Interdisciplinary and Multi-Faceted Research Aimed at Accelerating the Adoption of Solar Energy Technologies

Prof. Kristopher O. Davis

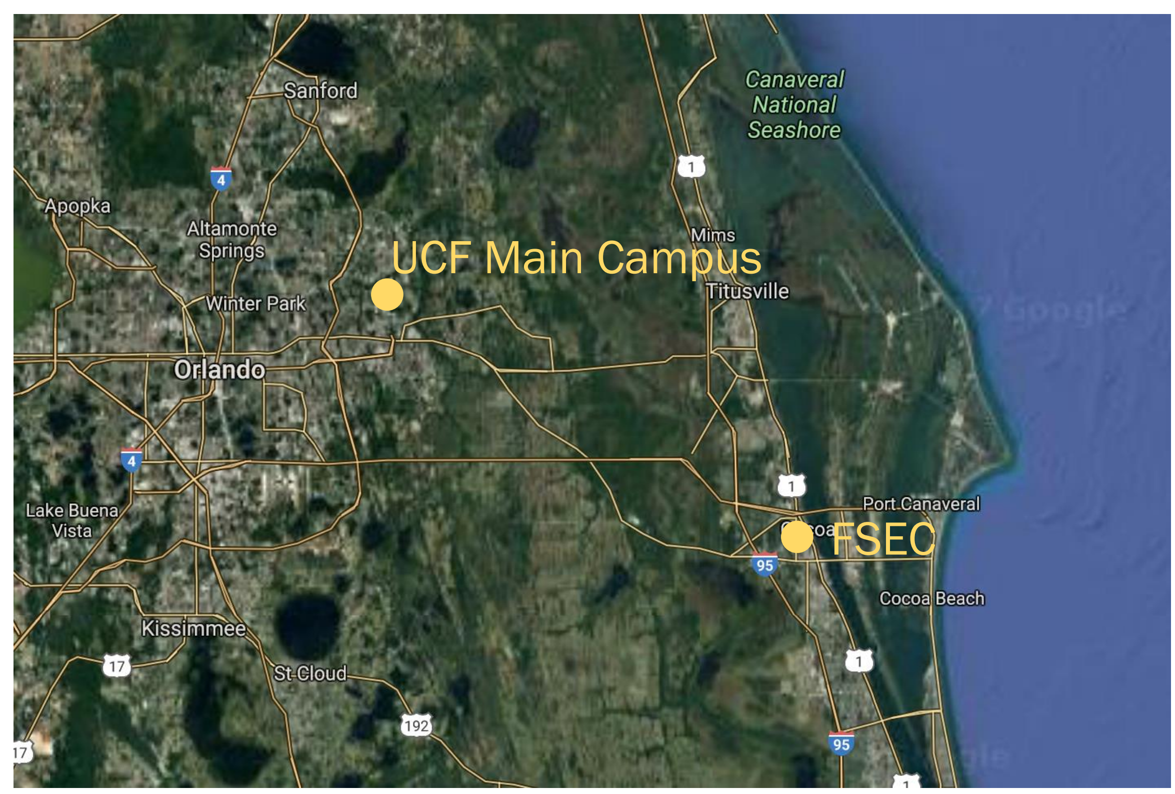
Contributors: Dylan Colvin; Mengjie Li; Max Liggett; Jarod Kaltenbaugh; William Oltjen; Xuanji Yu; Manjunath Matam; Hubert Seigneur; Andrew Gabor; Philip Knodle; Greg Horner; Laura Bruckman; Roger French

Organizations: University of Central Florida; Case Western Reserve University; BrightSpot Automation; Tau Science

College of Engineering and Computer Science

CREOL, The College of Optics and Photonics

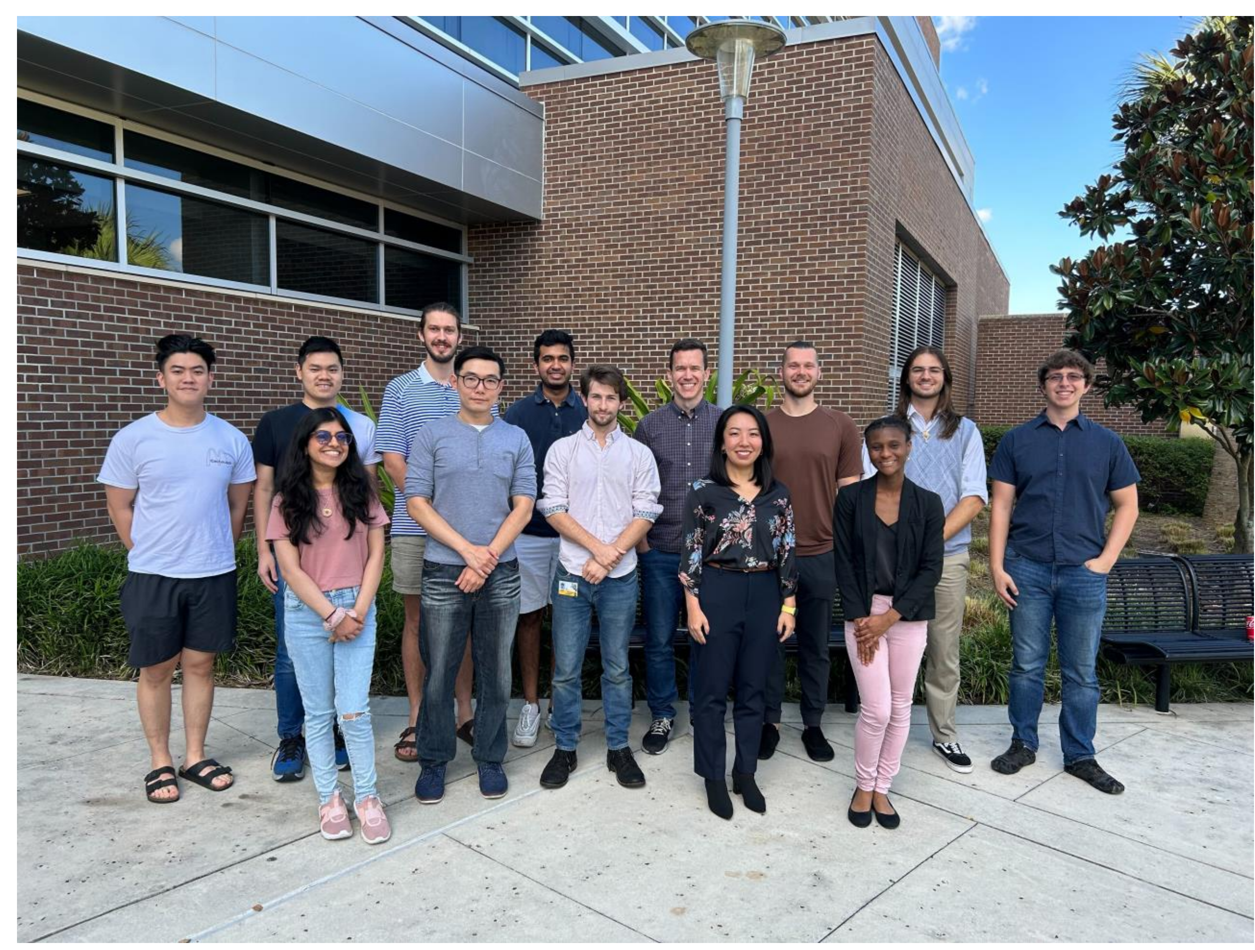
University of Central Florida



UCF | College of Engineering and Computer Science

UCF | CREOL, The College of Optics and Photonics

UCF Team Members and Key Collaborators

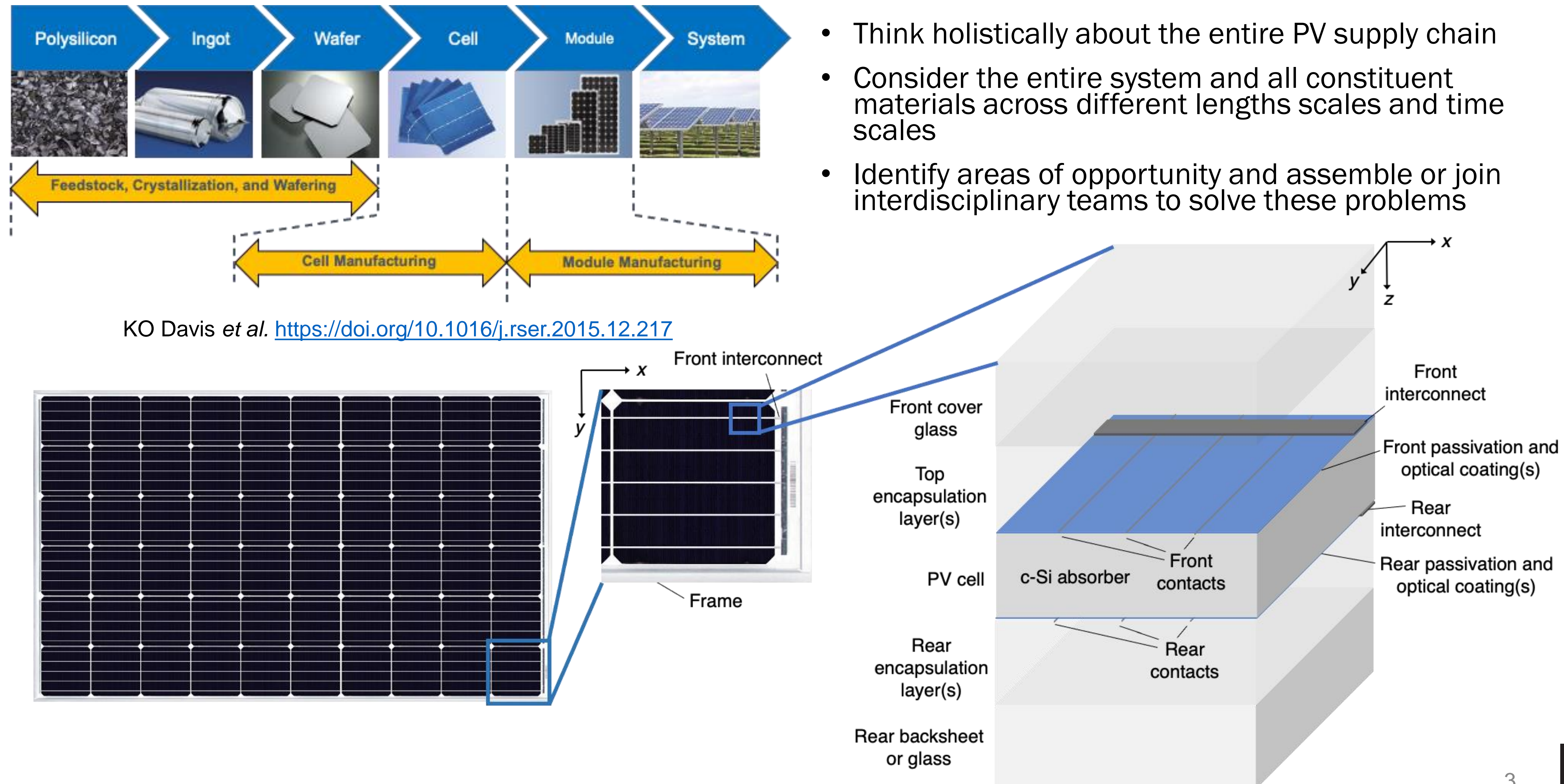


UCF Data-Enabled Photovoltaics Team

CWRU SDLE Team at UCF

Interdisciplinary Research Strategy for Photovoltaics (PV)

- Think holistically about the entire PV supply chain
- Consider the entire system and all constituent materials across different lengths scales and time scales
- Identify areas of opportunity and assemble or join interdisciplinary teams to solve these problems



KO Davis *et al.* https://doi.org/10.1016/j.rser.2015.12.217

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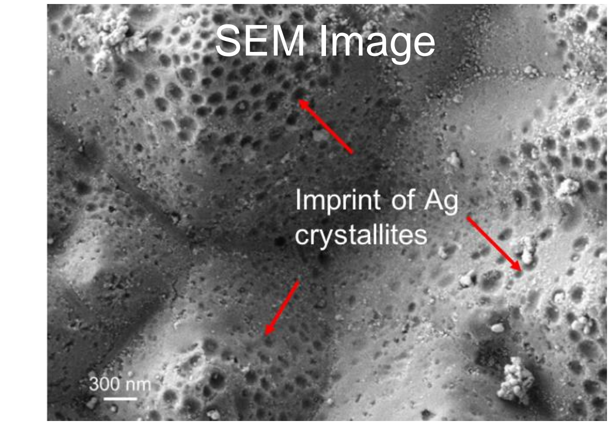
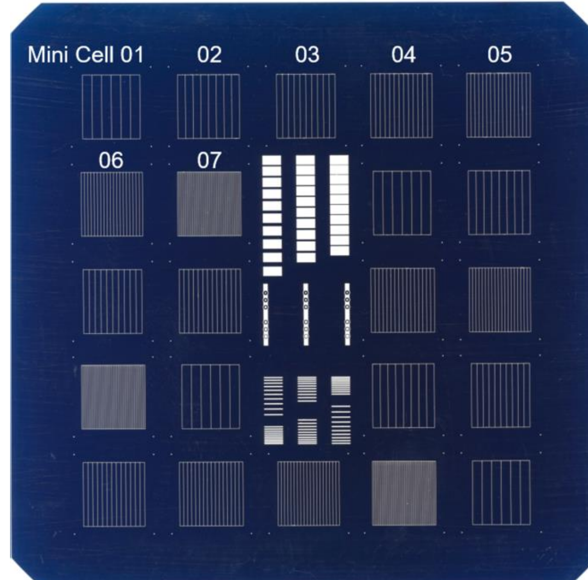
Problem: Charge Carrier Recombination at Metal Contacts

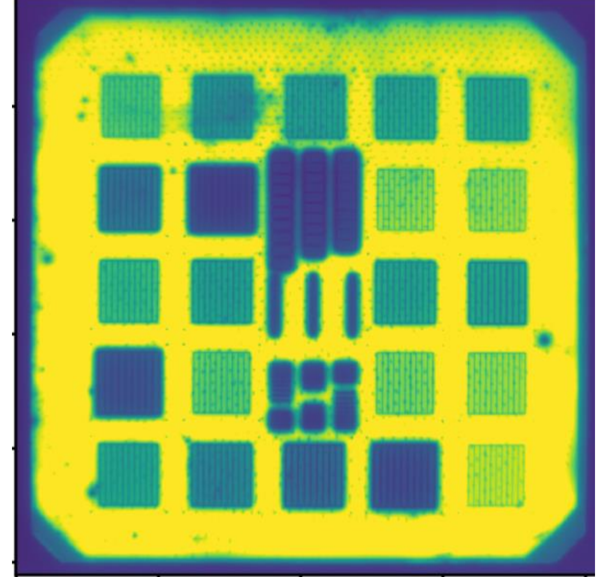
- A key loss mechanism in photovoltaics is charge carrier recombination at the metal/semiconductor interface of the electrical contacts
- This sets a ceiling on the voltages one can obtain and $P = IV$

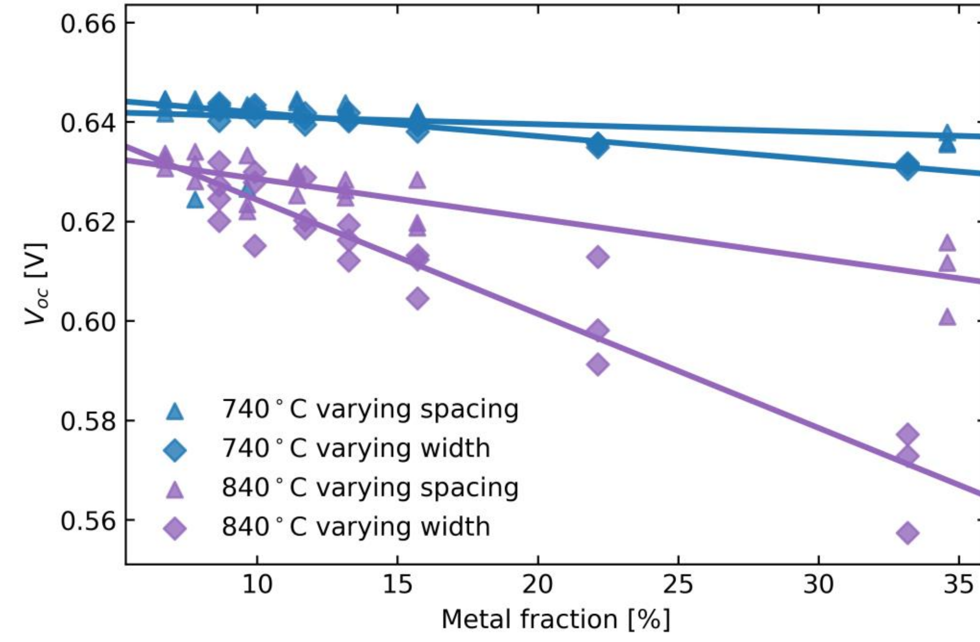


Optical Image



Photoluminescence (PL) Image



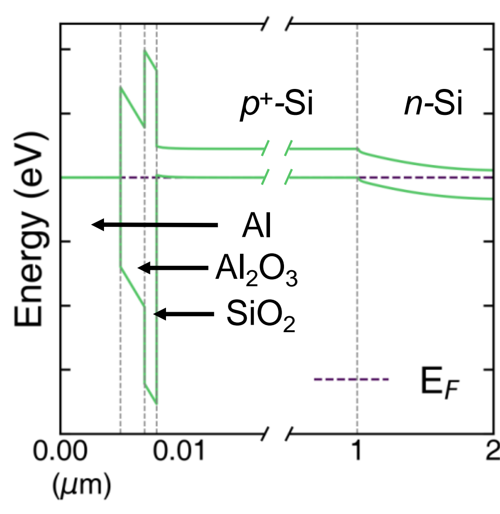


M Li *et al.* https://doi.org/10.1109/JPHOTOV.2020.3003792

Passivating, Carrier-Selective Contacts

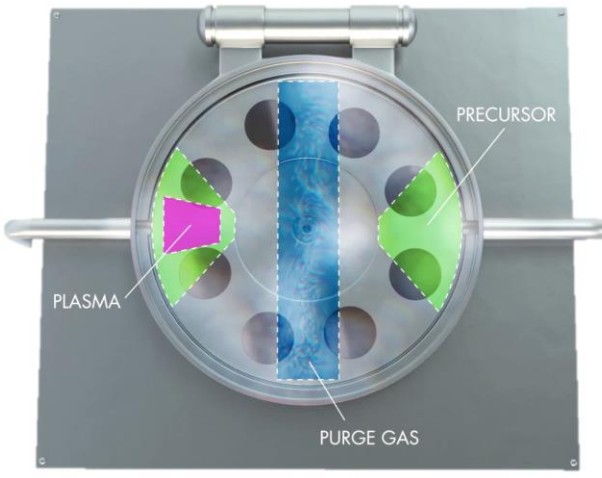
- A key loss mechanism in photovoltaics is due to charge carrier recombination at the metal/semiconductor interface of the electrical contacts
- Our group is exploring new approaches and materials that can passivate surface defects and are selective to either electrons or holes (i.e., carrier-selectivity)
- UCF Collaborators: Prof. Banerjee (MSE, REACT), Prof. Jurca (Chemistry, REACT), Prof. Kumar (Mechanical), Prof. Kar (CREOL), Prof. Schoenfeld (FSEC, CREOL), Prof. Kushima (MSE)
- External Collaborators: Fraunhofer ISE, Schmid Group, Beneq, ANU, UC-Berkeley, University of Melbourne

Atomic Layer Deposition of Al_2O_3 on p^+-Si



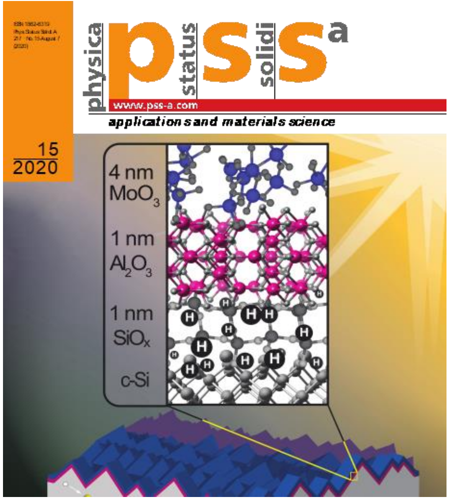
K. Ogutman *et al.*, *pss (a)*, 2020.

Atomic Layer Deposition of Hole-Selective MoO_x



G. Gregory *et al.*, *Advanced Materials Interfaces*, 2020.

Atomic Layer Deposition of Hydrogenated Al_2O_3/MoO_x



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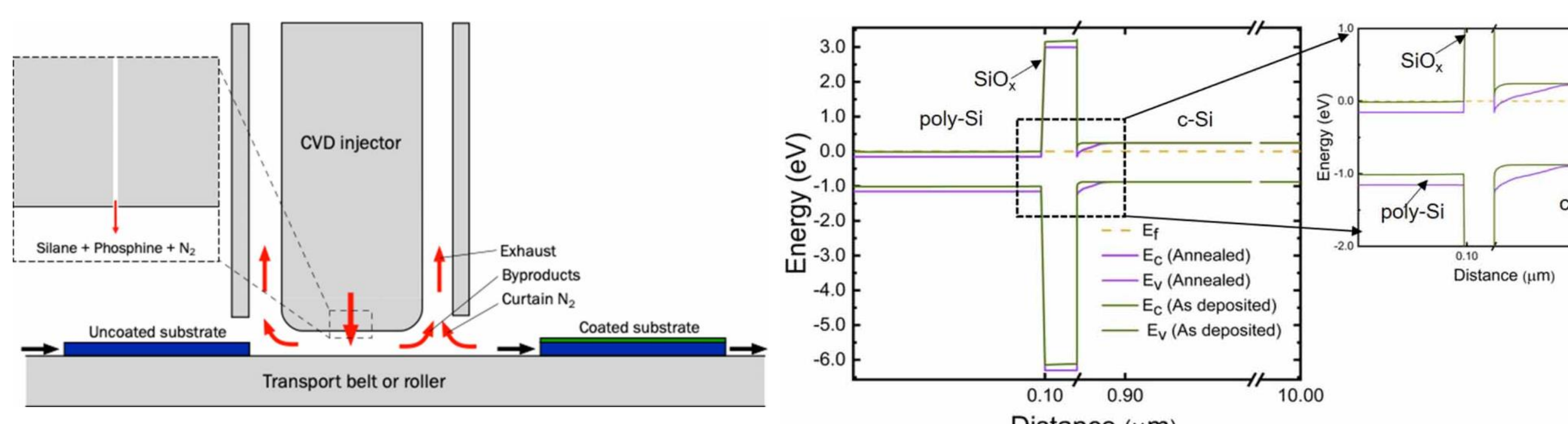
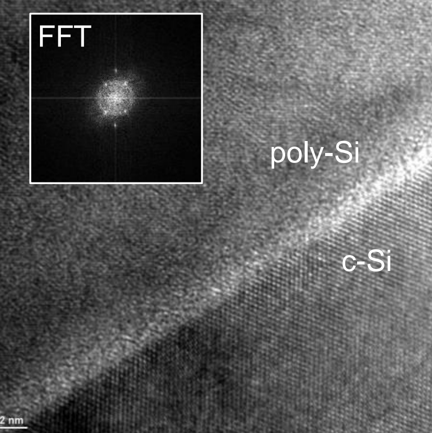
Passivating, Carrier-Selective Contacts

APCVD of Electron-Selective Polycrystalline Silicon Films

- Our group is exploring new approaches and materials that can passivate surface defects and are selective to either electrons or holes (i.e., carrier-selective = block one carrier type, allow the other to pass)
- This can be accomplished by growing a very thin silicon oxide (SiO_x) film (~1.5 nm) followed by either an electron- or hole-selective material
- Atmospheric pressure chemical vapor deposition (APCVD) is a low cost, high throughput process well suited for the PV industry, and we are using this to deposit doped polycrystalline silicon (poly-Si) films that serve as electron-selective layers
- Collaborators: Dr. P. Banerjee (MSE, REACT), Dr. R. Kumar (Mechanical), Dr. A. Kar (CREOL), Schmid Group, Rutgers, ANU



TEM Image



Invited: JF Mousumi *et al.* https://doi.org/10.1088/1361-6463/ac0e5c

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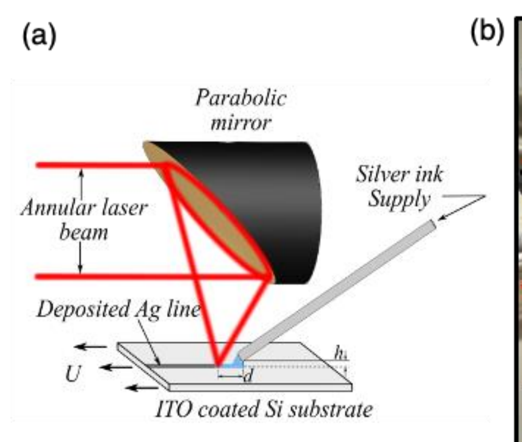
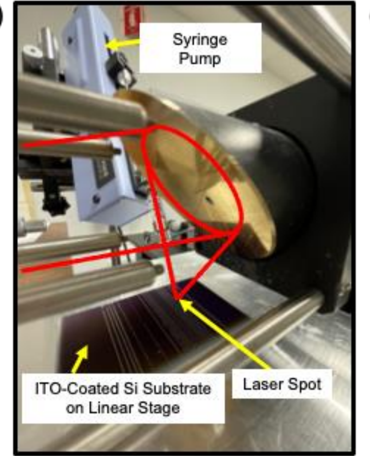
Invited: JF Mousumi *et al.* https://doi.org/10.1002/pssr.202100639

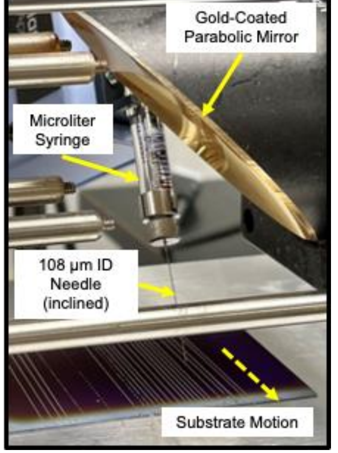
Photonic Curing of Silver Metallization

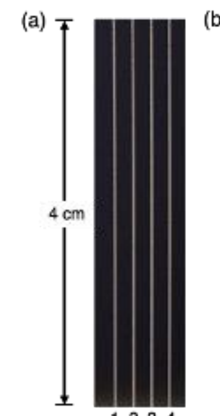
Printing and Laser Sintering High Viscosity Silver Pastes

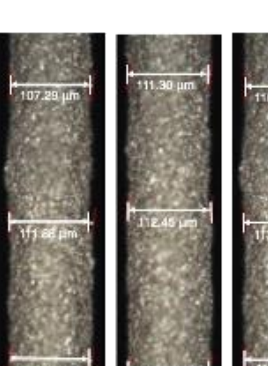
- Printed silver (Ag) pastes undergo a thermal sintering process to coalescence µm-nm scale particles and improve electron transport
- Some of these passivating heterojunction materials are very temperature sensitive, so the low sintering temperature process leads to high bulk resistivity
- Ag is expensive and the high bulk resistivity means a larger volume of Ag is needed
- Collaborators: Dr. R. Kumar (Mechanical), Dr. A. Kar (CREOL)

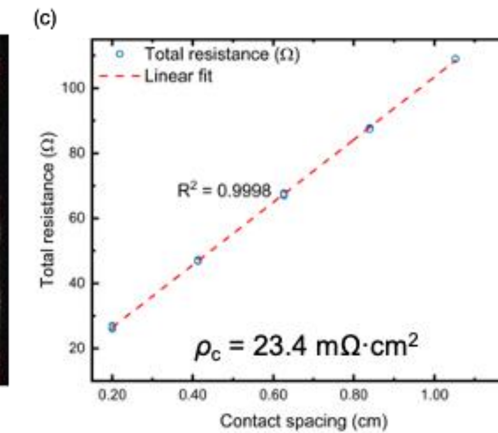










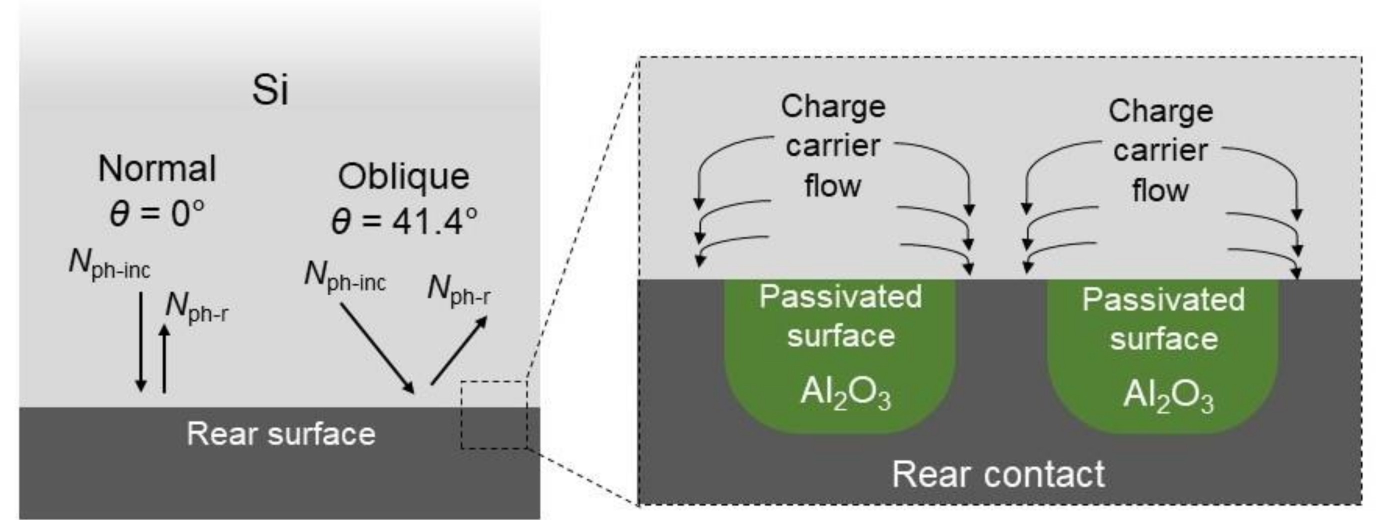


T Li *et al.* https://doi.org/10.1364/OE.455313

Multifunctional Nanomaterials

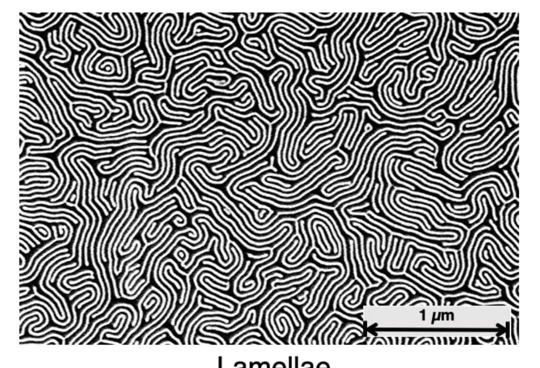
Self-Assembled Al_2O_3 Nanostructures: Electronic + Photonic Functionality

- Can we develop new materials with unique properties that can serve multiple functions?
- Yes – we showed how self-assembled Al_2O_3 nanostructures can electronically passivate surfaces provide improved light trapping, electronic + photonic functionality
- Collaborators: Dr. P.G. Kik (CREOL), Brookhaven National Laboratory

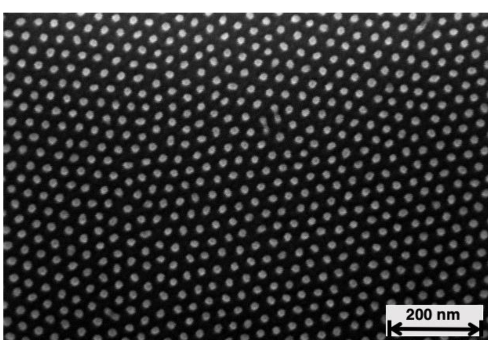


Hossain *et al.* https://doi.org/10.1515/nanoph-2021-0472

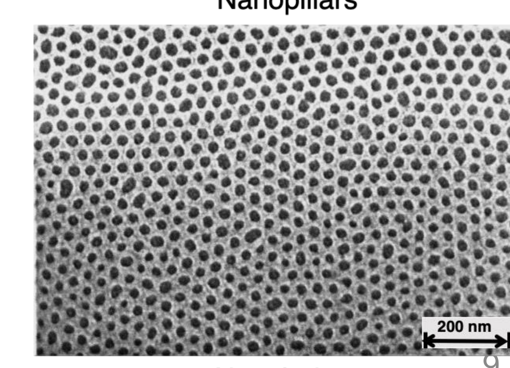
SEM Images



Lamellae



Nanopillars



Nanoholes

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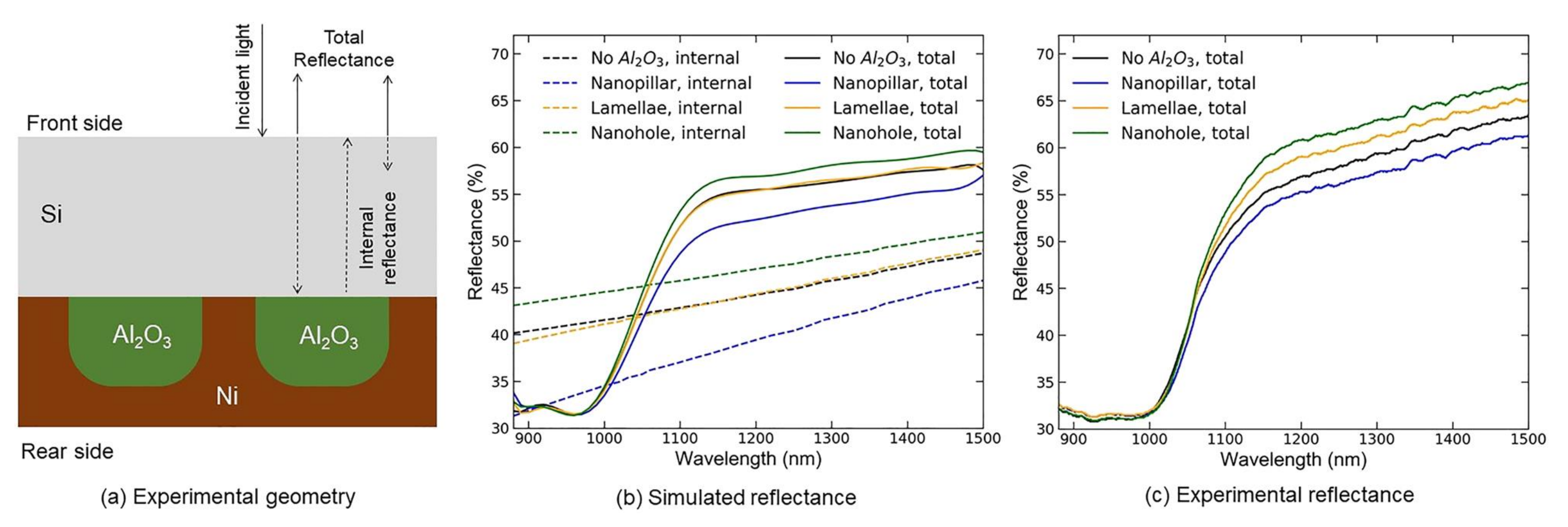
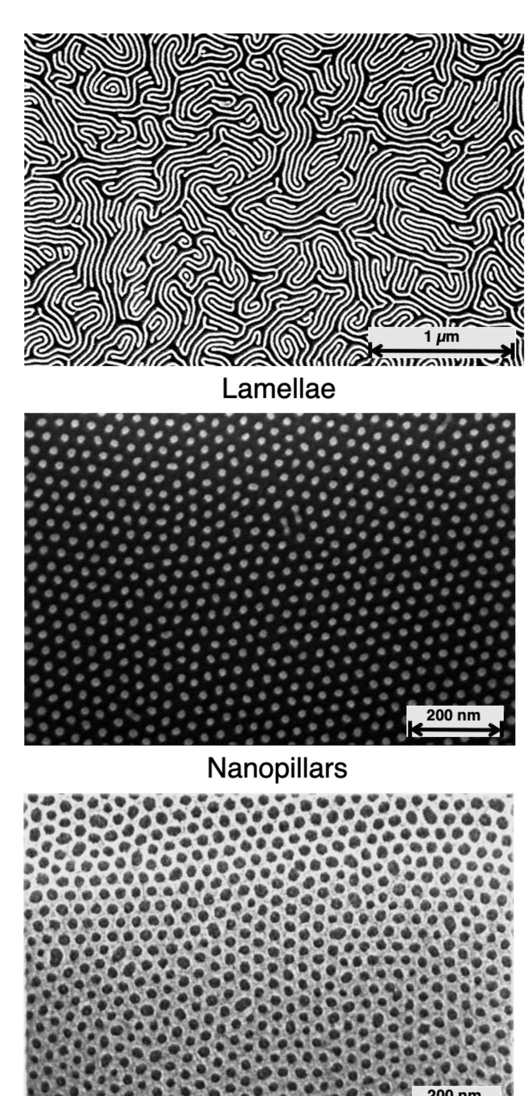


(a) Experimental geometry (b) Simulated reflectance (c) Experimental reflectance



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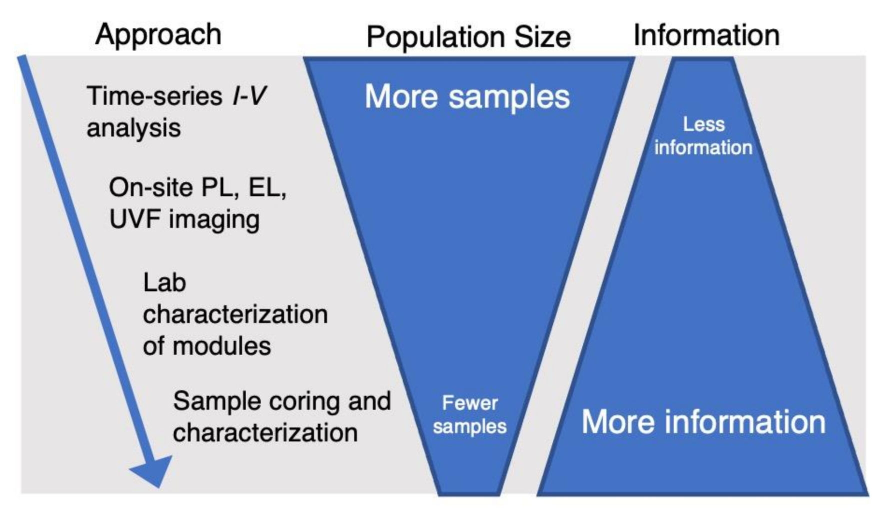
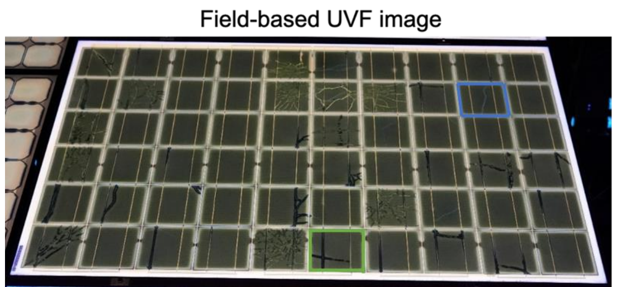
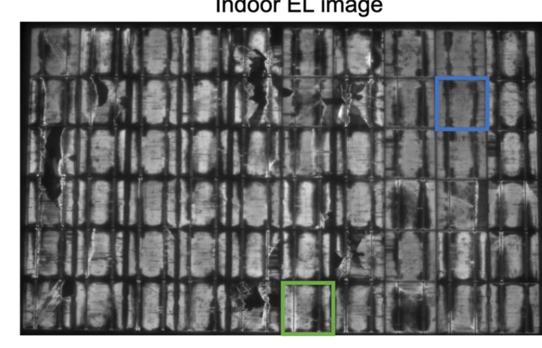
Multiscale Characterization of PV Modules in the Field

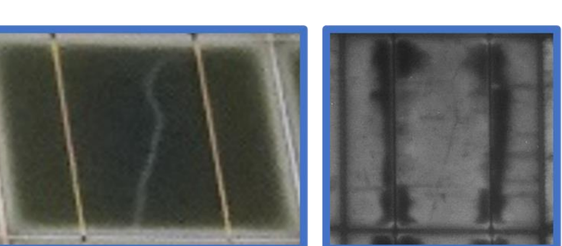


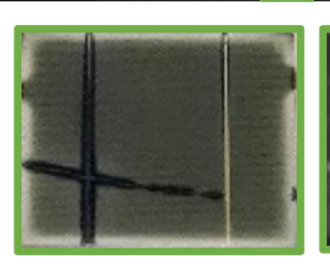
Field-based UVF image

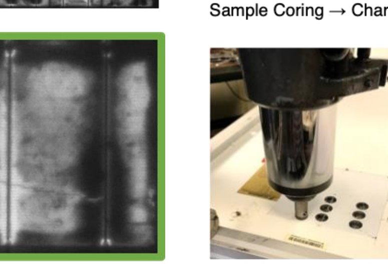


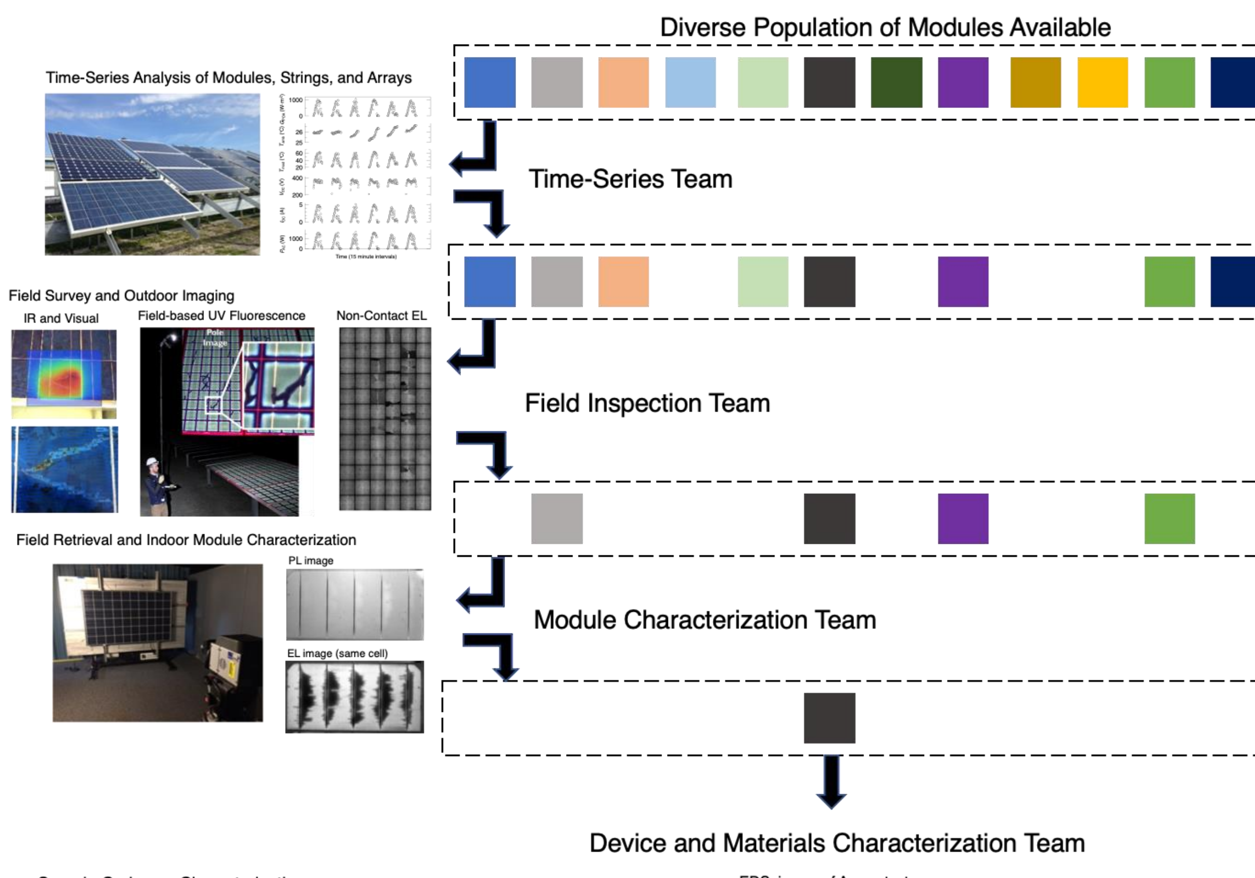
Indoor EL image



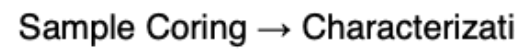




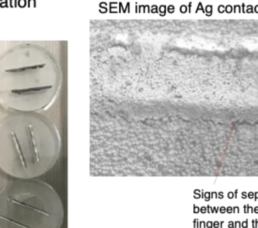


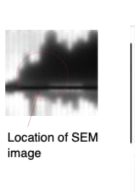


Sample Coring → Characterization

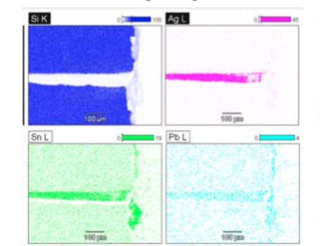


SEM image of Ag contact

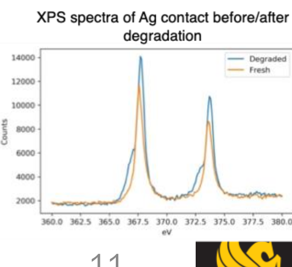




EDS image of Ag contact



XPS spectra of Ag contact before/after degradation



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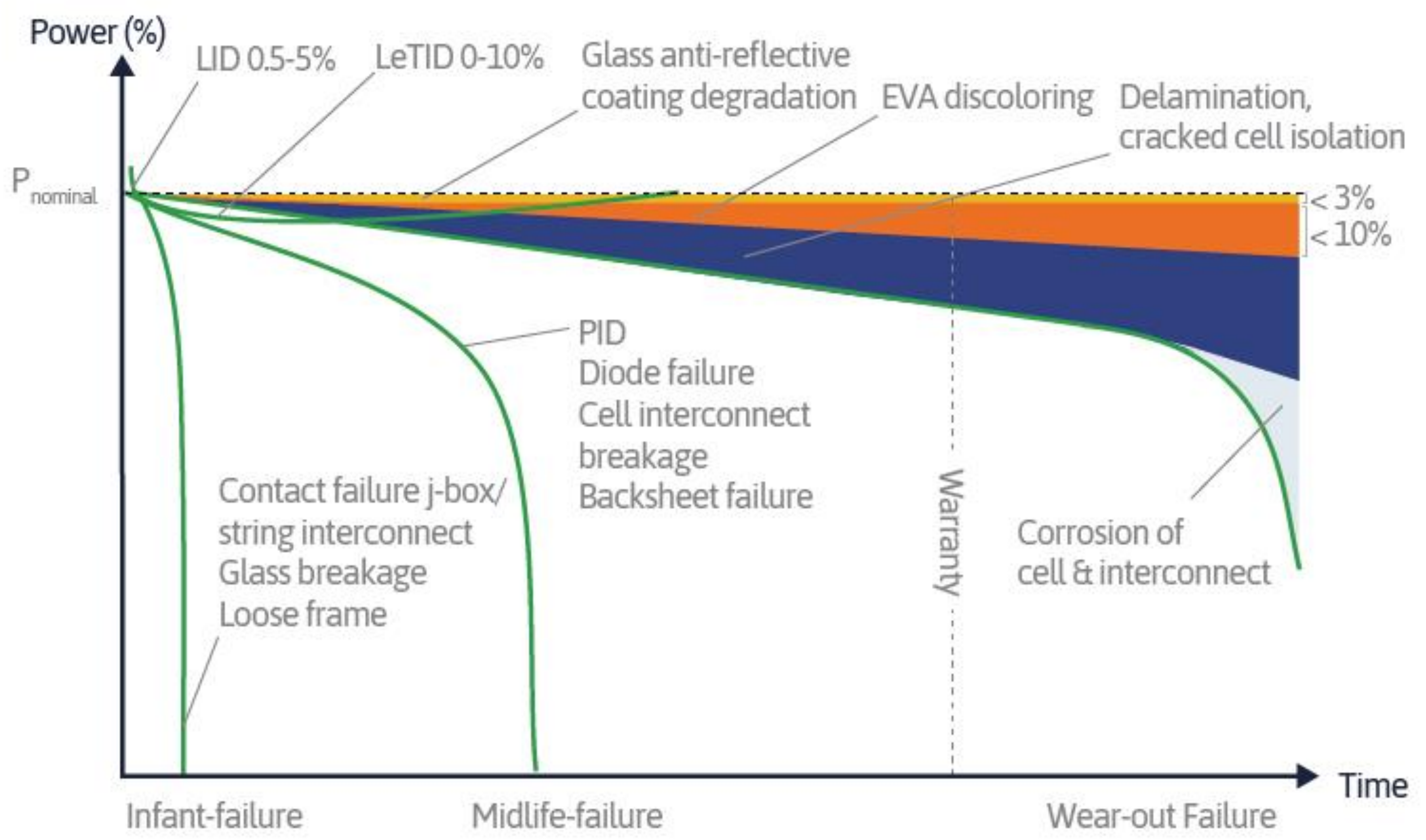
Reliability and Durability Challenges

- Complex combinations of materials susceptible to a wide range of degradation pathways
- Technologies are changing rapidly, along with the materials and manufacturing processes used
- Demands for high volume and low cost limit where and how in-line metrology can be used
- Different climate zones have different stressors, but cost pressure precludes tailored designs for specific climates
- Nevertheless, warrantied lifetimes are typically 25+ years with a push to go to 50 years



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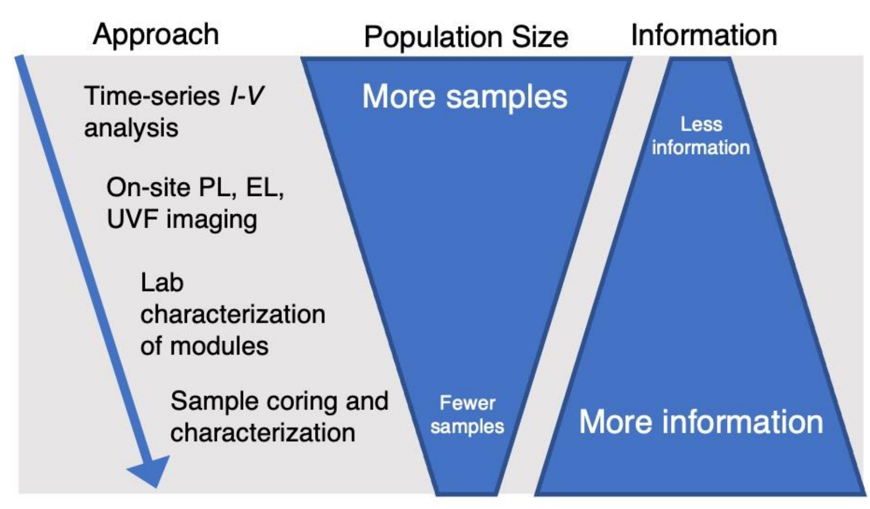
Multiscale Characterization of PV Modules in the Field



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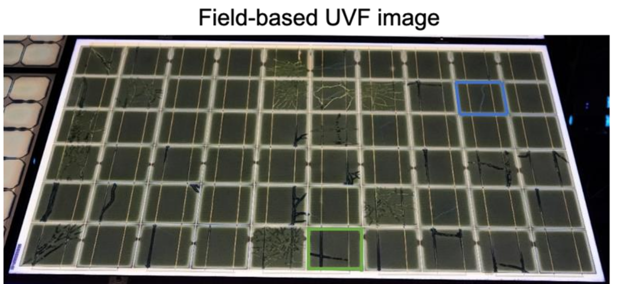
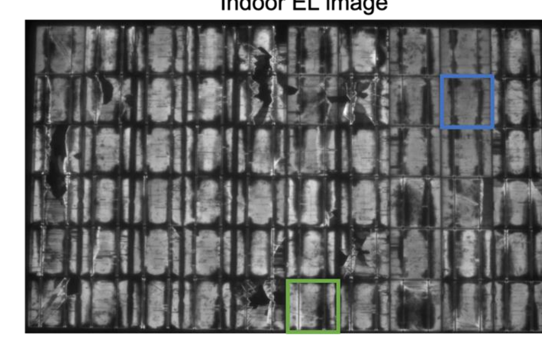
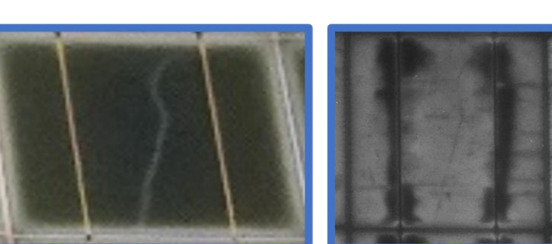
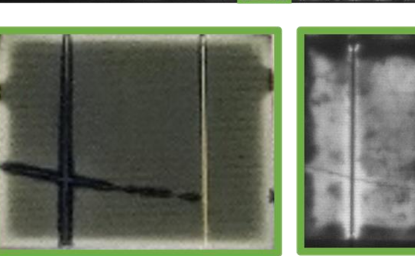
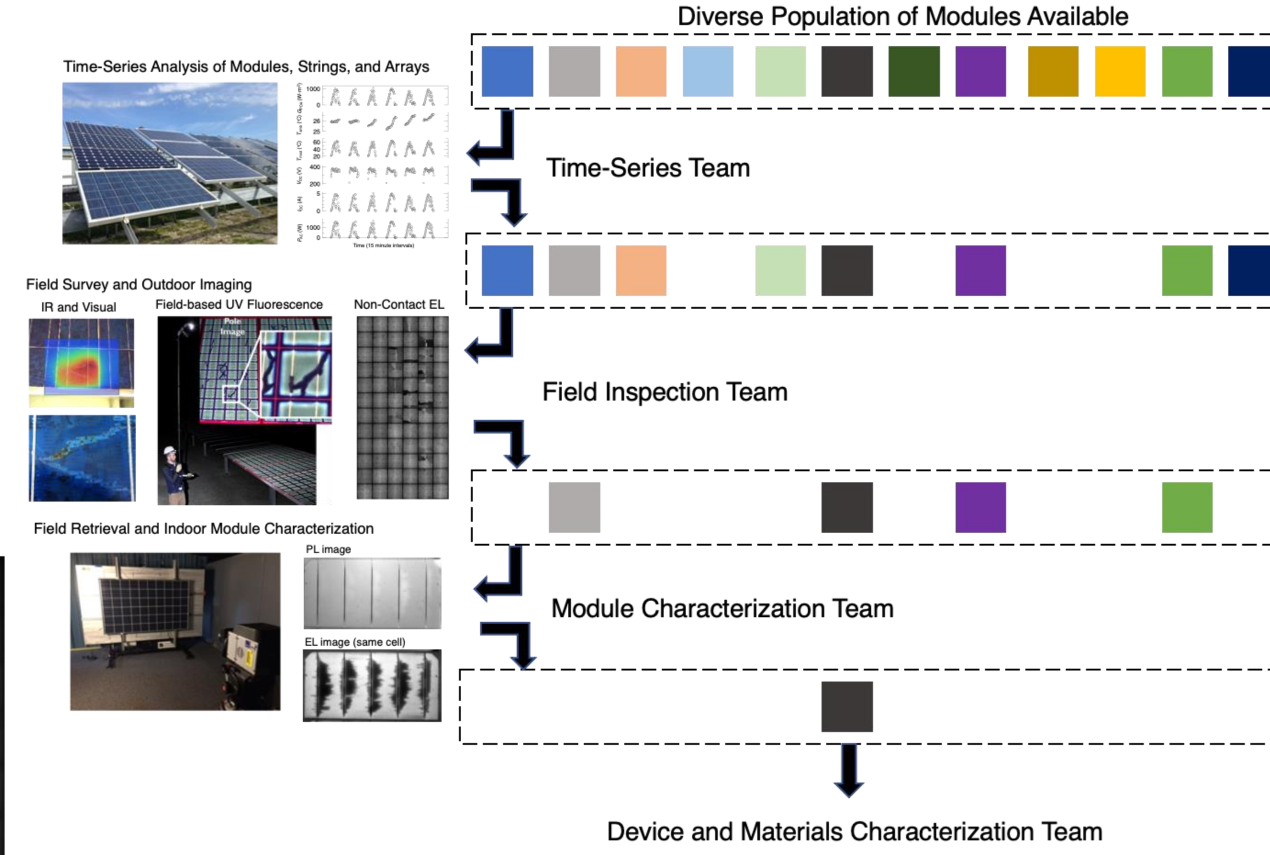


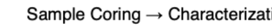
Indoor EL image











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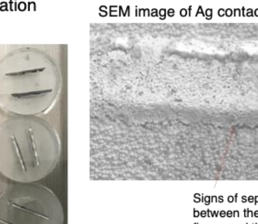

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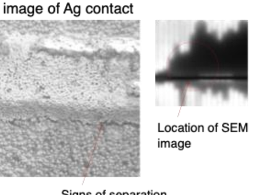

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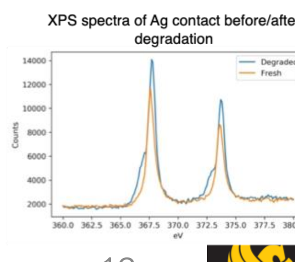


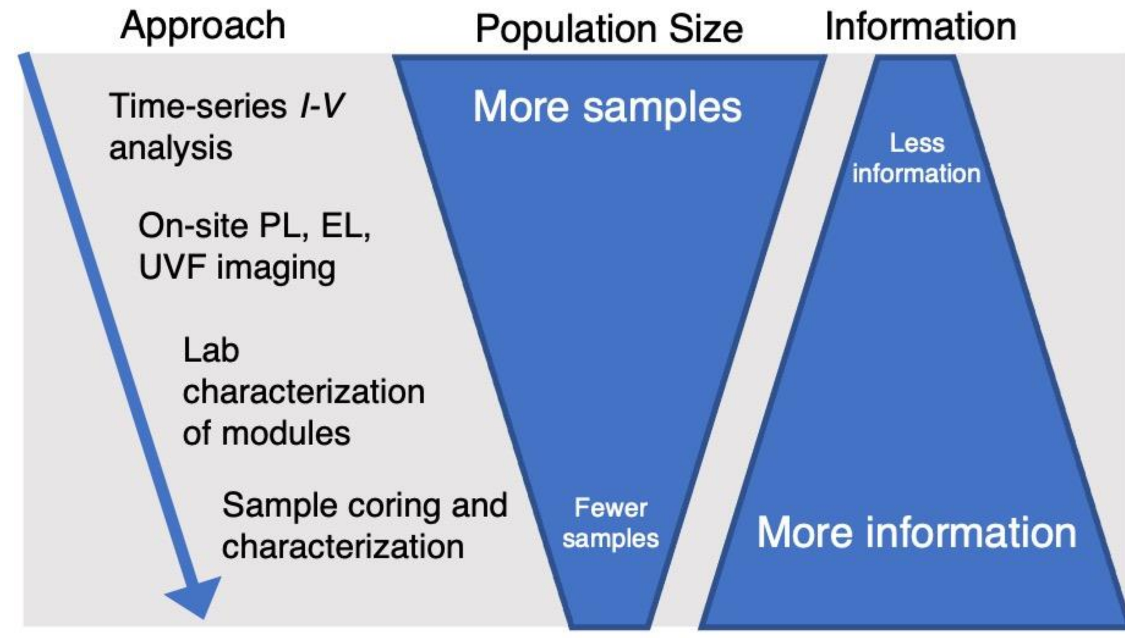
Data Challenges

Challenges

- Many samples of various types featuring different device technologies and materials
- Drilling down to the materials-level is expensive, so sampling needs to strategic and guided by the data
- Diverse datasets of different types and large in magnitude
  - Time-series vs. asynchronous
  - Data collected at the system-, module-, device-, and materials-level
  - Point data, curves, and images
  - In some cases, physical models known and well understood, while others this isn't the case

Needs

- Scalable data sources that are fast and information dense
- Automated analysis pipelines for each of these data streams
- Effective means of storing data, models, and results to make links across different samples and measurement types



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UCF Florida Solar Energy Center – Cocoa, Florida

- Long-standing PV test facility for the DOE and the DOE Regional Test Center for Hot-Humid Climates
- Many diverse types of modules installed at various times
- Great access co-located with indoor module characterization labs

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Florida Gulf Coast University – Fort Myers, Florida

- 2 MW PV system installed at Florida Gulf Coast University (FGCU) in Fort Meyers, Florida
- We performed imaging on this system before and after Hurricane Ian

CWRU Sunfarm – Cleveland, OH

Project collaborator: Prof. Roger French and Prof. Laura Bruckman

- 50 kW test site operated by CWRU
  - 148 modules installed in 2013
  - 20 brands with 6 replicates of each

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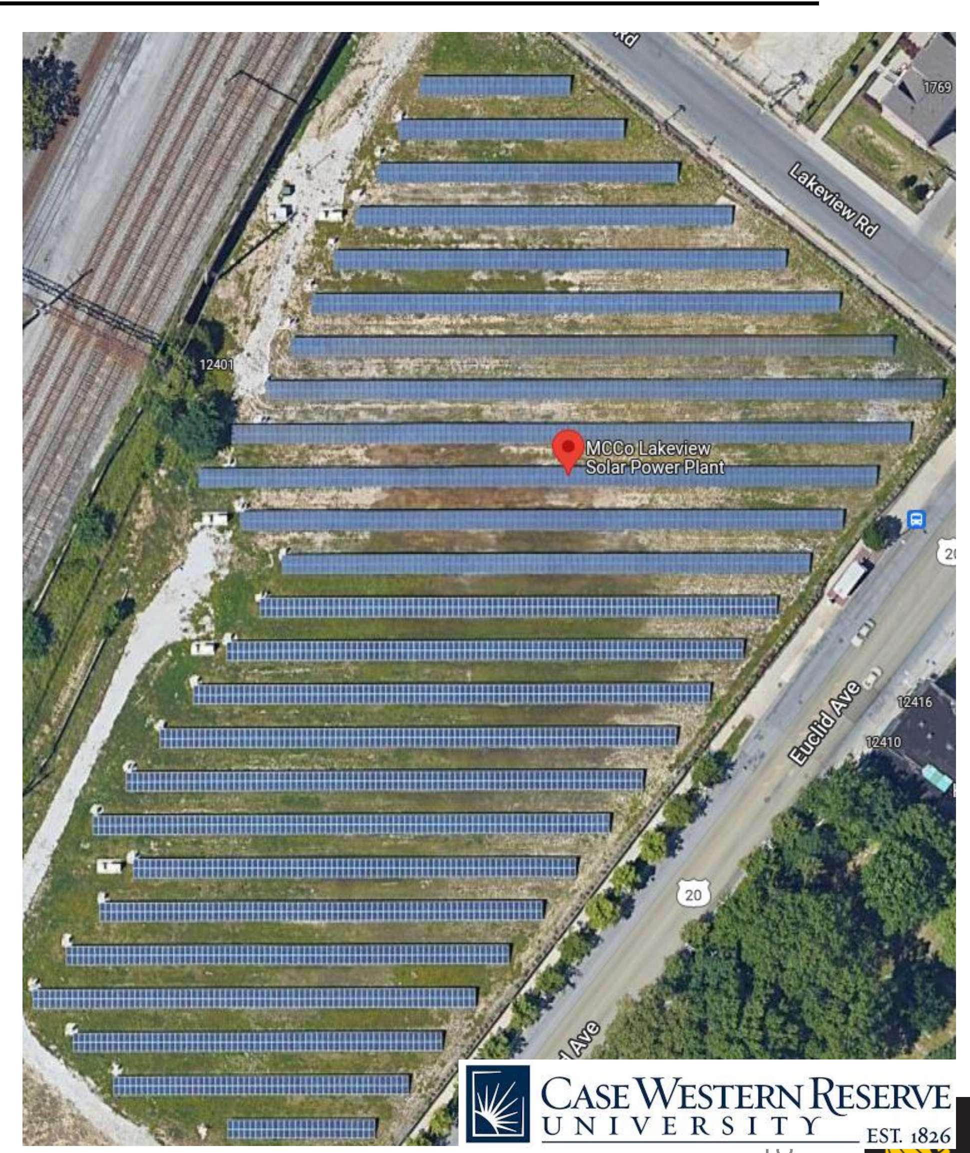
CWRU MCCo – Cleveland, OH

1 MW power plant owned by Case Western

- ~4,000 modules on site installed 2016
- 2 brands
  - Each about ½ of site



Time Series Team

Methods

- Remote time-series electrical performance and weather data

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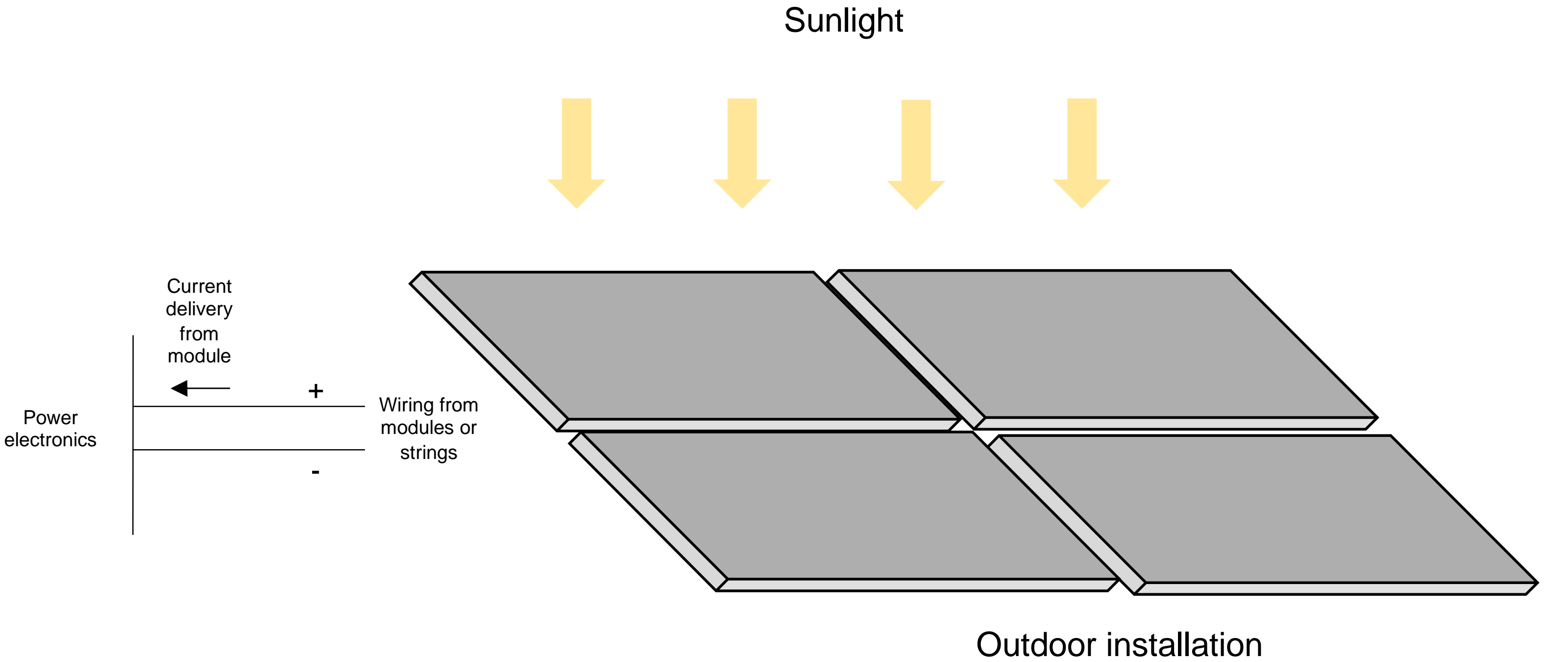
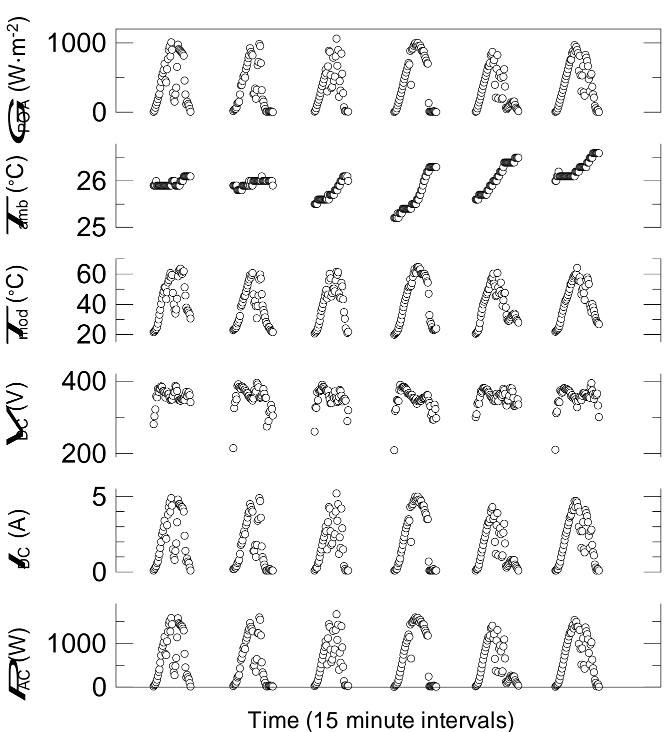
Time Series Team





Time series setup

Time Series Dashboard

Development of automated interactive dashboard (Will Oltjen *et al.* at CWRU)

- Missingness and data quality
- Performance loss rate calculation
- System information

Grade:

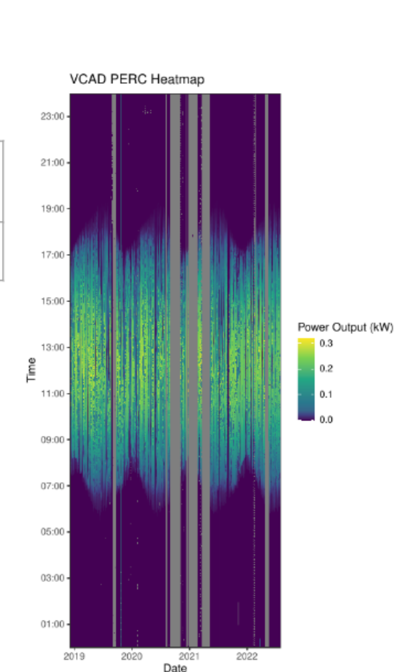
Outlier %	Missingness %	Longest Missing Gap	Length Requirement
B	A	C	P

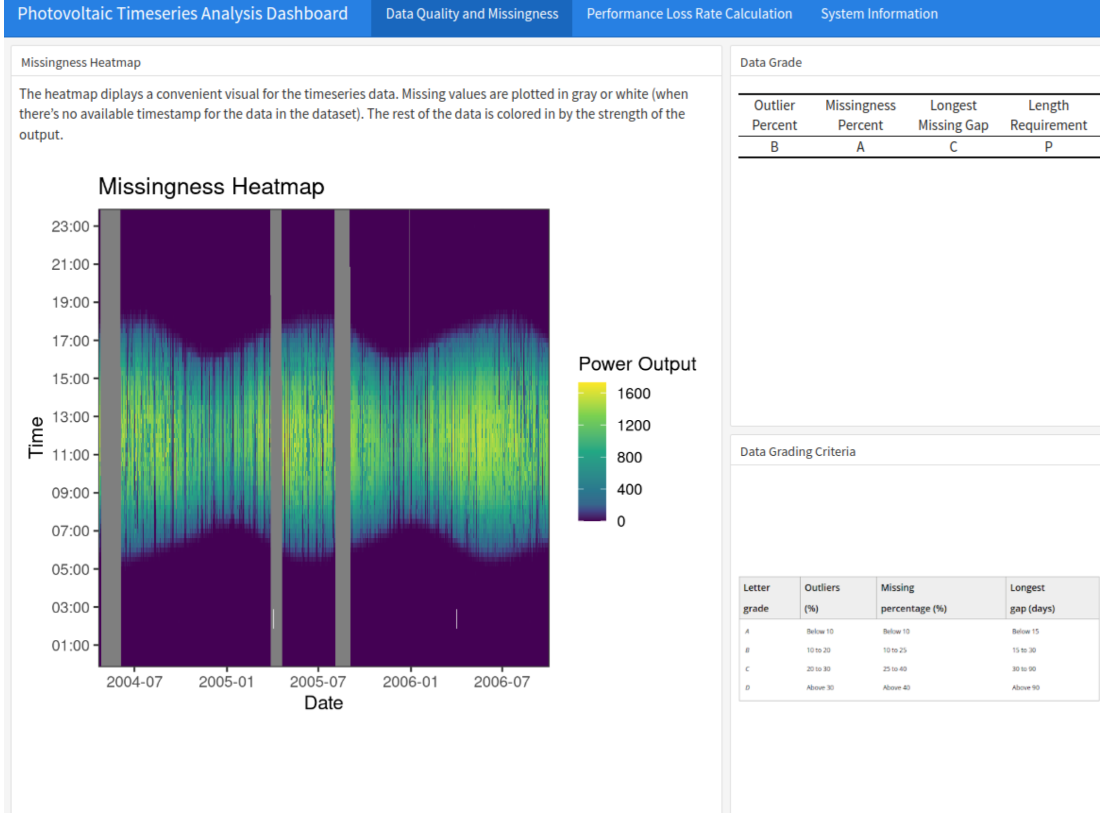
Performance Loss Rate:

- -1.093 ± .215 %

Method

- XbX + Universal Temperature Correction
  - Year on Year Regression
- Bootstrapped Uncertainty





Time Series Analysis – Extreme Weather

Motivation: Hurricane Dorian 2019

72-Cell Module
60-Cell Module
72-Cell Module with Railpad

Displacement (cm)

0.6
0.4
0.2
0.0
−0.2

Peak Wind Speed
15-Minute Average

Wind Speed (mph)

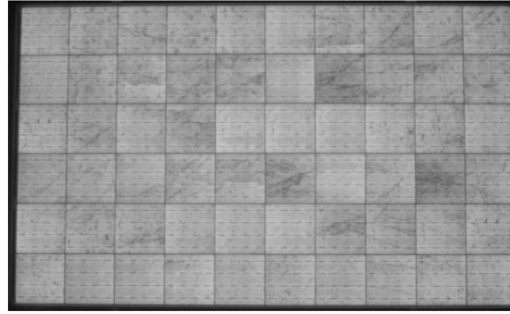
35
30
25
20
15
10
5

5-Minute Average
30-Minute Average

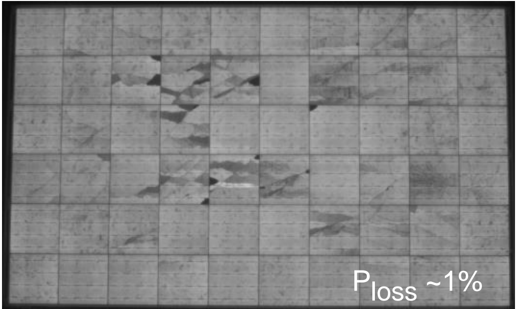
Wind Direction

South
East
North
West
South

09-03 00
09-03 06
09-03 12
09-03 18
09-04 00
09-04 06
09-04 12
09-04 18
09-05 00



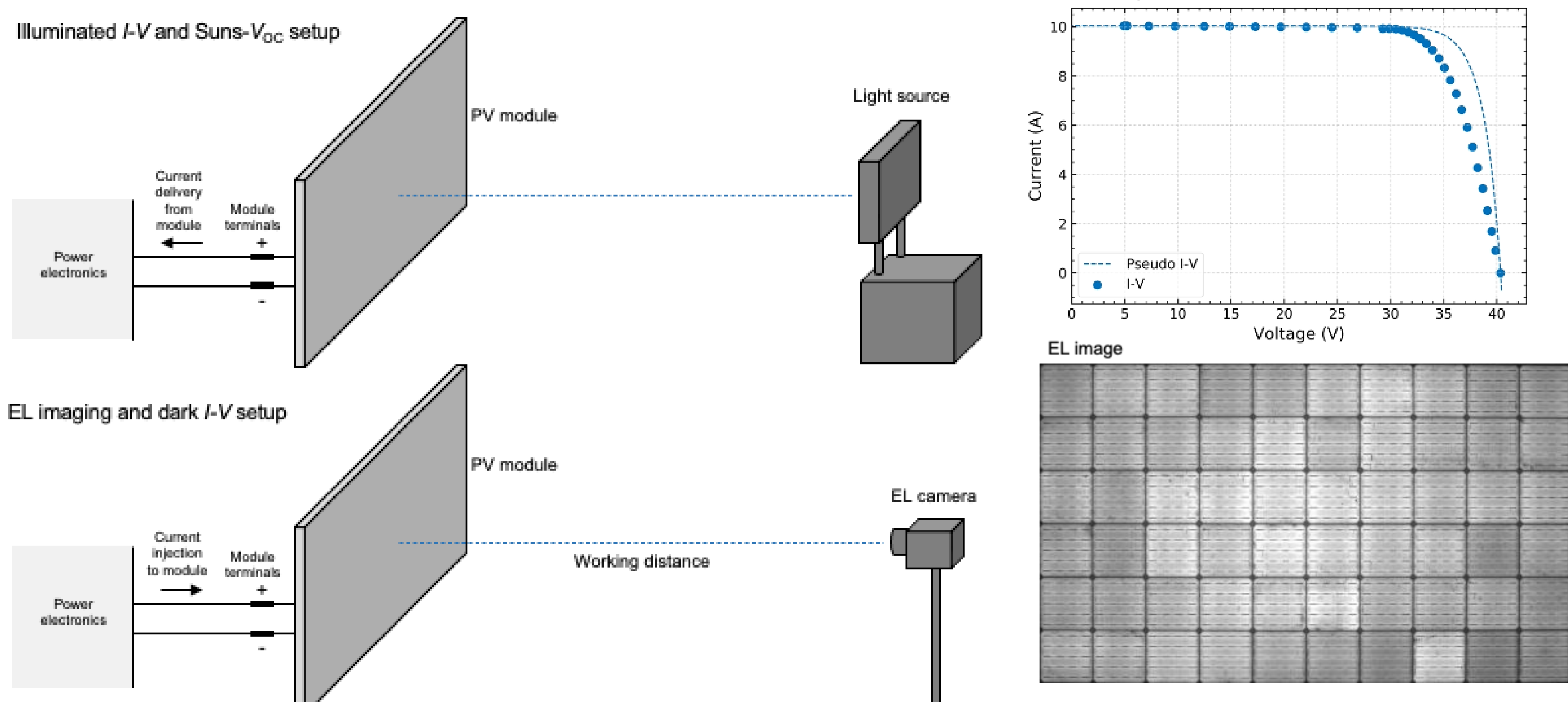
Before



After

Indoor Module Characterization Team

- Current-voltage (*I-V*) or current density-voltage *(J-V)* curves curves under illuminations
- Electroluminescence (EL) image performed in the dark under bias



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Indoor Module Characterization Team

- Current-voltage (*I-V*) or current density-voltage *(J-V)* curves curves under illuminations
- Electroluminescence (EL) image performed in the dark under bias

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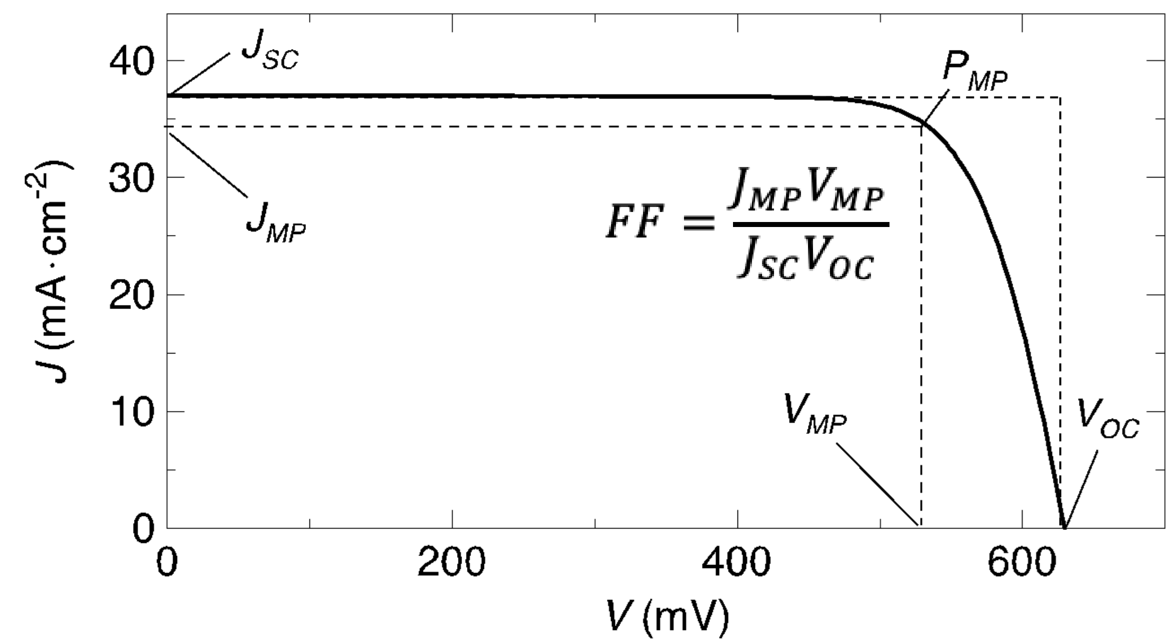
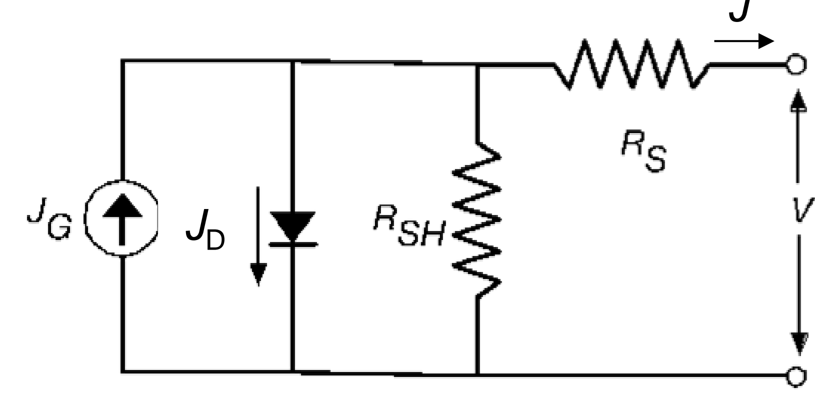
Illuminated *J-V* Curves – Simple Models

- Photogenerated current density, J_G (A/cm^2 or mA/cm^2)
- Diode current density, J_D (A/cm^2 or mA/cm^2)
- Saturation current density, J_0 (A/cm^2 or fA/cm^2)
- Ideality factor, n or m
- Series resistance, R_S (Ω or $\Omega\cdot$cm^2)
- Shunt resistance, R_{SH} (Ω or $\Omega\cdot$cm^2)
- Boltzmann constant, k
- Charge of an electron, q



$$J = J_G - J_0\left(e^{\frac{q(V+JR_S)}{kT}} - 1\right) - \frac{V + JR_S}{R_{SH}}$$

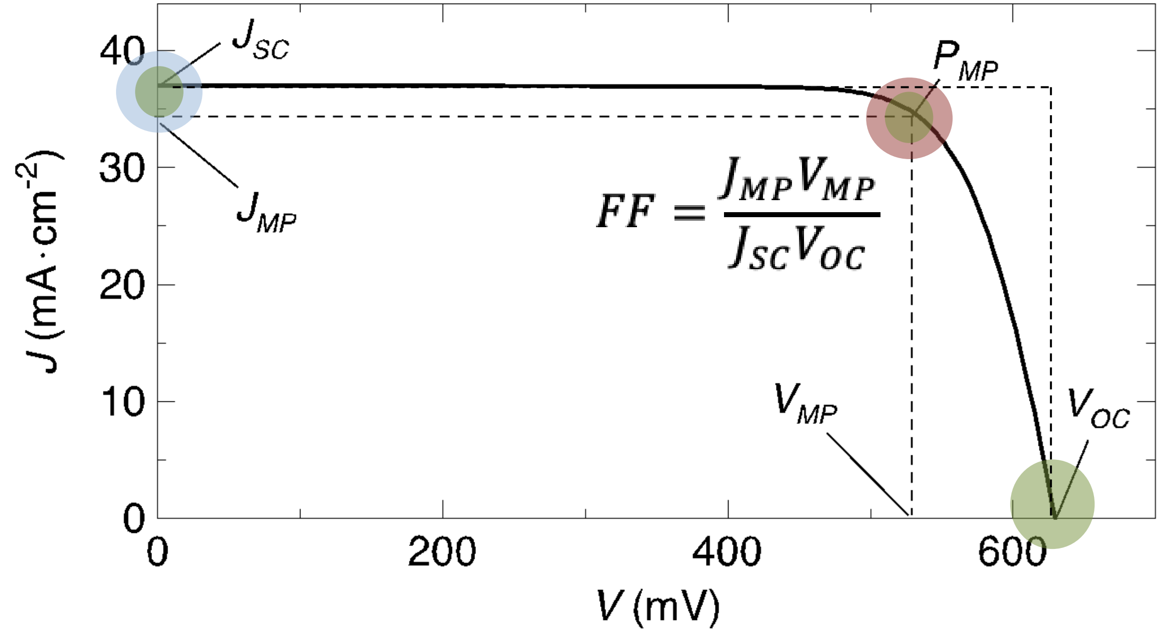


Illuminated *J-V* Curves – Loss Mechanisms

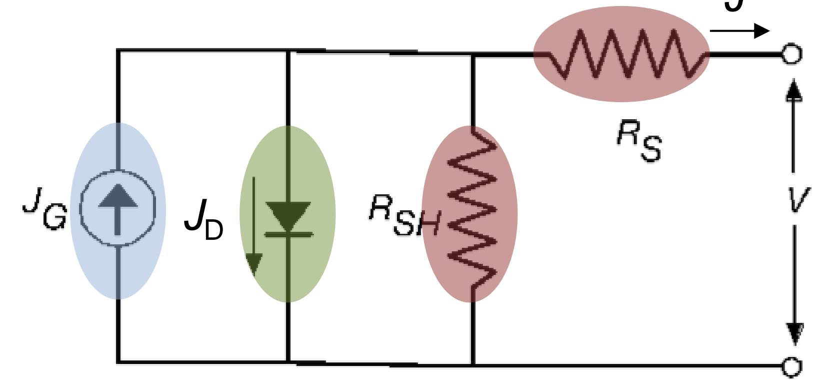
Optical losses lower J_{SC}

Resistive losses lower the *FF*

Recombination losses lower V_{OC}, J_{SC}, *FF*



$$J = J_G - J_0\left(e^{\frac{q(V+JR_S)}{kT}} - 1\right) - \frac{V + JR_S}{R_{SH}}$$



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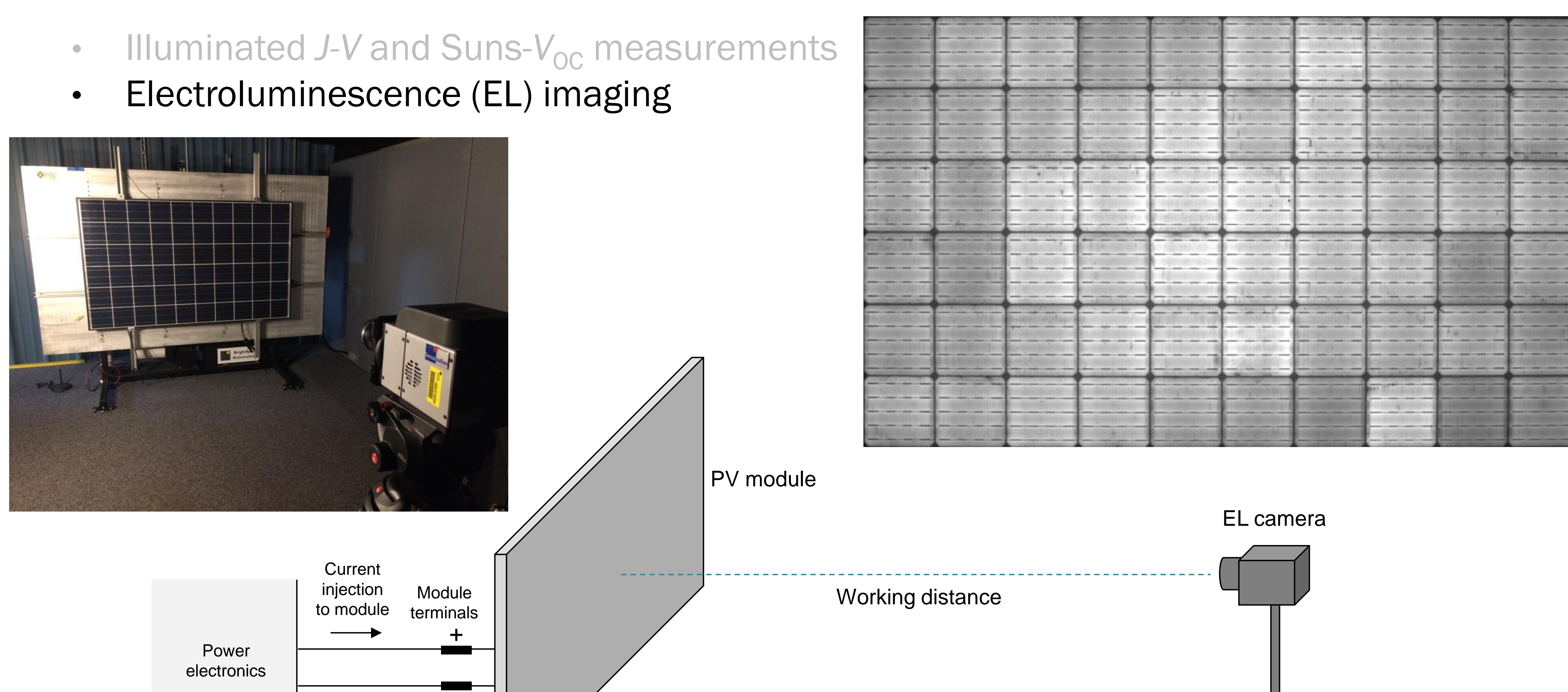
Measurement Methods

- Illuminated *J-V* and Suns-V_{OC} measurements
- Electroluminescence (EL) imaging



EL Image Analysis Approaches Developed

Efforts to make EL image analysis more quantitative and less subjective

- EL sweep – Turn EL images of modules measured at different currents into dark *J-V* curves of cells to extract R_S and J_0
- Pixel R_S – Use that in turn to determine the local R_S of each pixels in the EL image
- EL defect segmentation – Use supervised deep learning for semantic segmentation of EL images based on different defect classes

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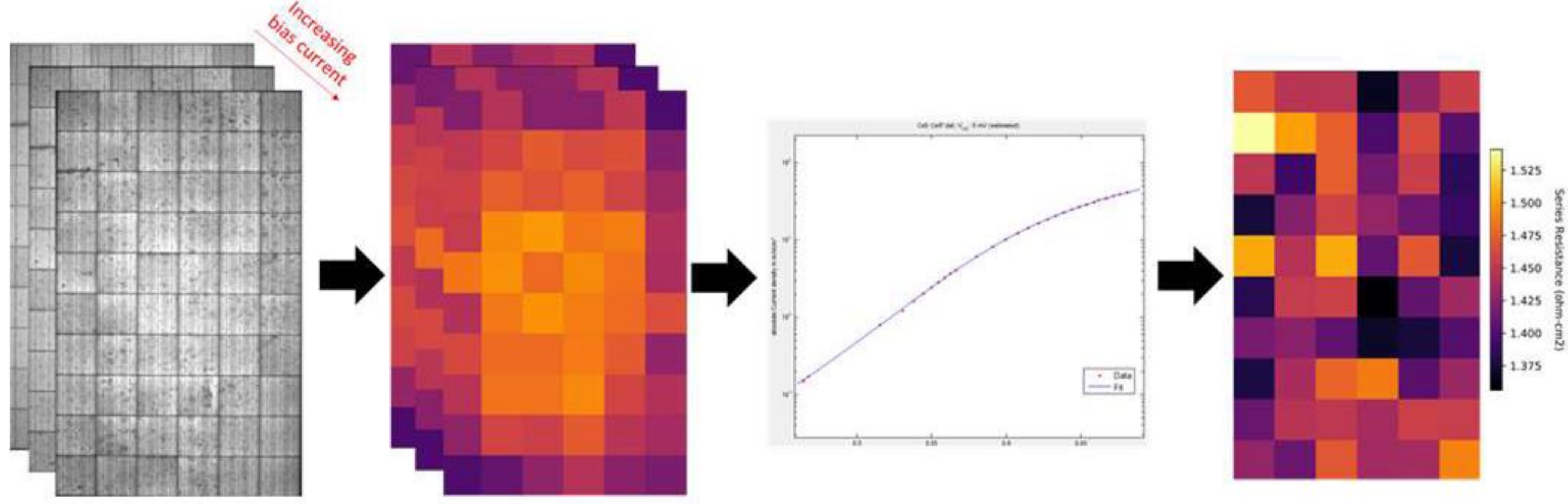
EL Sweep



1. Obtain EL images at increasing bias currents
2. Calculate voltage for each cell within each image
3. Repeat for each image to build dark *I-V* curve for each cell
4. Analyze dark *I-V* curves to extract performance characteristics

D.J. Colvin, *et al.* https://doi.org/10.1016/j.solener.2022.08.043

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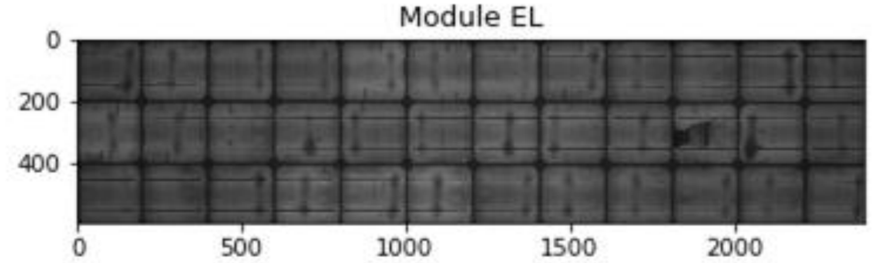
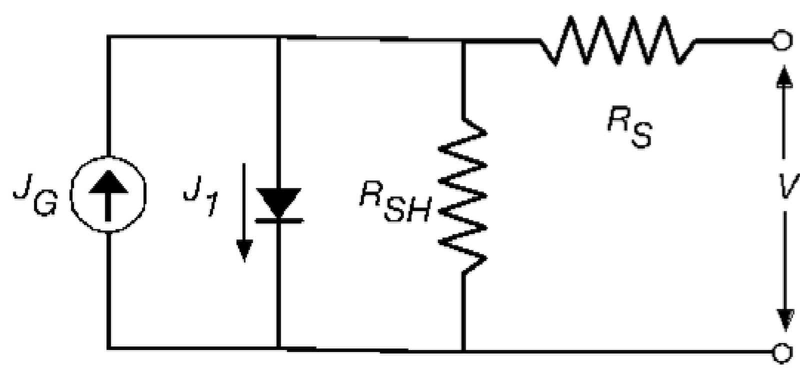
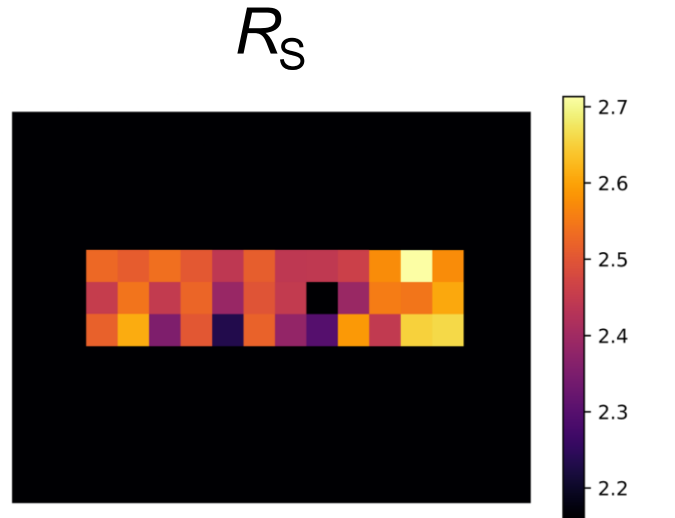
EL Sweep of Two M55 Modules - R_S and J_0 Maps



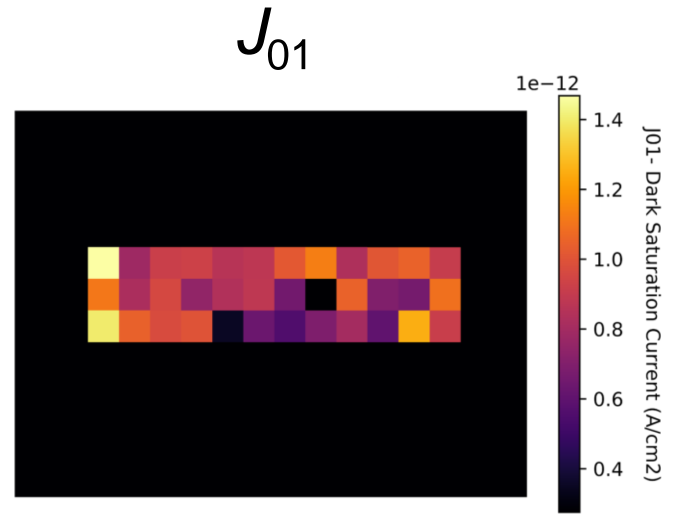


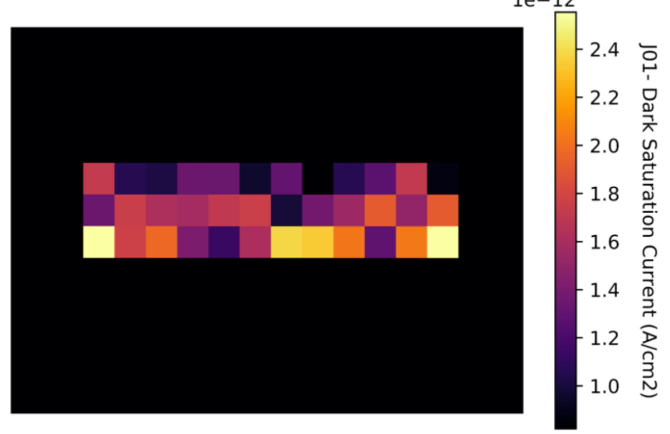
$$J = J_G - J_0\left(e^{\frac{q(V+JR_S)}{kT}} - 1\right) - \frac{V + JR_S}{R_{SH}}$$

R_S



J_{01}





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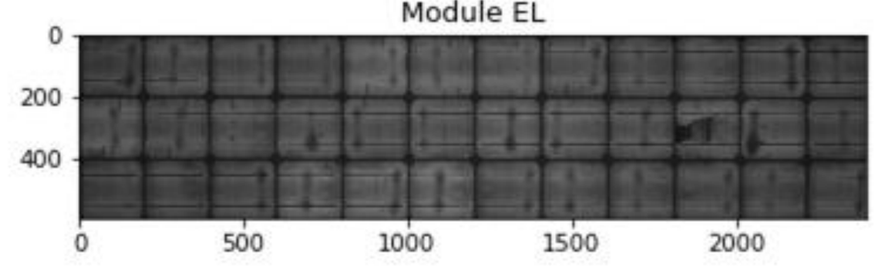
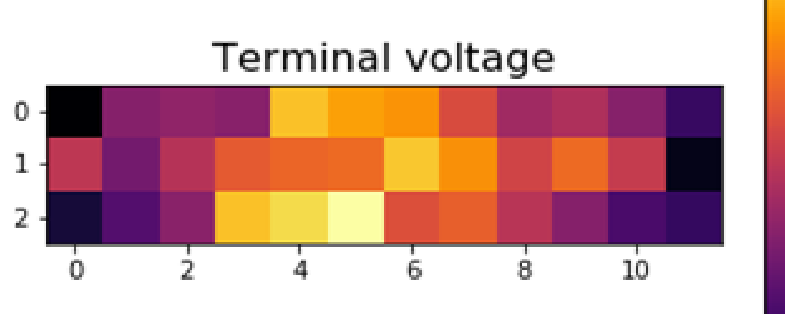
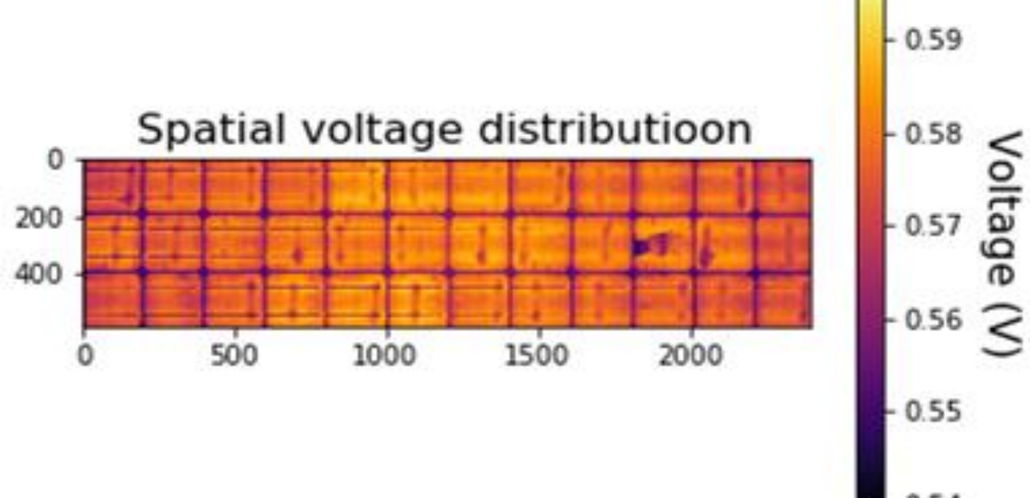
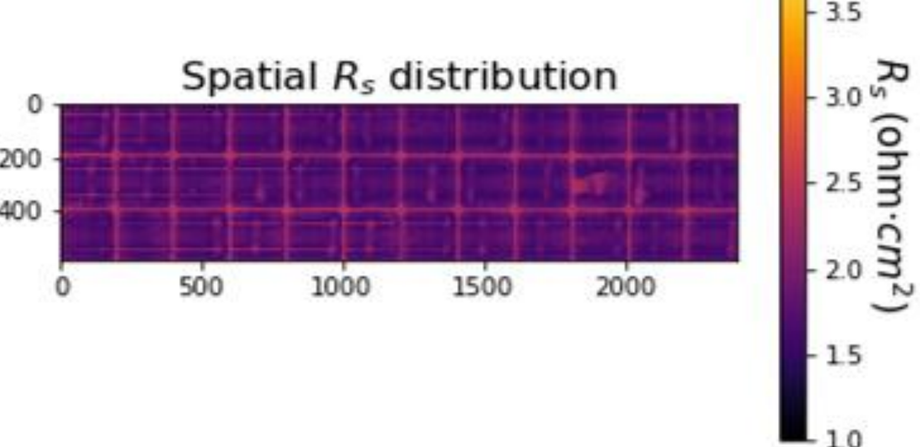
Pixel R_S – Control M55 Module

M. Li *et al.* https://dx.doi.org/10.2139/ssrn.4367178









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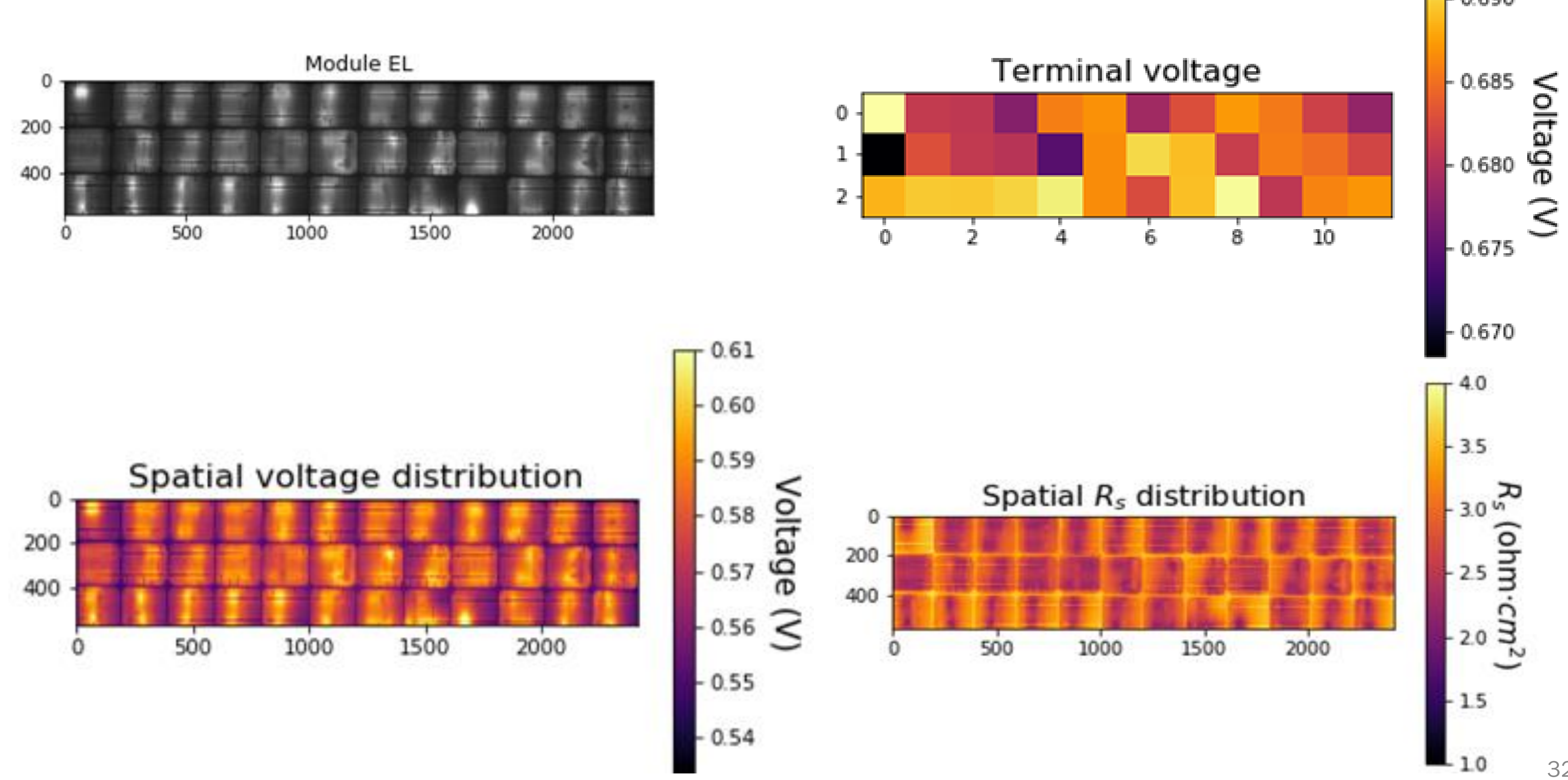
Pixel R_S – Degraded M55 Module



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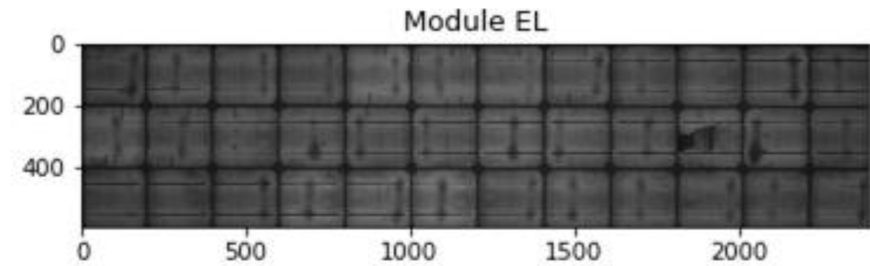
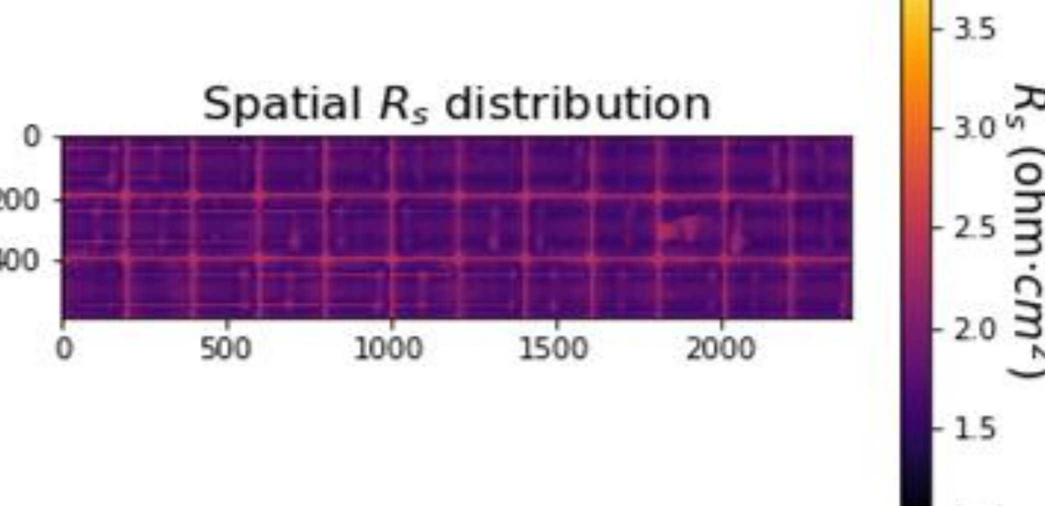
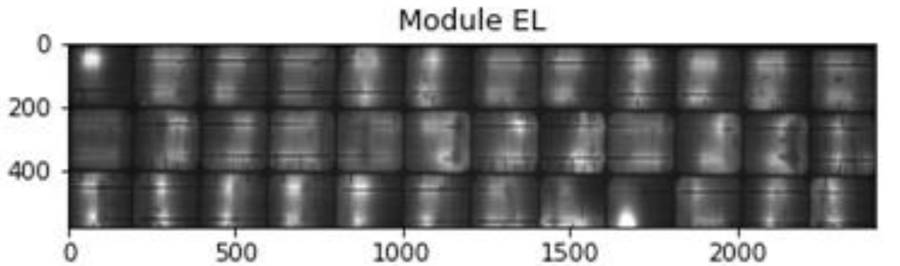
Pixel R_S - Comparison

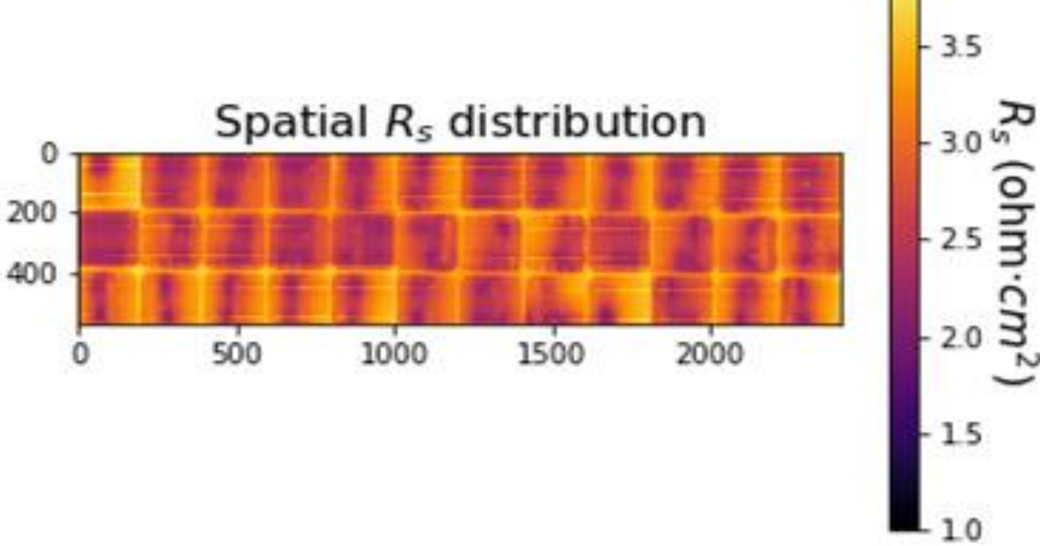
Control M55 Module

Degraded M55 Module









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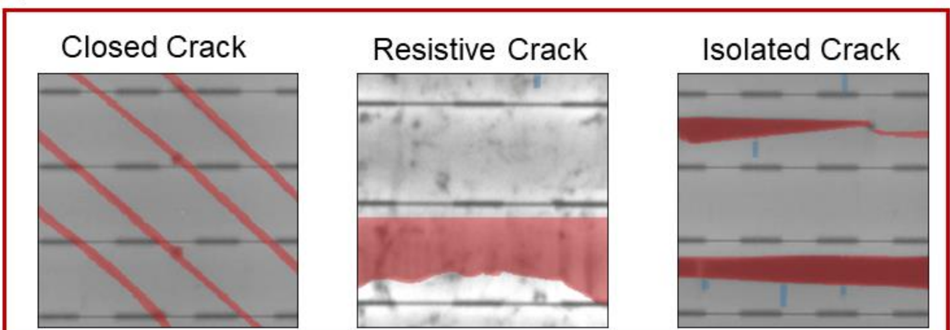
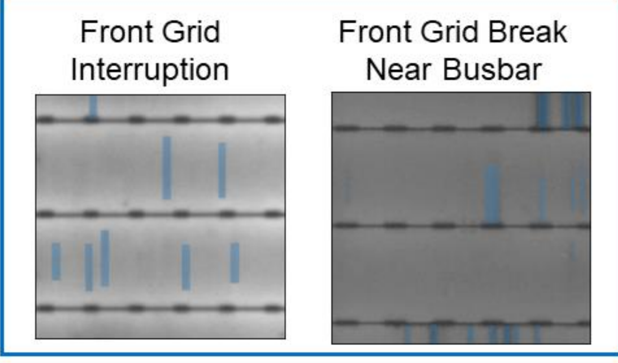
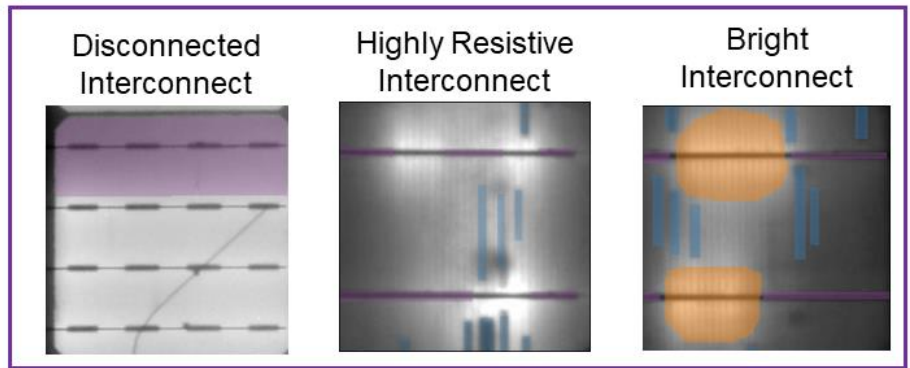
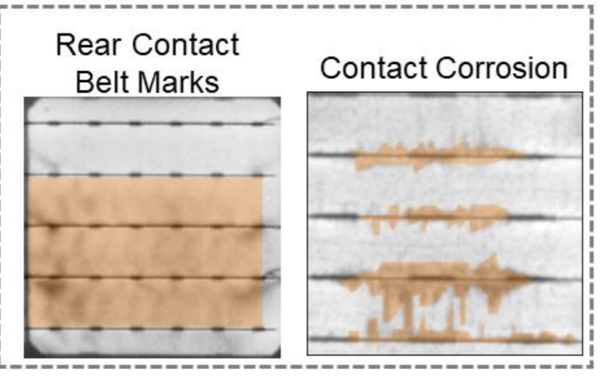
Data-Driven Approach to Defect Classification and Localization

- Supervised deep learning model with CNN (Deeplabv3 model with a ResNet-50 backbone)
- Model trained with 17,064 EL images - fully annotated dataset
- Defect classes shown below - 95.4% pixel-level accuracy achieved









J. Fioresi, *et al.* https://doi.org/10.1109/JPHOTOV.2021.3131059

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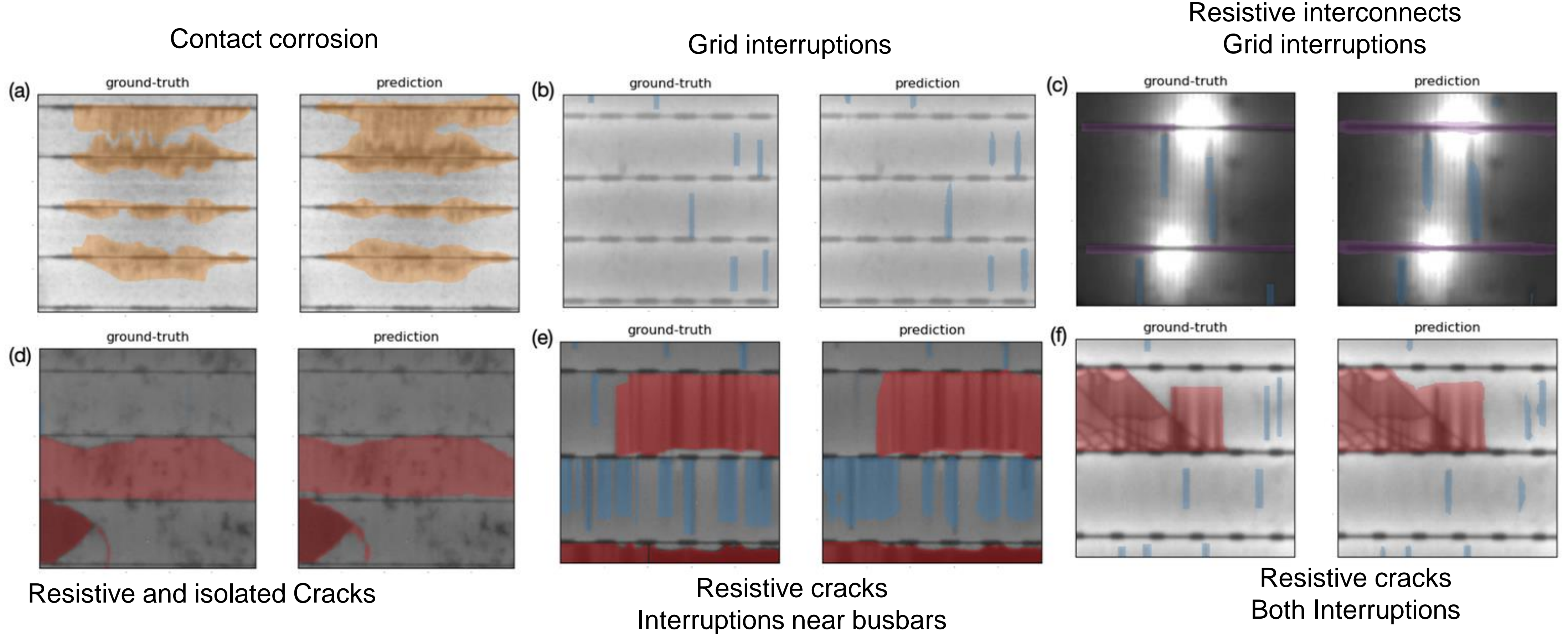
Examples



J. Fioresi, *et al.* https://doi.org/10.1109/JPHOTOV.2021.3131059

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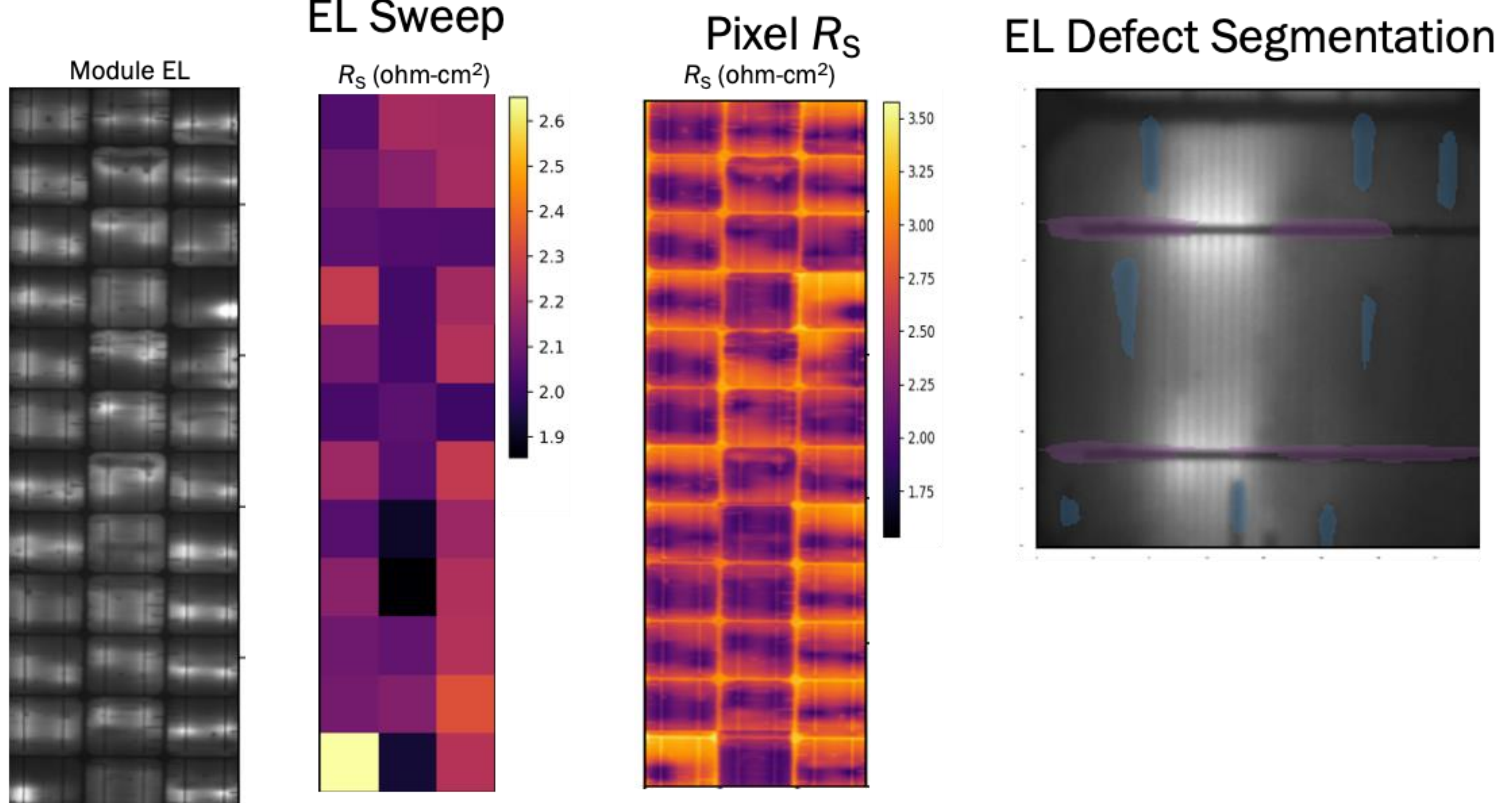
Complete EL Image Analysis Sequence



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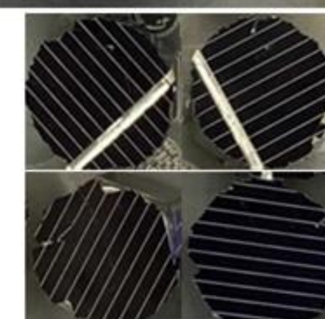
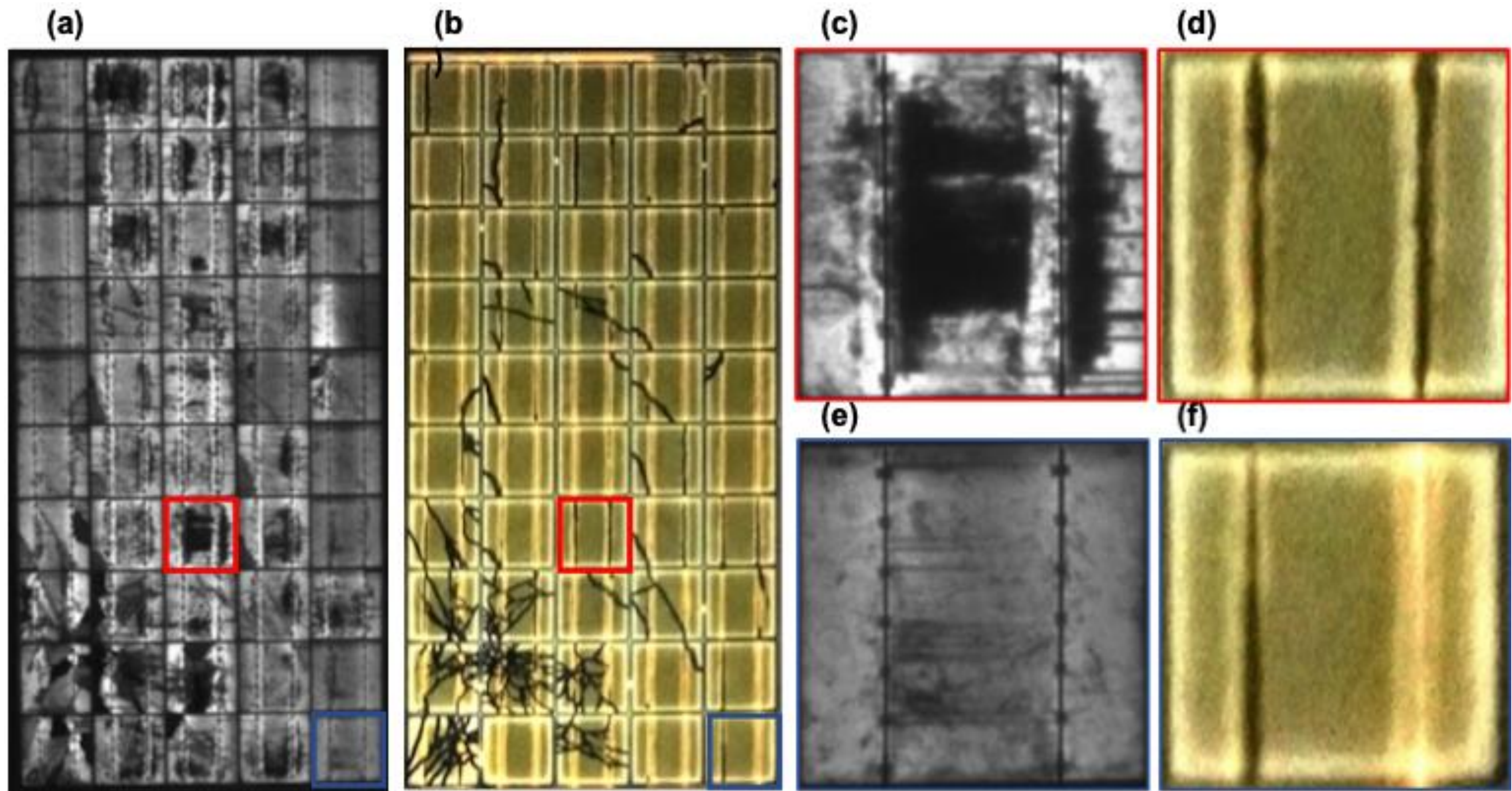
Module Characterization –Coring

- Module characterization guides us to select regions for extracting cell samples
- Curves tell us more on the loss mechanisms and magnitude of the power loss
- Images tell us the location of possible defects and the patterns can indicate the possible root cause



Device and Materials Characterization



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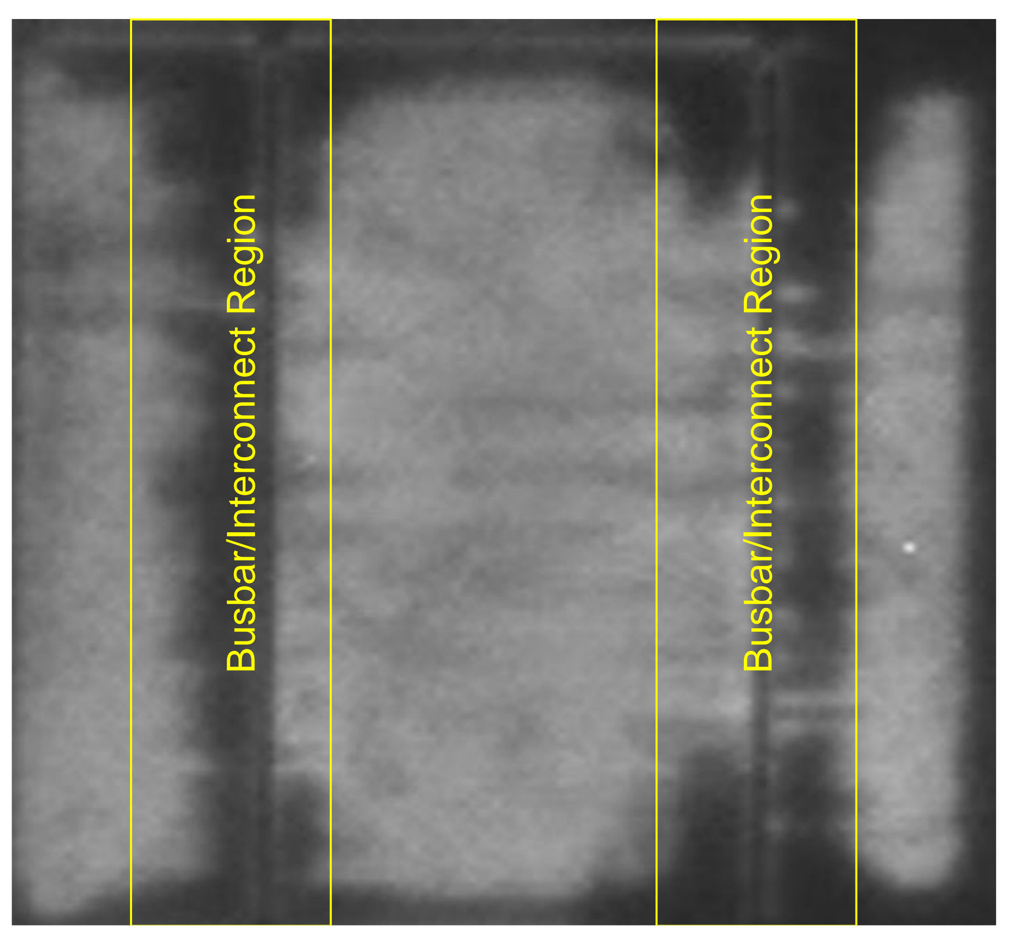
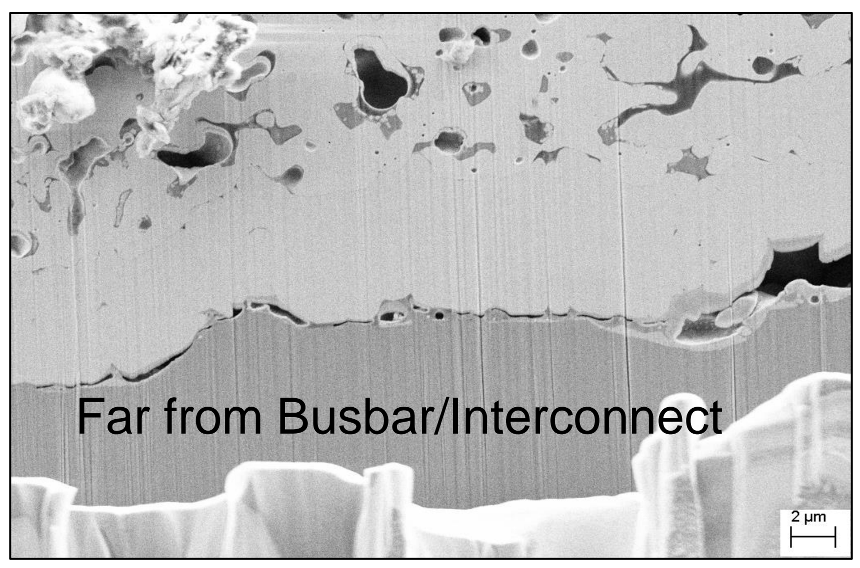
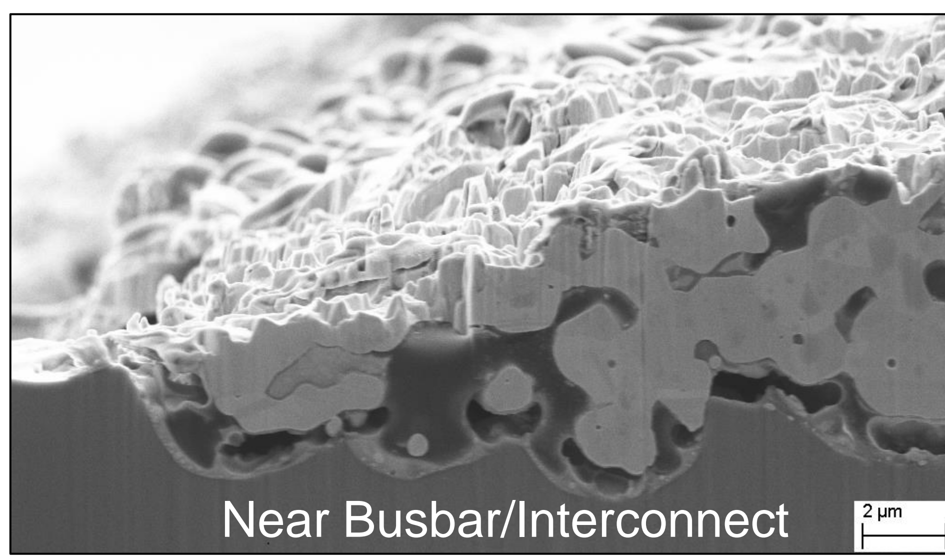
Device and Materials Characterization

- Multi Al-BSF

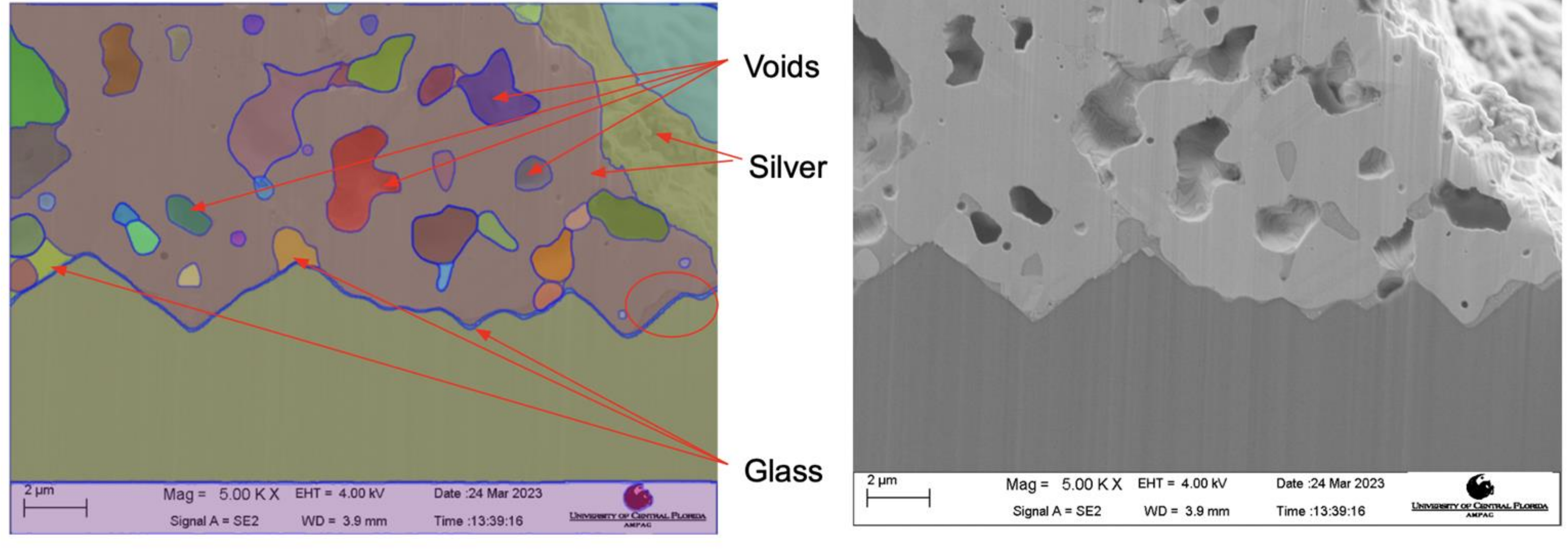






Automated Analysis of SEM Images

- Semantic segmentation of cross-sectional SEM images
- Again – goal is to make the evaluation of these images more automated and less subjective



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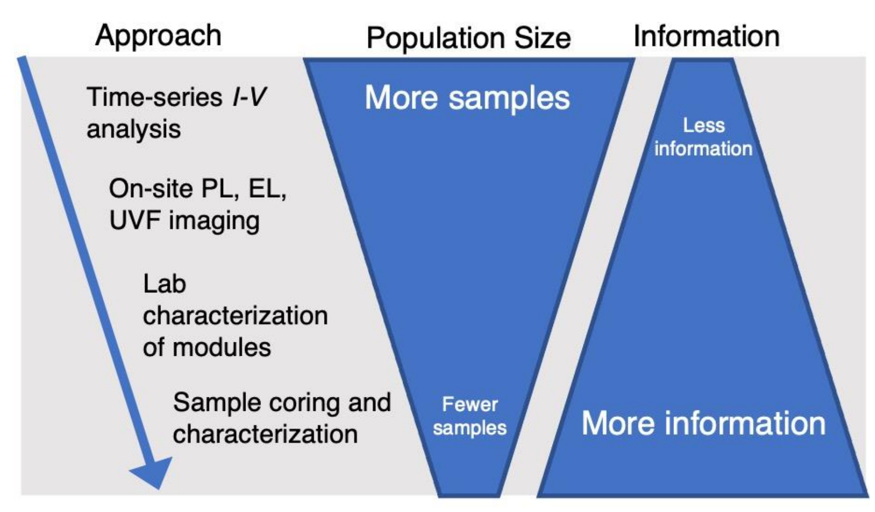
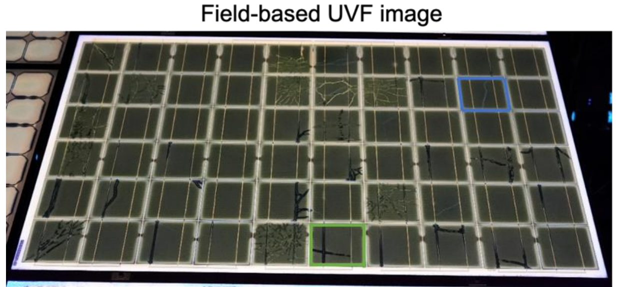
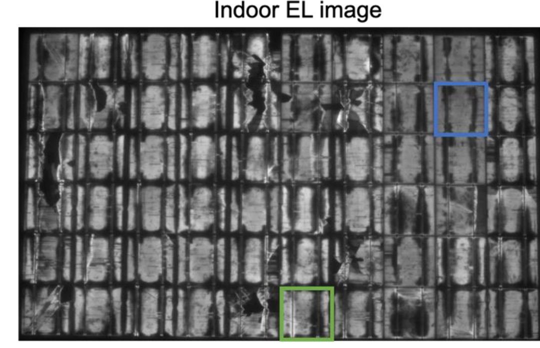
Multiscale Characterization of PV Modules in the Field

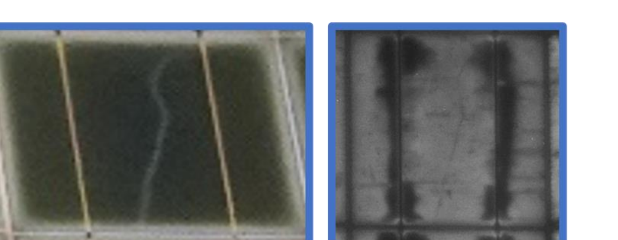


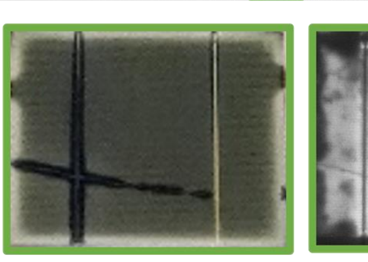
Field-based UVF image

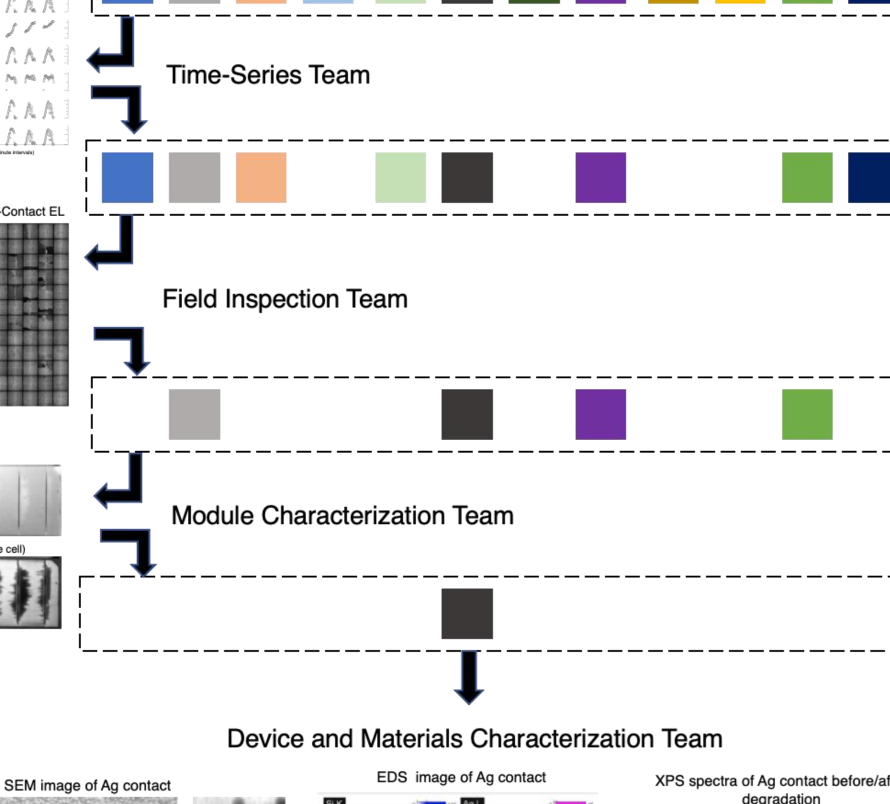


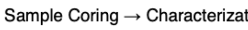
Indoor EL image

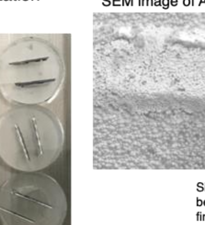


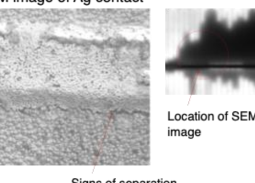












EDS image of Ag contact

XPS spectra of Ag contact before/after degradation

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Field Inspection Team

- Methods
  - Pole-mounted IR imaging
  - **Pole-mounted UV fluorescence (UVF) imaging**
  - Drone-based UVF imaging
  - Scanning photoluminescence (PL) and non-contact electroluminescence (EL)

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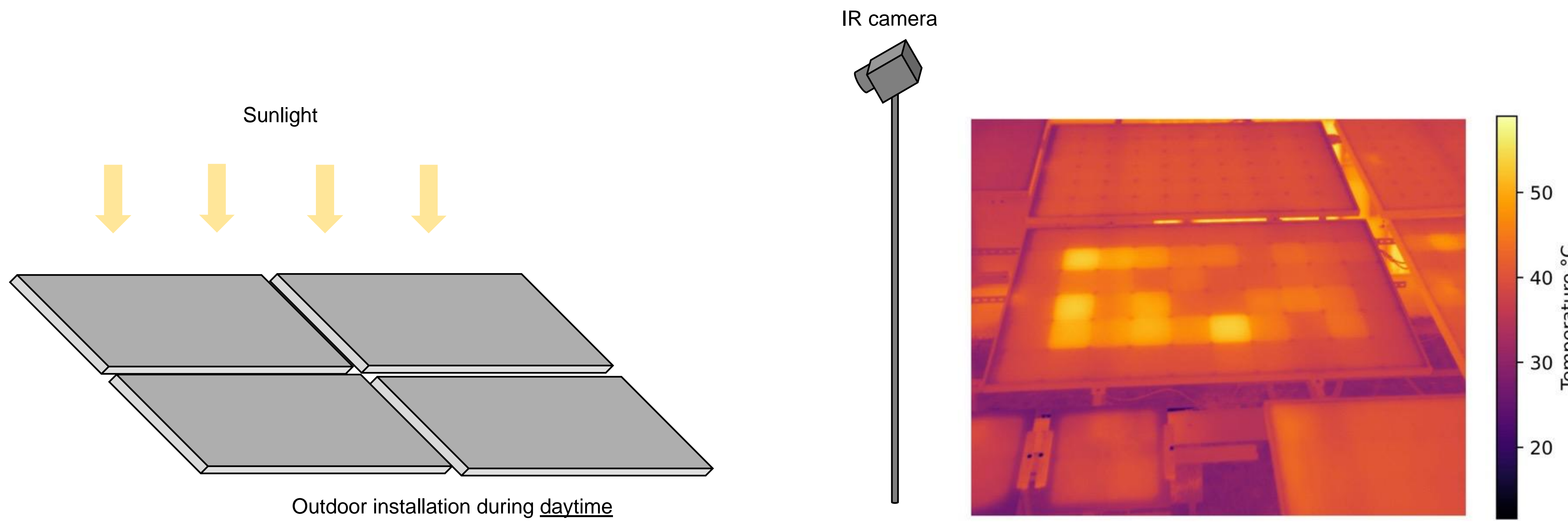
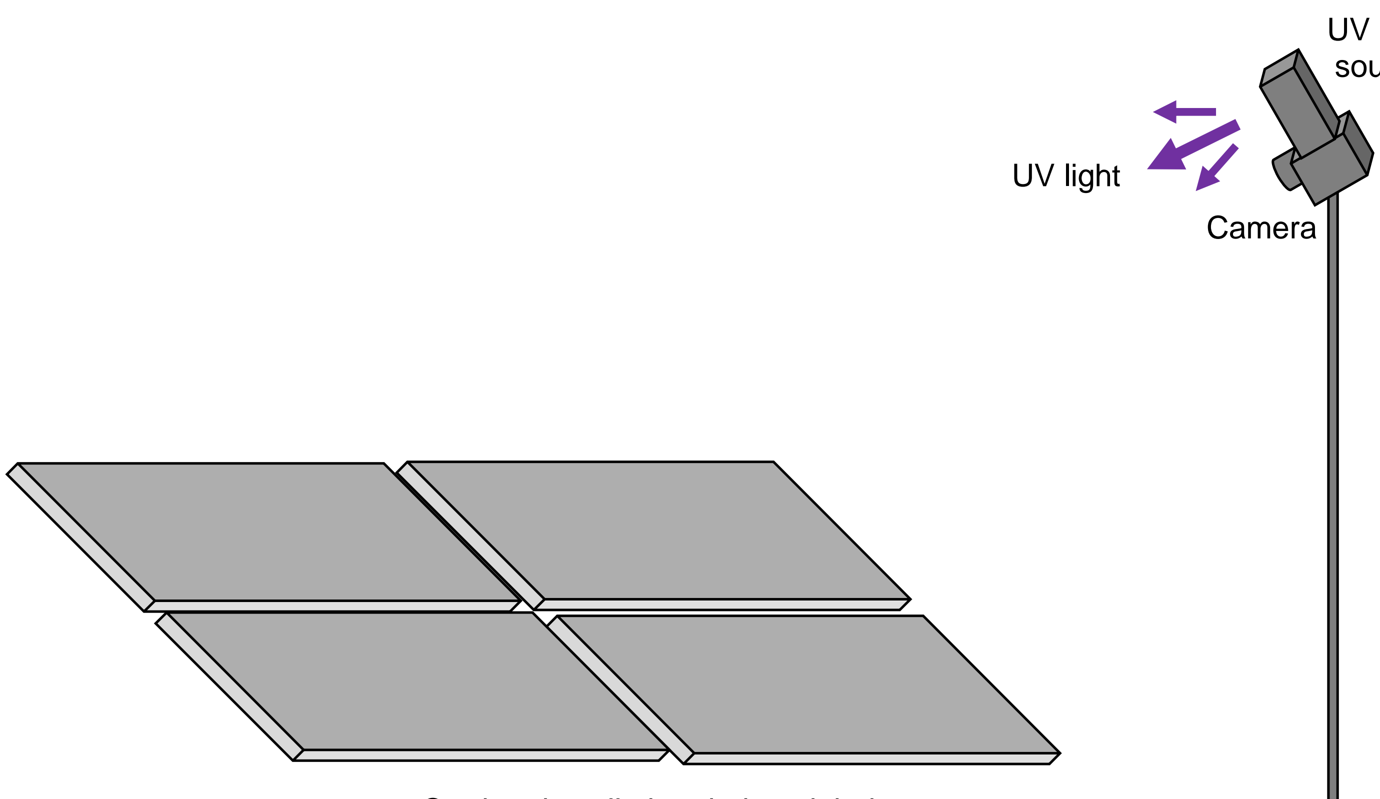
Pole-Mounted IR Imaging



Pole-mounted IR imaging setup

Pole-Mounted UVF Imaging



Outdoor installation during nighttime

Pole-mounted UVF imaging setup

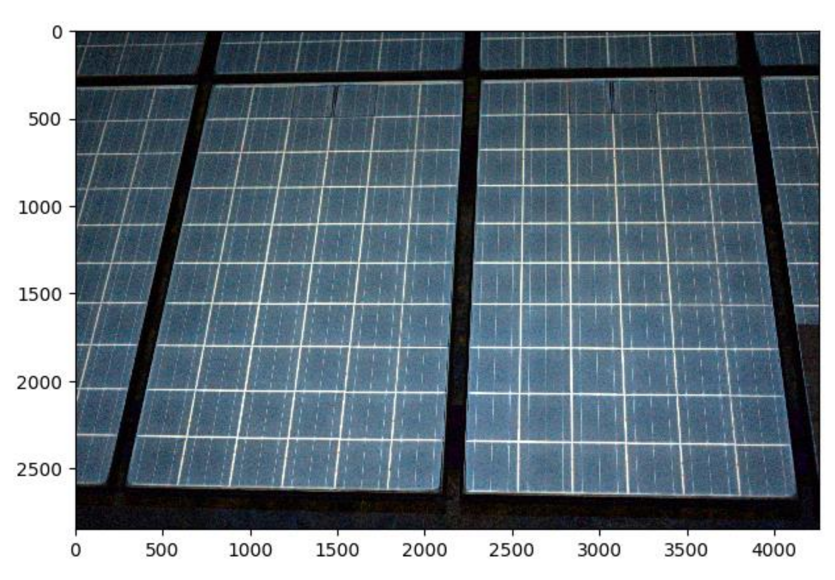
Pole-Mounted UVF Imaging

- What do you do with the images?
- Need to make sense of them, but there are too many to manually inspect
- Subject matter experts establish a process to interpret the patterns observed
- Then, images can become useful information
- Again, the analysis must be automated – there are far too many images to evaluate them all manually

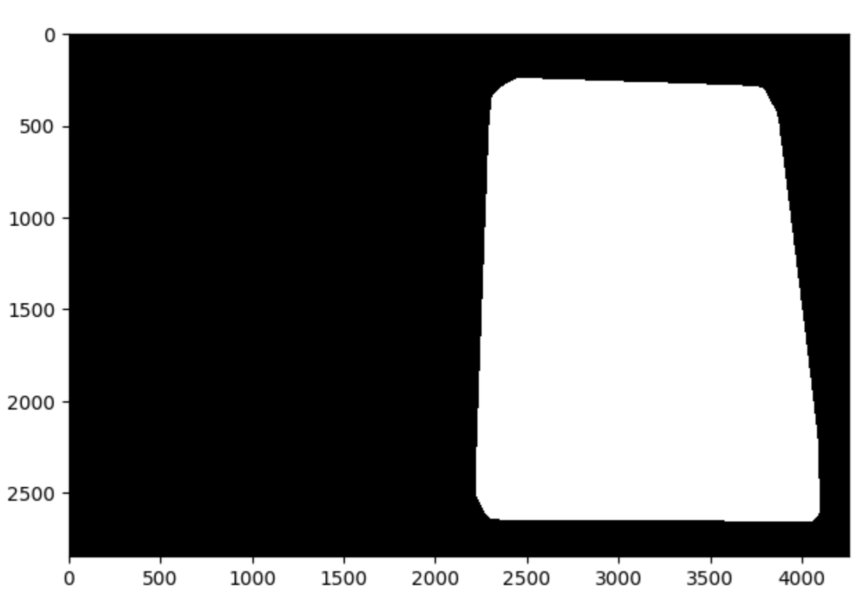
Feature	Description	Code	Examples
Rectangle	Bright square or rectangular pattern in the center of the cell. Oxygen ingress from the perimeter photobleaches fluorophores formed in the center of the cell, leading to dark perimeter.	Re	
Ring	Bright ring pattern slightly within cell perimeter. UV absorbing additives diffuse from the rear encapsulant to the front.	Ri	
Rectangle Crack	Dark lines within bright rectangle region. Oxygen ingresses through cracks quenching the fluorescence.	Re-C	
Ring Crack	More subtle than rectangle cracks, these appear as dark breaks in the rings.	Ri-C	
Busbar Crack	Dark line fully or partially along busbar in rectangle patterns (left) or breaks in ring along busbar length (right).	Re-C-BB or Ri-C-BB	
Bright Busbar	Bright UVF signature shown partially or fully along busbar length.	Re-BBB or Ri-BBB or BBB	
Dot Crack	Small round dark spot in rectangle pattern due to a short crack such as an X-crack.	Re-DC	
Bright Crack	Crack lines that appear bright due to UV absorbing additives diffusing into crack regions or backsheet UVF.	Re-BRC or Ri-BRC	
Hot Spot, Cell, Region	A cell or region is much brighter than the rest of the cells in the module. The examples show two hotspots and bright UVF in front of mounting rails glued to a thin film module.	Re-HS	
Gridline Darkening	Dark lines perpendicular to the busbar. Often accompanied by cracks beneath the busbar.	Re-GD	
Soiling	Dark spots, streaks, or otherwise irregular patterns related to soiling.	Re-SL or Ri-SL	
Encapsulant Delamination	Artificially bright regions due to reflection. Often starts at busbars.	Re-DL or Ri-DL	
Junction Box Sealing Issues	Characteristic dark region in front of junction box location that leads to dark region (left, rectangle) or dark region with warped rings (right, ring).	Re-JB or Ri-JB	

UVF Image Analysis

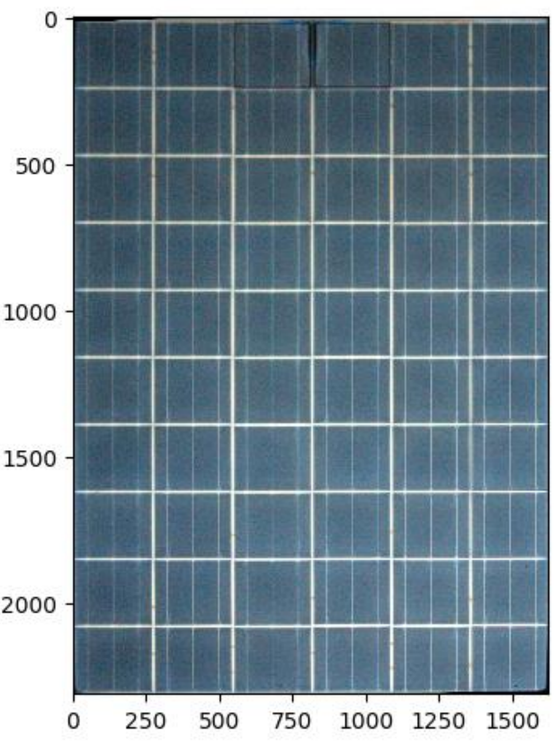
Input Image



Mask-RCNN Mask

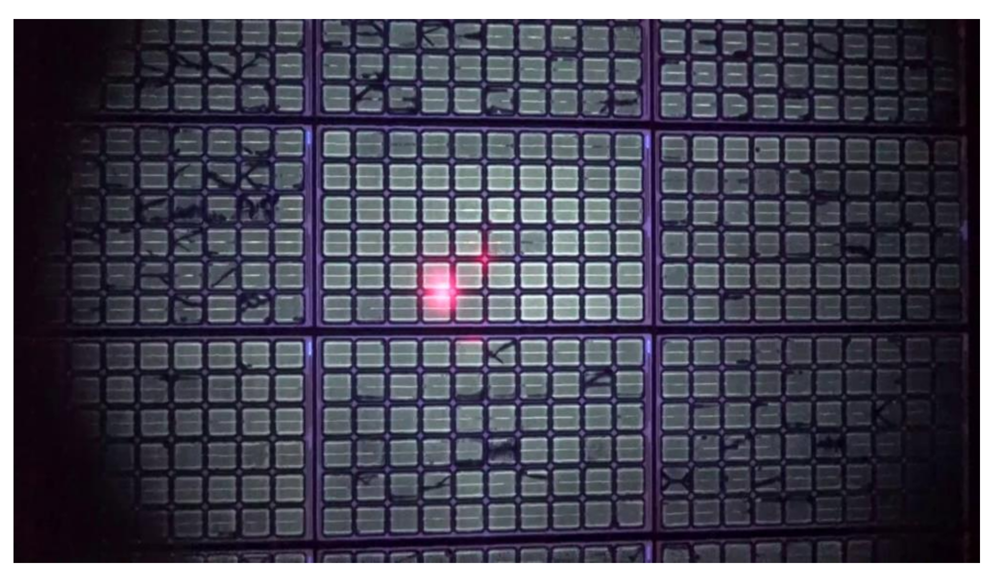


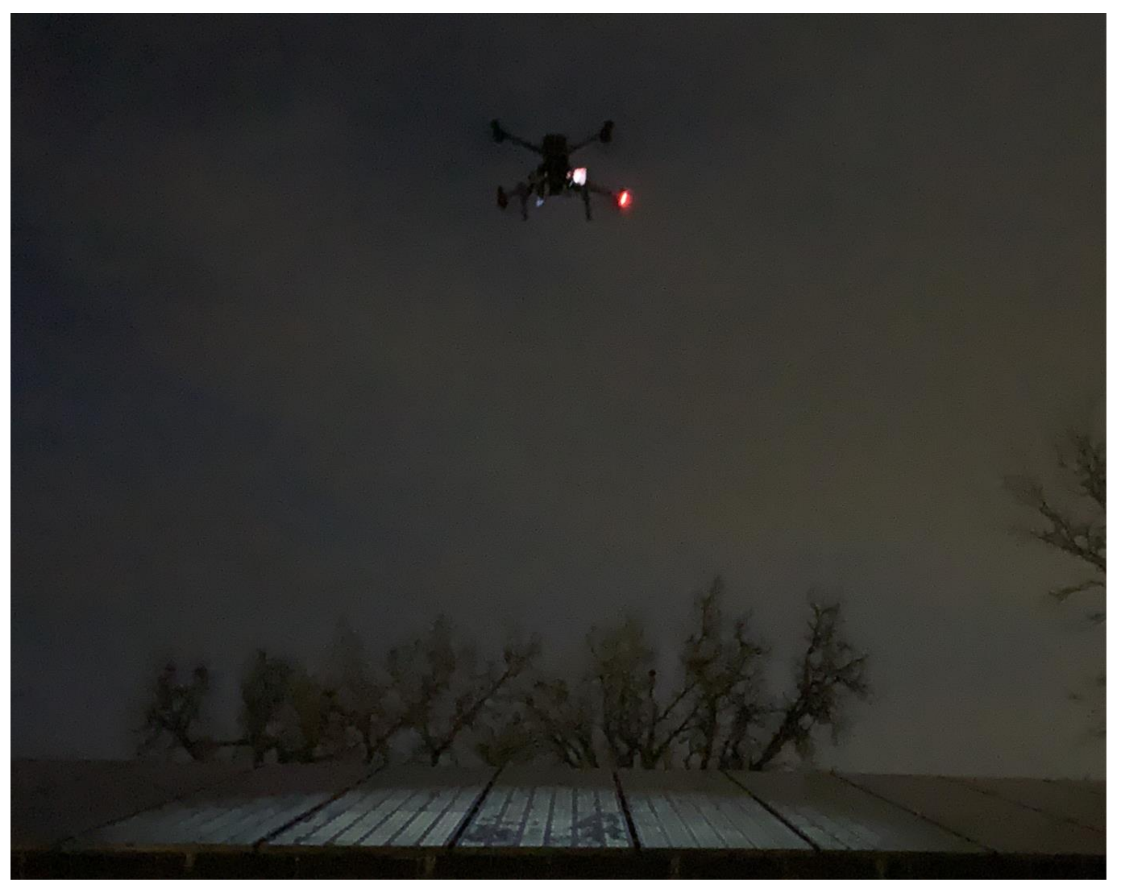
Planar Output



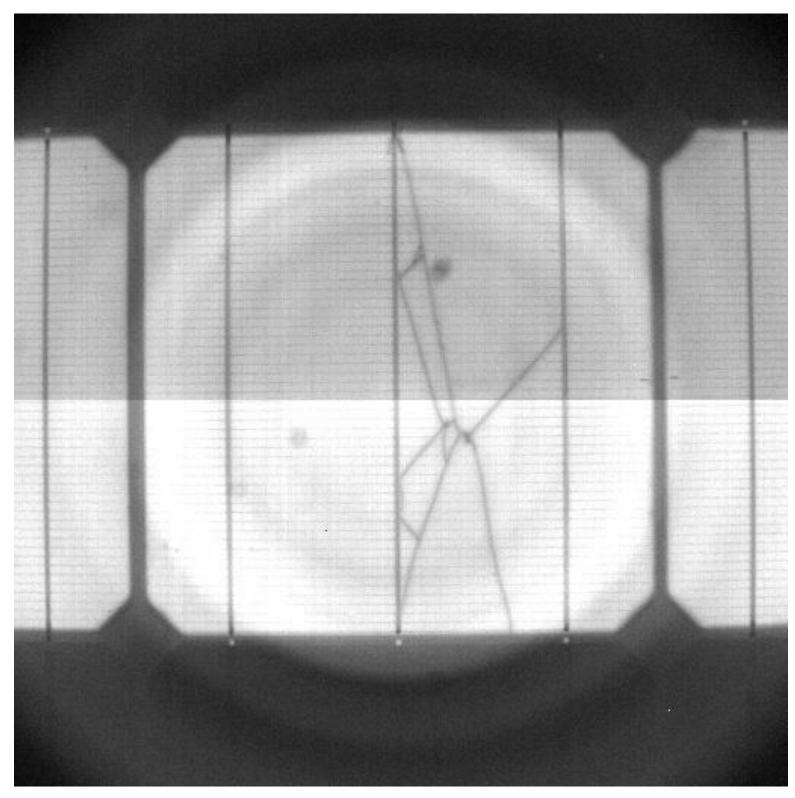
Drone-Based UVF with UV LEDs

- BrightSpot has performed several drone flights using a UV-LED payload
- Good for a low volume sites and for panels that fluoresce brightly





Outdoor PL and EL Imaging



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Need for Data FAIRification

Making Datasets & Models FAIR

- By “FAIRification”

Enables Models to find Data

- And Data to find Models

So that they can advance

- Without human intervention

This is an aspect of the Semantic Web

- And Resource Description Framework
- Hbase triples are an example of RDF

FAIR Data very active in Europe

- U.S. efforts just starting now

What is FAIR DATA?

Data and supplementary materials have sufficiently rich metadata and a unique and persistent identifier.
FINDABLE

Metadata and data are understandable to humans and machines. Data is deposited in a trusted repository.
ACCESSIBLE

Metadata use a formal, accessible, shared, and broadly applicable language for knowledge representation.
INTEROPERABLE

Data and collections have a clear usage licenses and provide accurate information on provenance.
REUSABLE

M. D. Wilkinson et al., “The FAIR Guiding Principles for scientific data management and stewardship,” Sci. Data, vol. 3, no. 1, pp. 1–9, Mar. 2016, doi: 10.1038/sdata.2016.18.

Future Work

- Through MDS^3 Center of Excellence with CWRU and Sandia (Elliott Fowler and Matthew Kottwitz), looking to adapt some of these process to electronic component reliability

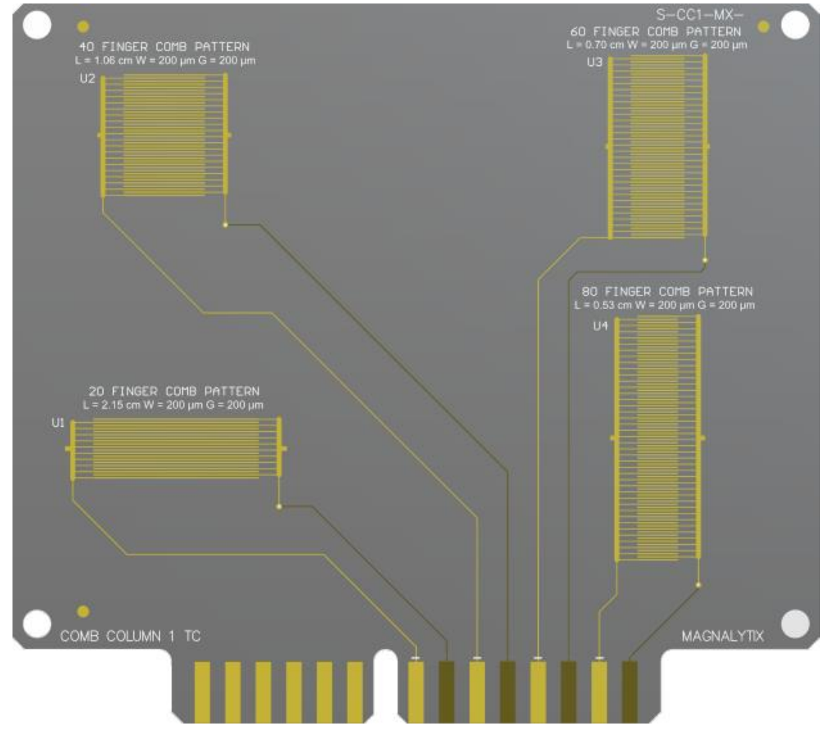

Figure: Courtesy of E. Fowler (Sandia)

Acknowledgements

UCF
Faculty: Kristopher O. Davis, Mengjie Li, Mubarak Shah
Postdoctoral Researchers: Dylan J. Colvin, Eric J. Schneller, Haider Ali
Students: Geoffrey Gregory, M. Jobayer Hossain, Nafis Iqbal, Jannatul F. Mousumi, Max Liggett, Rafaela Frota, Joseph Fioresi, Sofia Oliveira

Collaborators
CWRU: Roger H. French, Laura Bruckman, Jen Braid, Ina Martin
Tau Science: Greg Horner
BrightSpot Automation: Andrew Gabor, Phil Knodle
Sandia: Elliott Fowler, Matthew Kottwitz

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