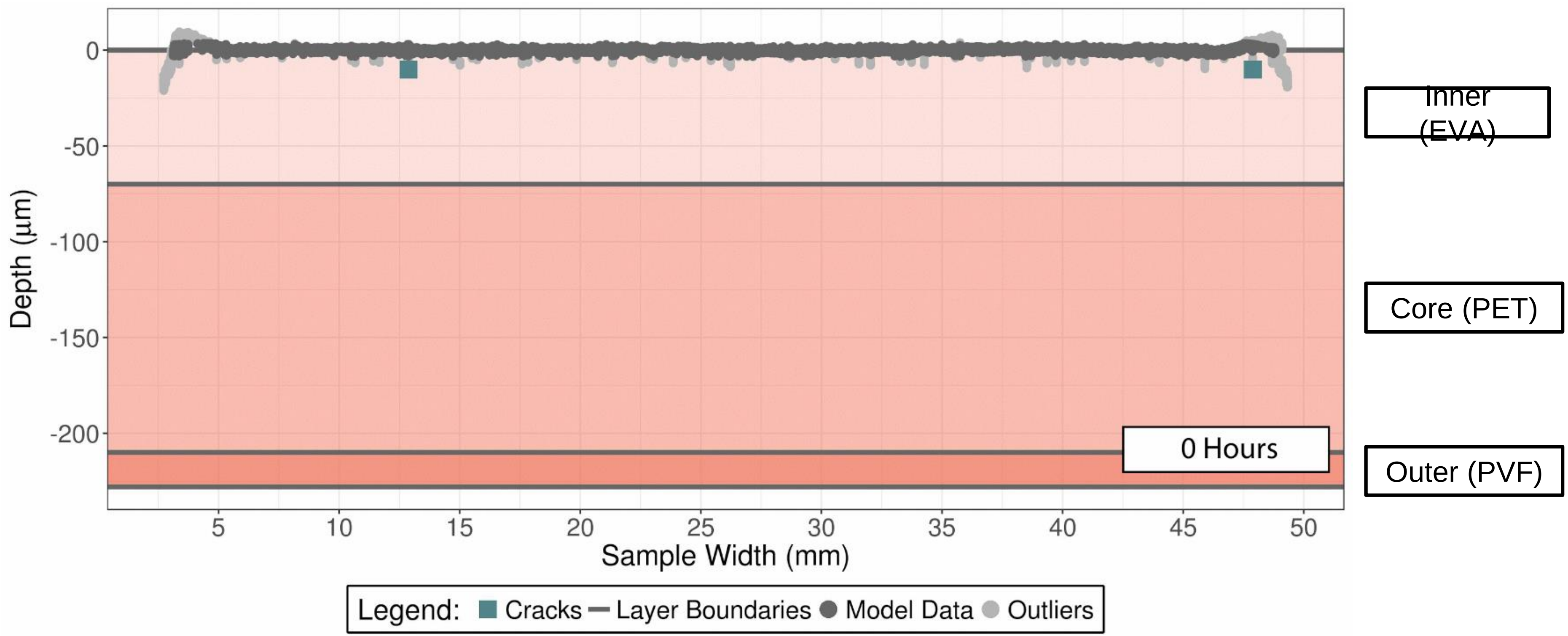
Automatically Generated Reference Plots - Delamination (FPE2)

- Delamination (right side of profile) results in large trough
- Incorrectly handled by outlier detection → now part of the “surface” is on the inner/core layer interface



Crack Progression Over Time: Residual Plots (FPE1 Cyclic QUV)

- Density, depth, and number of cracks increases with exposure
- Can visualize propagation of cracks through backsheet layers



Convolution Neural Network for Image Analysis

Image Analysis of Backsheet Cracking

- Convolution neural network
- Identification of cracking patterns
- Discoloration

Field Survey Application

- Image analysis of backsheets

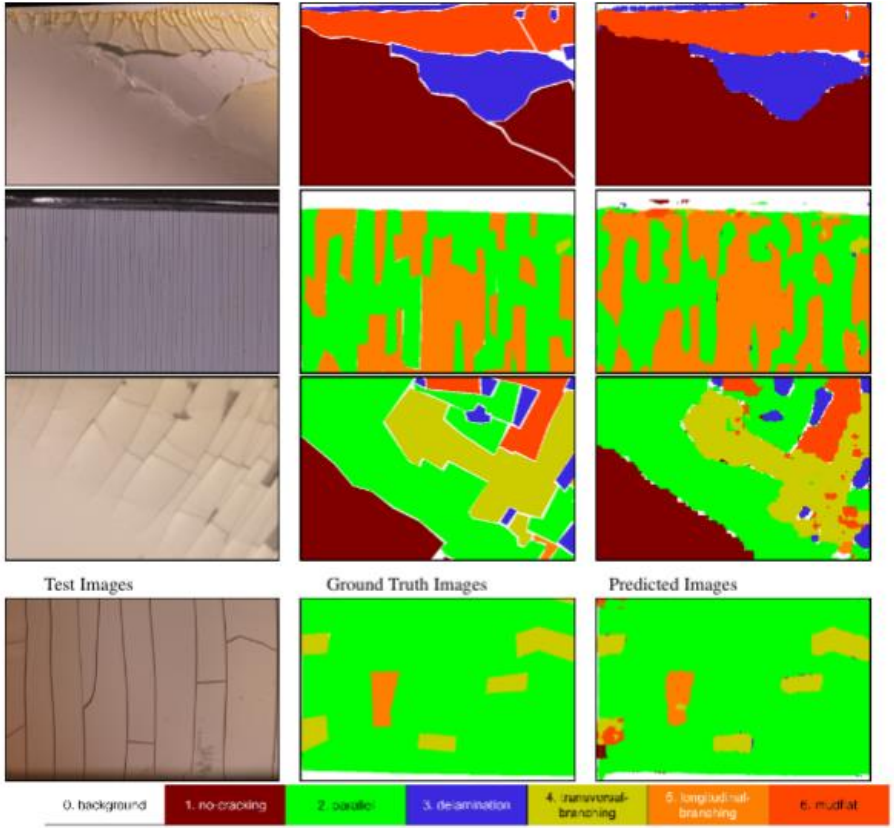


Figure 8. Six examples of crack inspection task performed on the test images using the trained Model O. The different color
in the (b) and (c) column images indicated different crack classes shown in the color bar.

Zhang, B., Grant, J., Bruckman, L. S., Wodo, O., & Rai, R. (2019). Degradation Mechanism Detection in photovoltaic Backsheets by fully convolutional neural network. *Scientific reports*, *9*(1), 1-13.

Thank You!