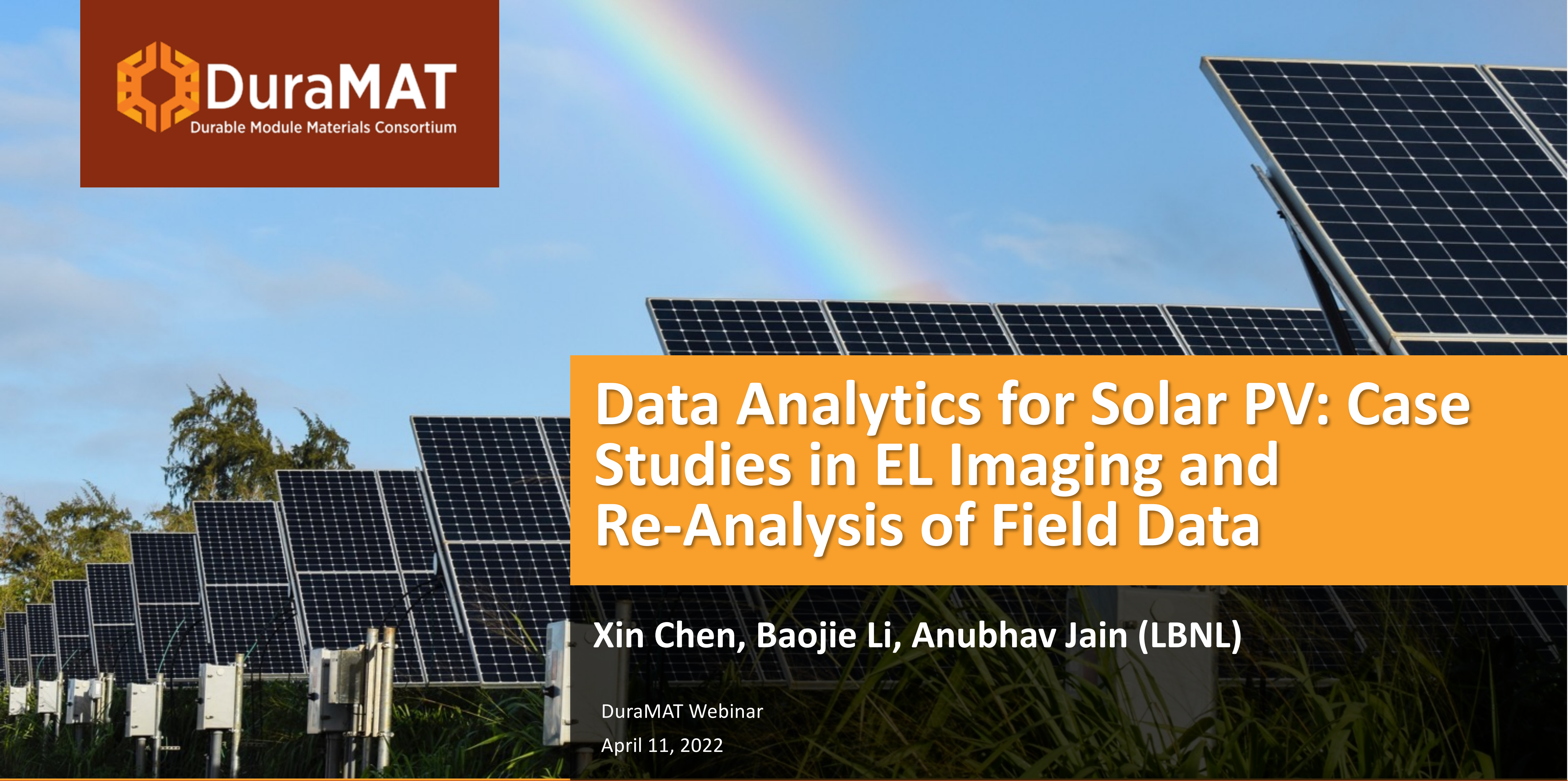


DuraMAT
Durable Module Materials Consortium

Data Analytics for Solar PV: Case Studies in EL Imaging and Re-Analysis of Field Data

Xin Chen, Baojie Li, Anubhav Jain (LBNL)

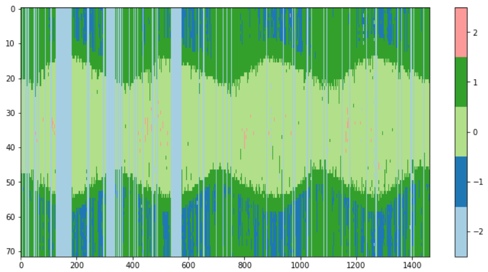
DuraMAT Webinar

April 11, 2022

CONTENT

PART 1 Automatic Defect Identification in Electroluminescence (EL) Images of Solar Modules

PART 2 Field PV Data Mining Using PVPRO for Degradation Analysis



PART 1

Defect Identification in EL Images of Solar Modules

OUTLINE:

- Automatic module transform and cell crop

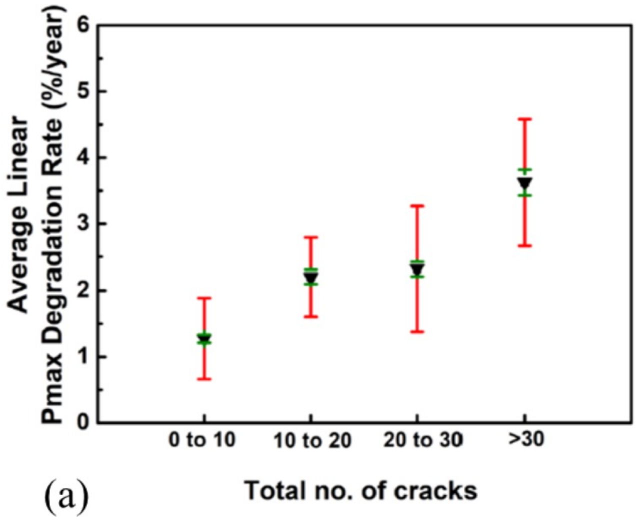
- Automatic defect identification with deep learning
  - Analyze position distribution of defects on solar modules

- Automatic crack segmentation with deep learning
  - Predict worst-case degradation area based on crack patterns
  - Explain the mechanism underpinning the correlation between crack features and degradation (IV data)

- PV-Vision: Open-source package for EL image analysis of PV modules
  - https://github.com/hackingmaterials/pv-vision

Background

- The power loss of solar modules is considered a threaten to the durability of the solar cells
- Cracks can propagate and lead to the electrical isolation and accelerate the degradation rate
- Other defects induced by fire, humidity, etc. can also cause power loss
- Electroluminescence imaging is used to inspect defects on solar modules



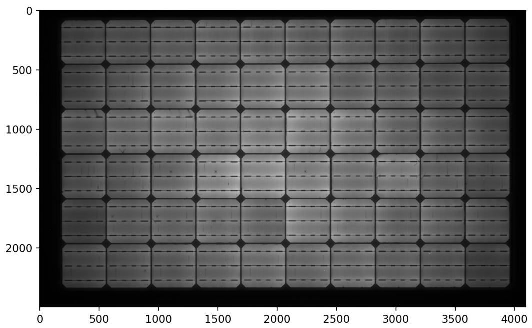
Relation of degradation rate and crack number[1]

- How do cracks influence degradation?
- How to collect the features of the cracks from thousands or more solar modules?
- How to quickly determine whether the module in field needs to be replaced due to defects?
- Is there correlation between EL images and IV parameters (which determines degradation)?
- ……

Electroluminescence image of solar module in lab

[1] N. Shiradkar, "Key Results from All India Survey of PV Module Reliability: 2016," in NREL PV Reliability Workshop, Lakewood, CO, 2018.

Image preprocess



Raw image

Binary threshold

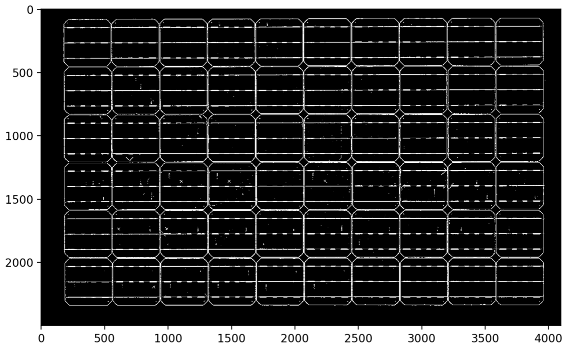
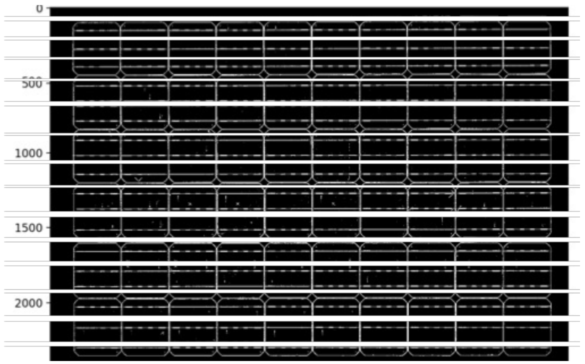


Image after binary threshold

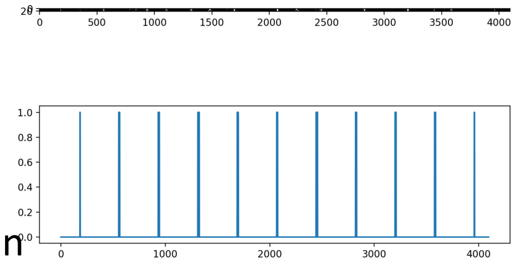
Split along axis



Schematic diagram of splits

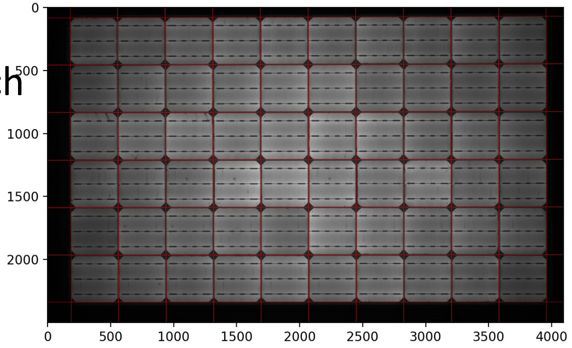
Gray scale sum up

Detect edges in each split



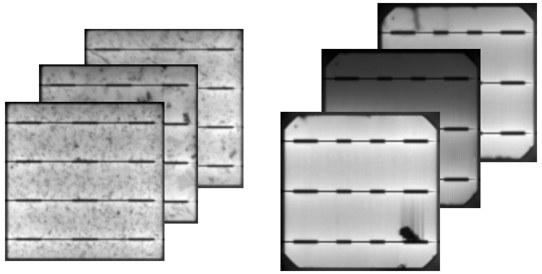
Detected internal edges from split

Linear fit edges in each split



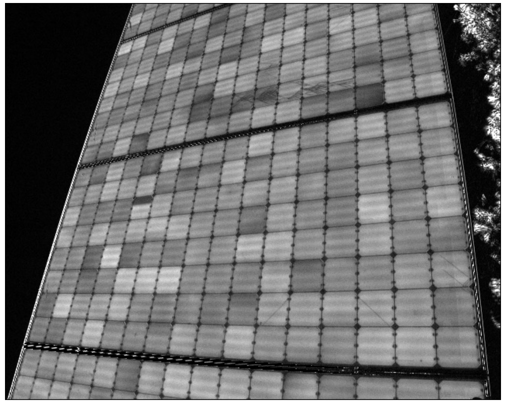
Detected internal edges from module

Crop out



Around 30,000 single cells cropped out with ~90% successful rate, excluding truncated(~3%) or poorly exposed(~10%) pictures

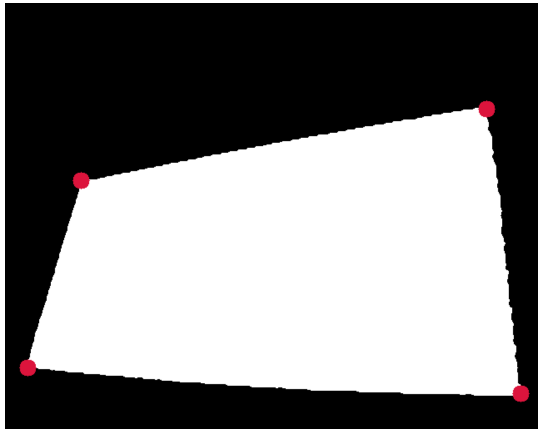
Image preprocess



Raw image (field)

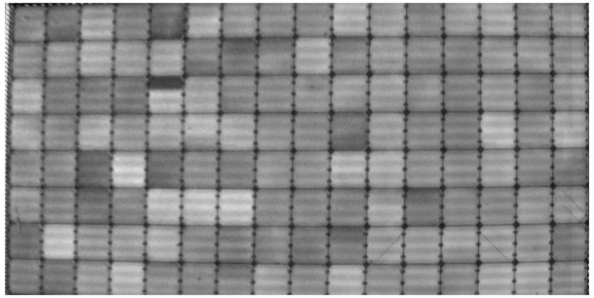
Semantic segmentation

Corner detection



Mask with corner detection

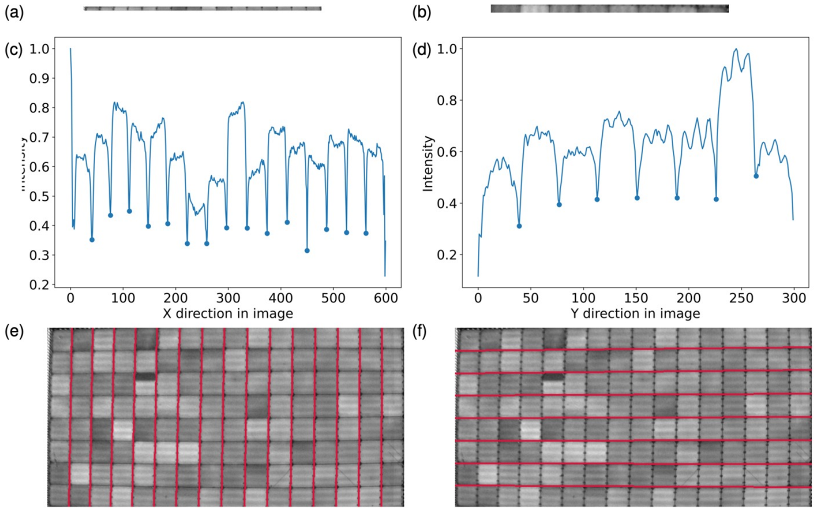
Perspective transform



Transformed solar module

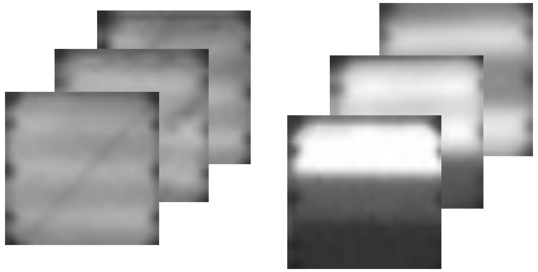
Gray scale sum up

Detect edges



Detected internal edges from module

Crop out

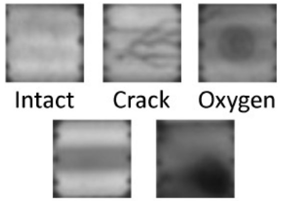


98.6% (18954/19228) modules successfully transformed

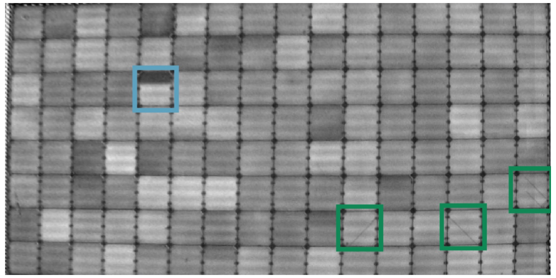
Deep learning methods

- Image analysis of EL images

classifier → LeNet, ResNet

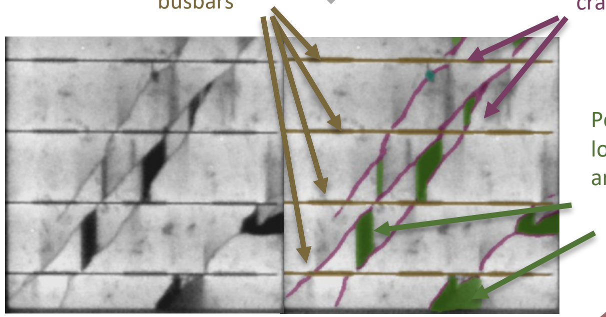


Object detection → YOLO model



Defect identification

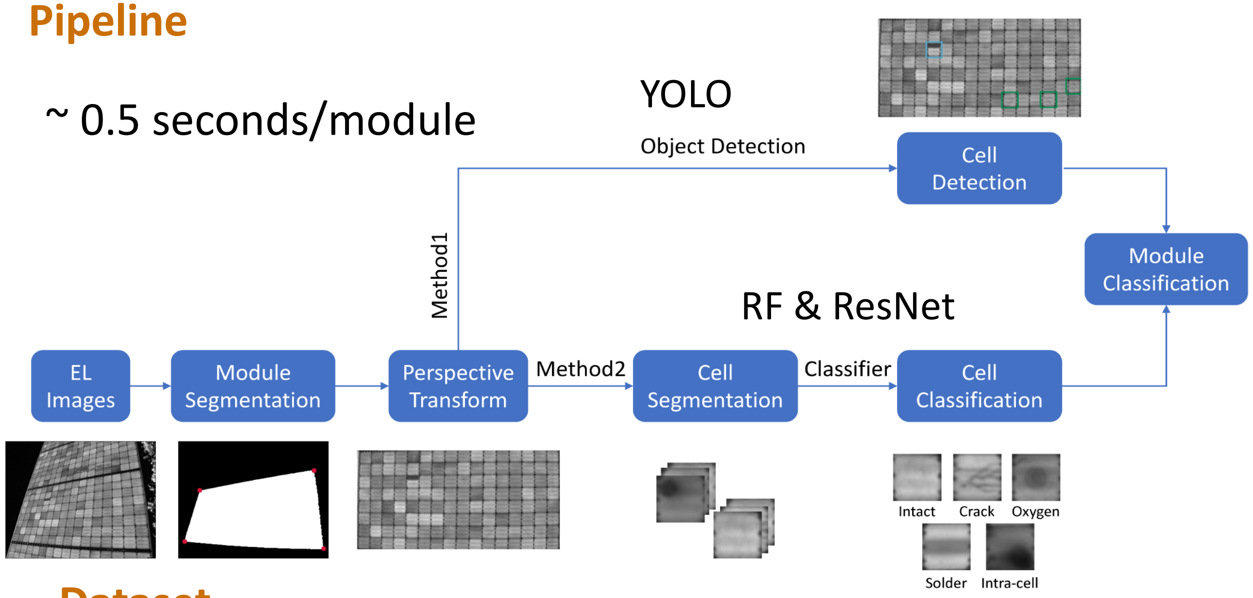
Semantic segmentation → Unet model



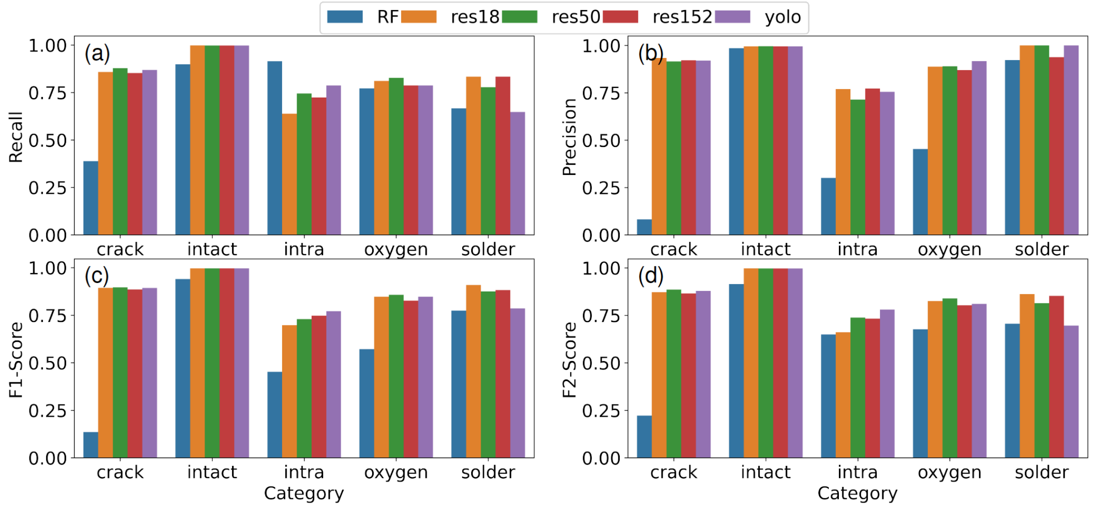
Crack segmentation

Defect identification

Pipeline



Evaluation



$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

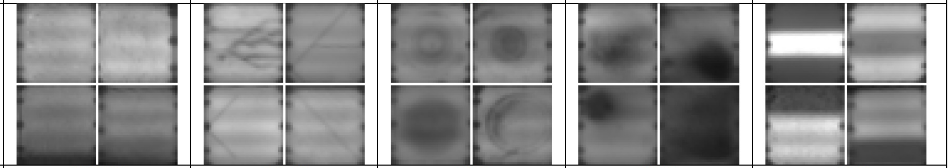
$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$F_1 = \frac{\sum 2\text{TP}}{\sum 2\text{TP} + \text{FN} + \text{FP}}$$

$$F_\beta = (1+\beta^2)\frac{\text{Precision} * \text{Recall}}{\beta^2 * \text{Precision} + \text{Recall}}, \beta = 2 \text{ for } F_2$$

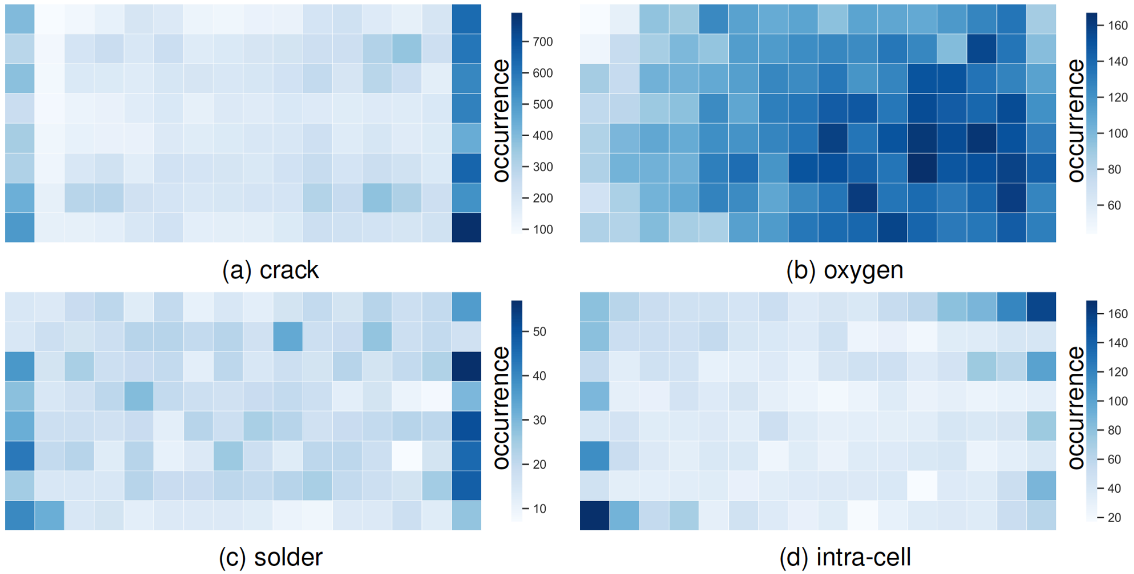
Model	YOLO	ResNet18	ResNet50	ResNet152	RF
Avg F1 (val)	0.86	0.87	0.87	0.87	0.57
Avg F1 (test)	0.78	0.83	Not tested		

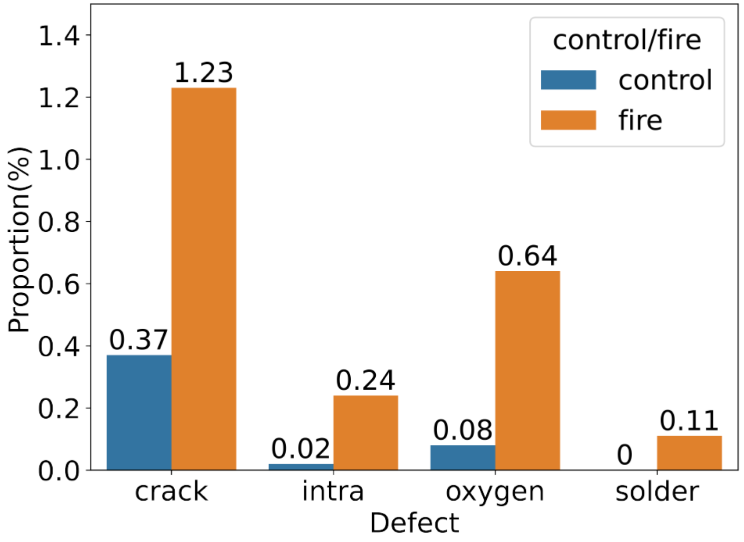
Dataset

Category	Intact	Crack	Oxygen	Intra-cell	Solder
Image					
Training 762 modules	95048 97.44%	1367 1.40%	709 0.73%	279 0.29%	143 0.15%
Validation 134 modules	16618 96.87%	345 2.01%	127 0.74%	47 0.27%	18 0.10%
Testing 129 modules	16082 97.4%	244 1.48%	126 0.76%	45 0.27%	17 0.10%

Defect identification

Position distribution



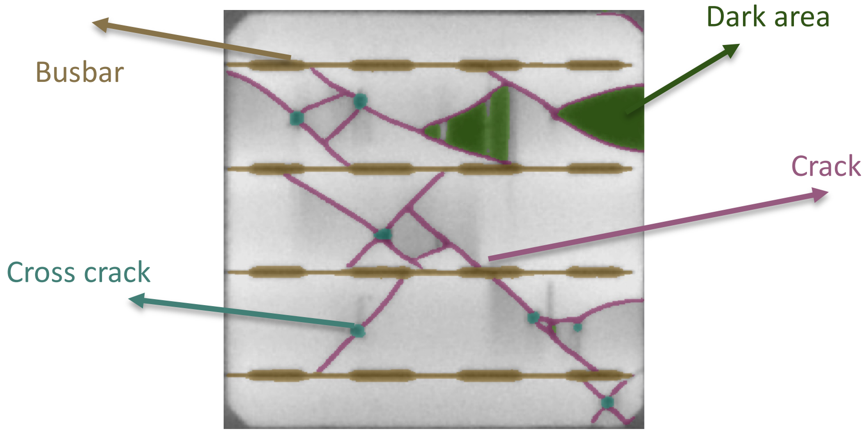


Distribution of defects on 18,825 PV modules affected by fire. Here each heatmap shows the quantity of defects observed in each cell in a 16x8 solar module. Defects are recognized by YOLO model. The right-hand side of the image is the side of the module closest to the ground during the EL survey.

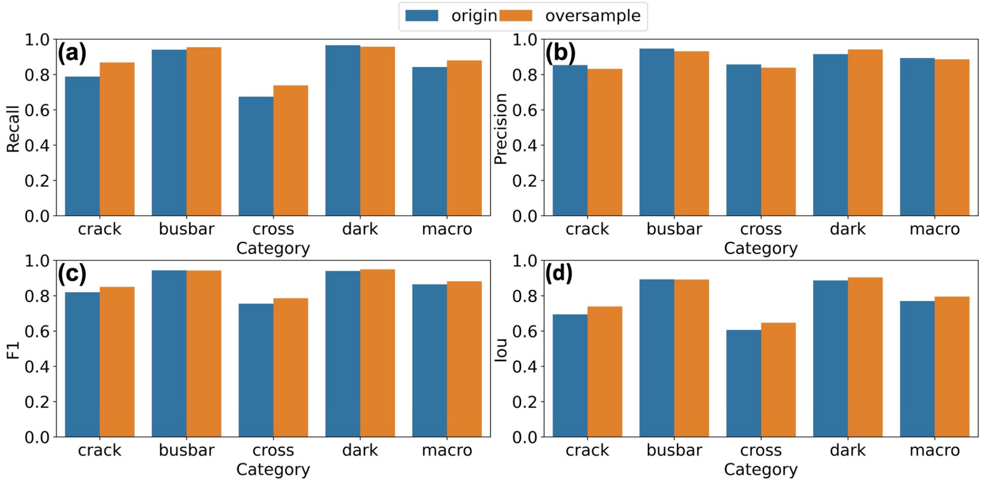
Crack segmentation

Dataset

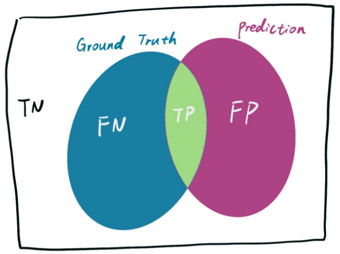
Dataset	Images	Crack	Busbar	Cross	Dark
Train	1272	493	1272	323	270
Train oversample	1765	986	1765	598	538
Val	206	79	206	57	40
Test	359	120	359	97	68
Test crack	322	290	322	225	171



Evaluation



Dataset	Avg Precision	Avg Recall	Avg F1	Avg IoU
Val	0.886	0.879	0.882	0.795
Test	0.883	0.867	0.875	0.782
Test crack	0.884	0.852	0.867	0.770

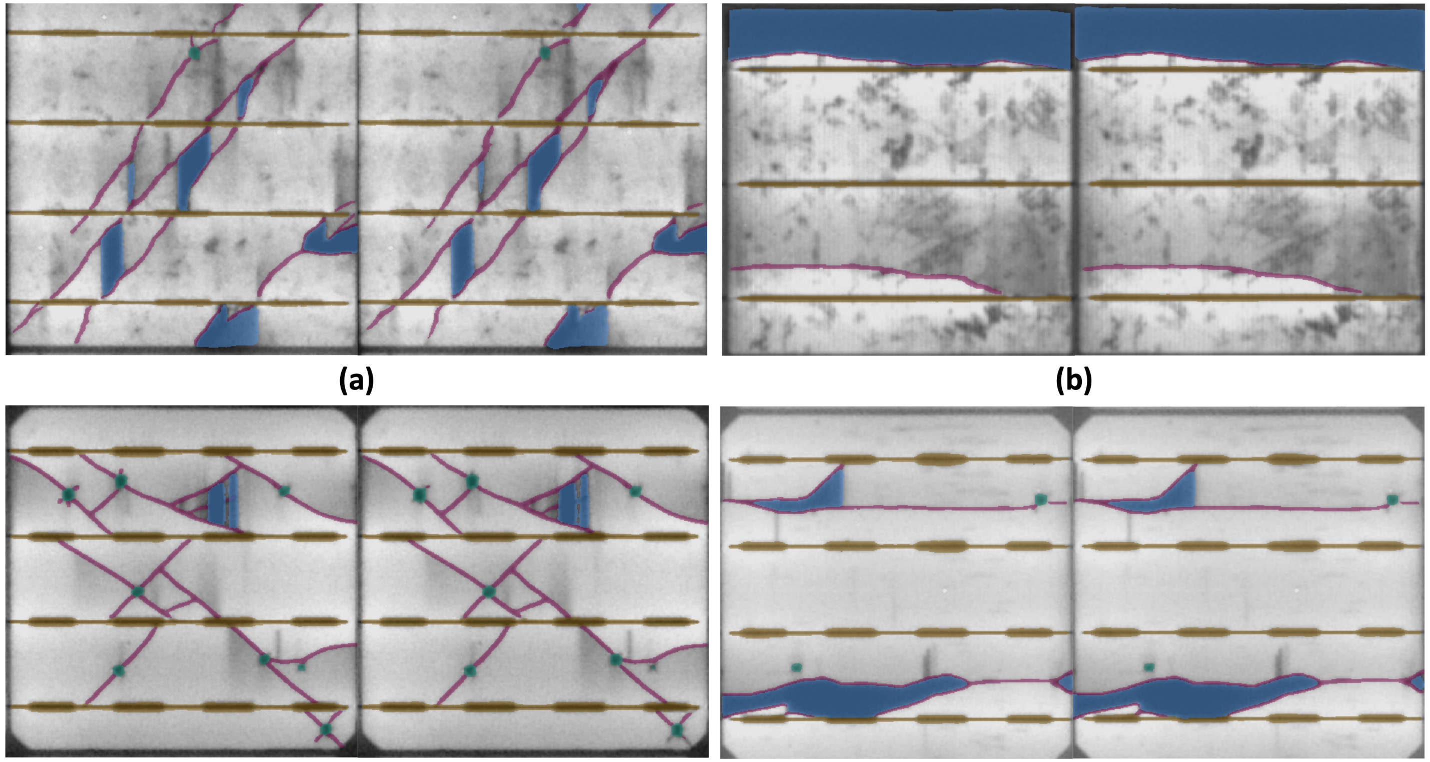


$$\text{Precision} = \frac{\sum_I \text{TP}}{\sum_I \text{TP} + \text{FP}}; \text{Recall} = \frac{\sum_I \text{TP}}{\sum_I \text{TP} + \text{FN}}$$

$$\text{F}_1 = \frac{\sum_I 2\text{TP}}{\sum_I 2\text{TP} + \text{FN} + \text{FP}}; \text{IoU} = \frac{\sum_I \text{TP}}{\sum_I \text{TP} + \text{FN} + \text{FP}}$$

Crack segmentation

Performance



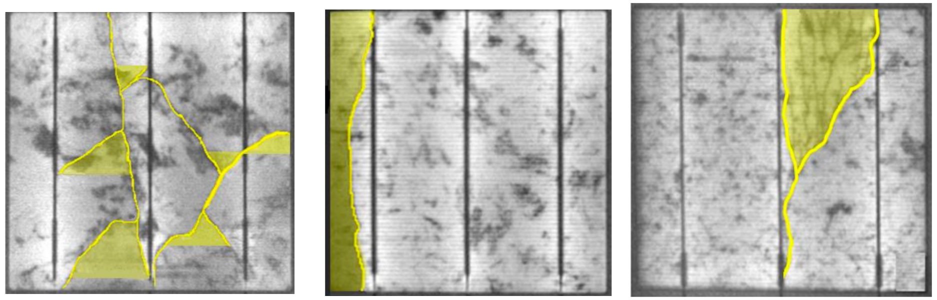
(a) (b) (c) (d)

Left: ground truth Right: prediction.

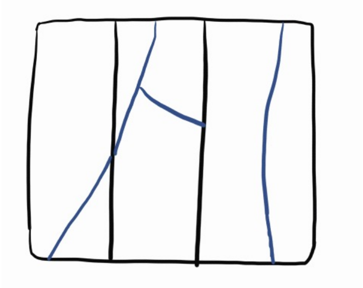
Crack segmentation

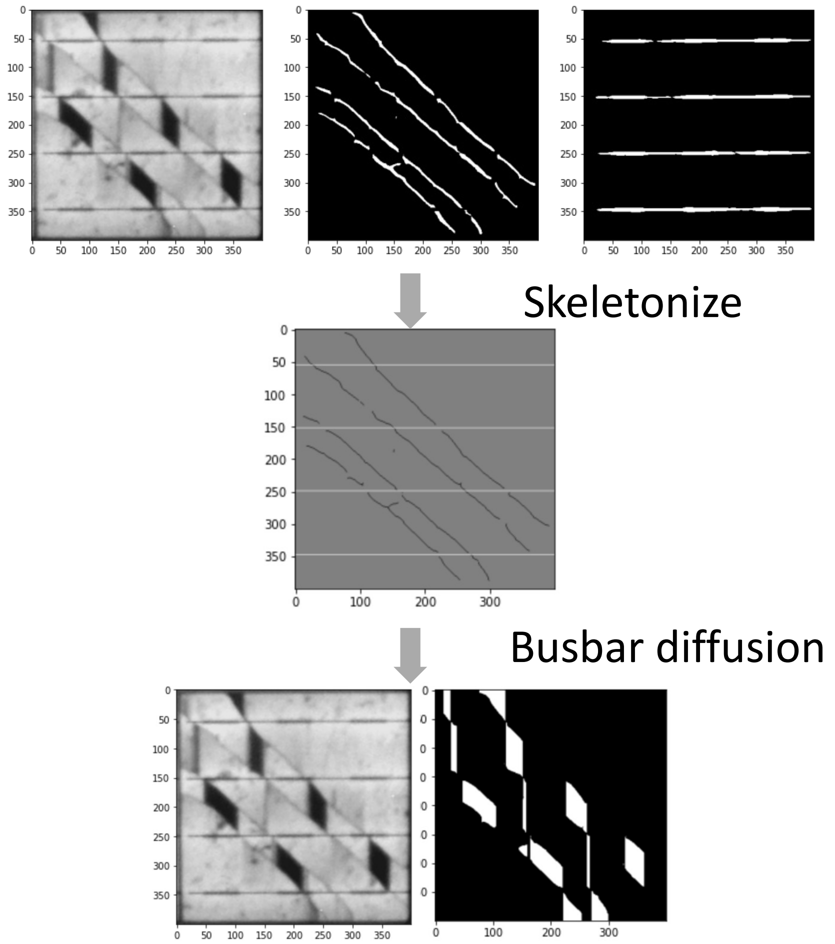
Inactive area prediction

Worst case: isolated part becomes inactive [1]



Algorithm: Horizontal diffusion of busbars



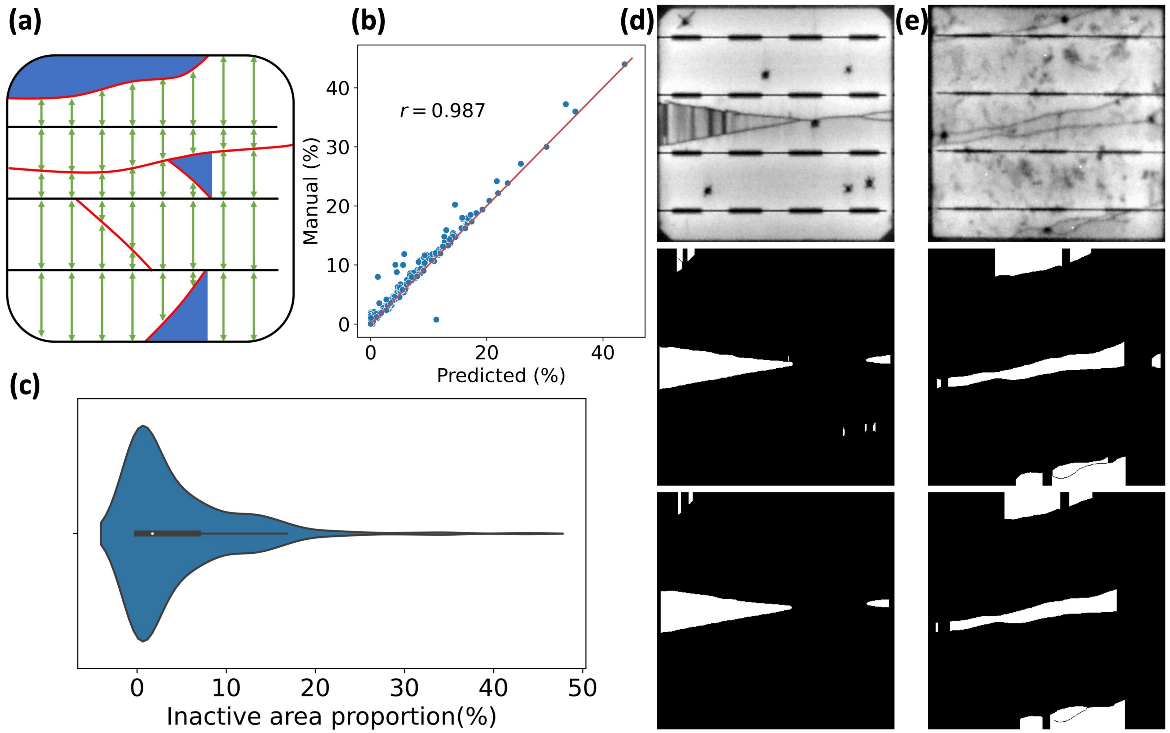


Inactive area: 10.23%

[1] MBJ, "MBJ Services - Solar Module Judgment Criteria EL," 2019.

Crack segmentation

Result



In the testing set:

- 75% of cells have inactive areas lower than 6.86%, and the average proportion is 4.54%.
- 31.4% of cells have zero inactive areas, which means they have insignificant cracks such as the one in the middle of figure (a).

To do

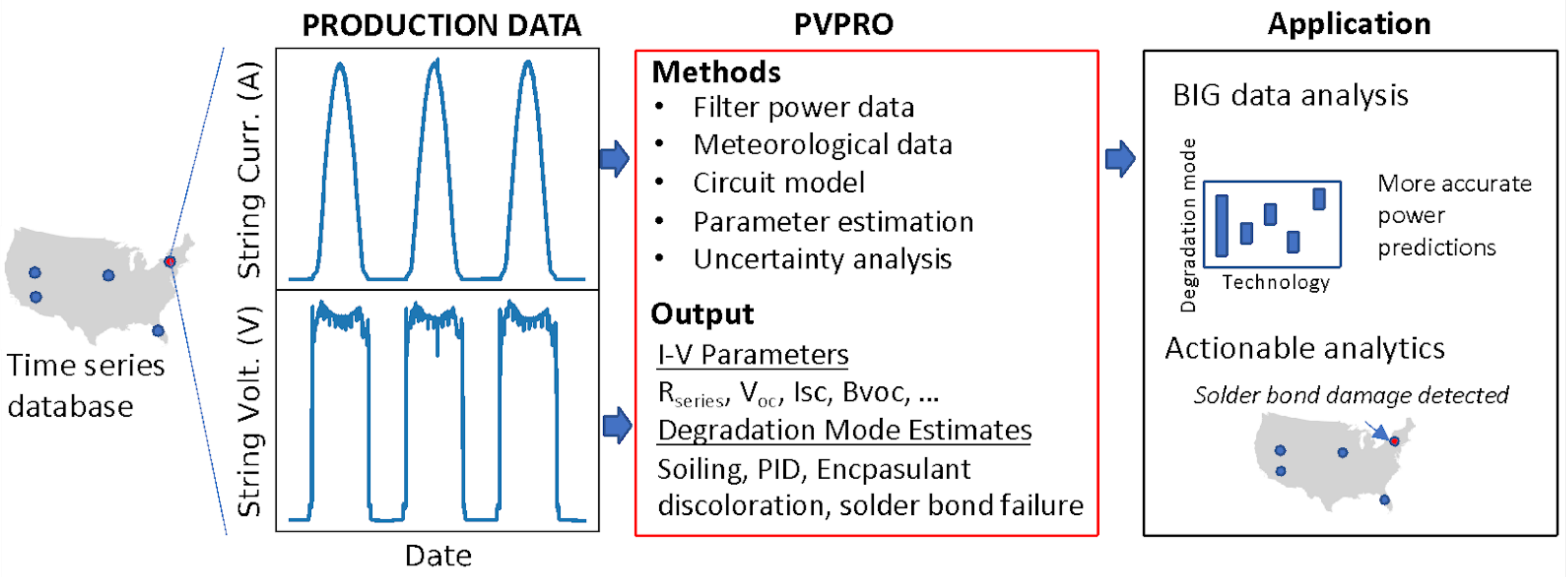
- Explain the mechanism underpinning the correlation between crack features and degradation (IV data)
- Explore correlation between EL images and IV data
- Predict output power with EL images

PART 2

Field PV Data Mining Using PVPRO for Degradation Analysis

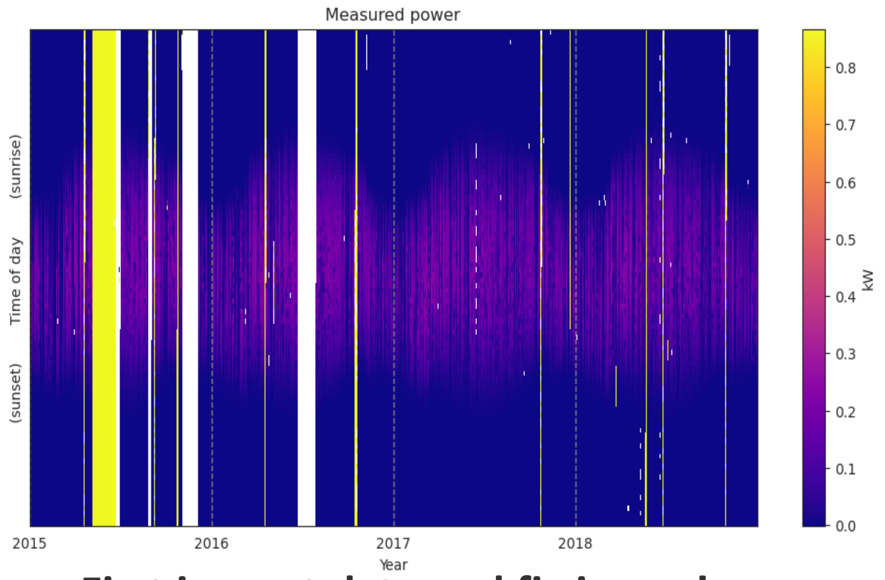
OUTLINE:

- **Goal:** Use operation data (DC current, DC voltage, module temperature and plane-of-array irradiance) to determine time-evolution single-diode model parameters of PV modules.



Methods – Data Cleaning

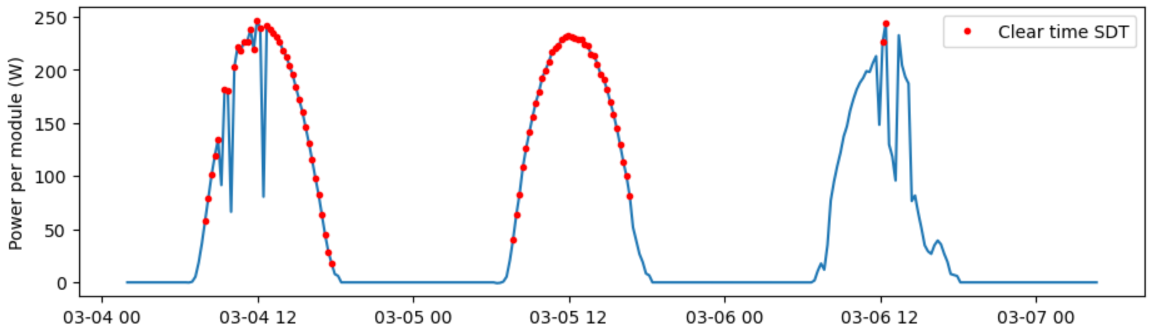
Basic Quality Checks



- **First inspect data and fix issues!**
- Use solar data tools for basic quality checks:
  - ➢ Time shifts.
  - ➢ Capacity changes.
  - ➢ Data completeness
  - ➢ Bad data detection.
  - ➢ Visualization.

Clear time detection

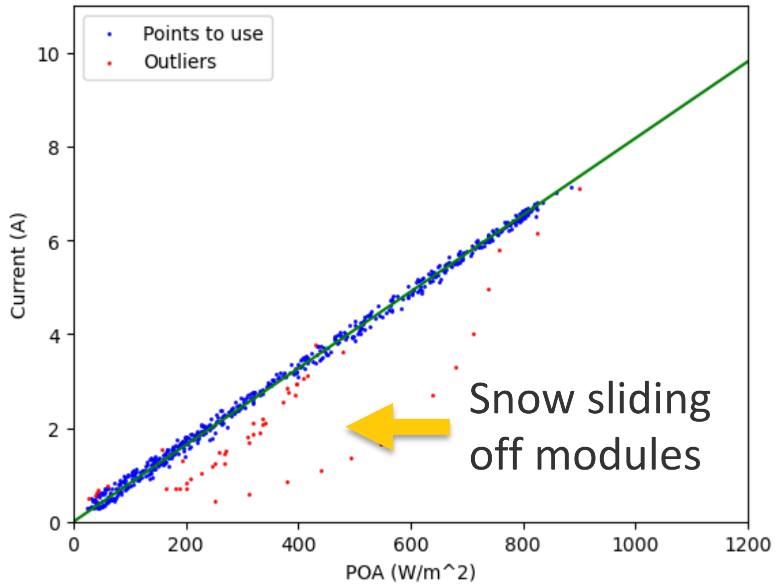
- Developed data-centric clear time filter (Solar data tools).
- Clear if:
  - ➢ Power is close to clear sky model and
  - ➢ Second-order difference is close to second-order difference for clear sky model.



Methods – Data Cleaning

Current irradiance filter

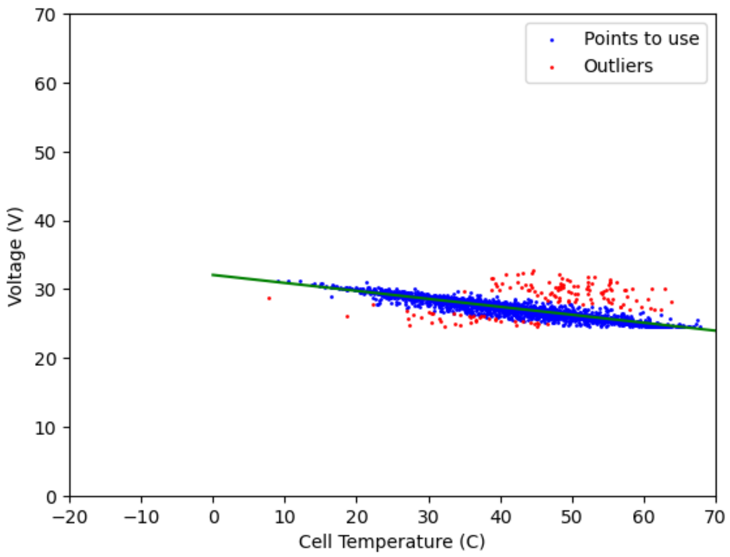
- Current at MPP is expected to be proportional to plane-of-array (POA) irradiance.



- **Method:** Use Huber regressor (scikit-learn) to perform a linear fit between current and irradiance, classifying points as points to use or outliers.

Temperature voltage filter

- Maximum power voltage and temperature should be linearly related.

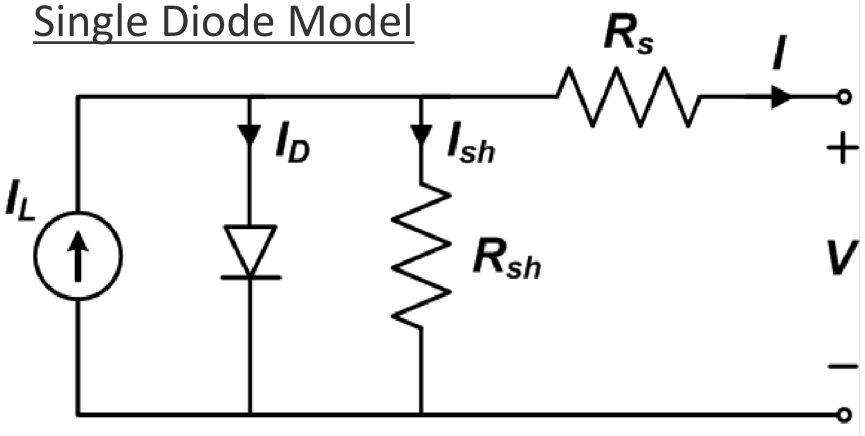


- Deviations can occur if:
  - MPP tracking errors.
  - MPP tracking window limits.

- **Method:** Use Huber regressor to perform a linear fit between voltage and temperature, classifying points as points to use or outliers.
- (Only classify as outliers if POA > 200 W/m2)

Methods – Maximum Power Point Fitting

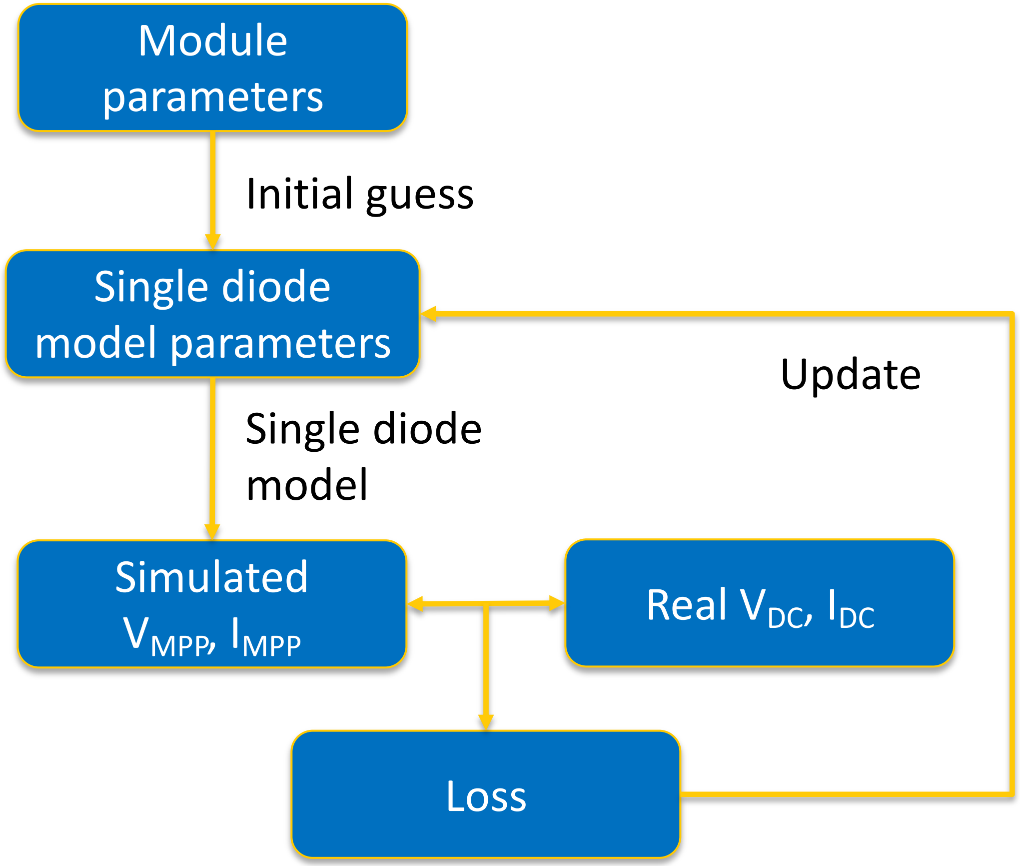
Single Diode Model



$$I = I_L - I_O\left[\exp\left(\frac{V + IR_S}{nV_{th}}\right) - 1\right] - \frac{V + IR_S}{R_{SH}}$$

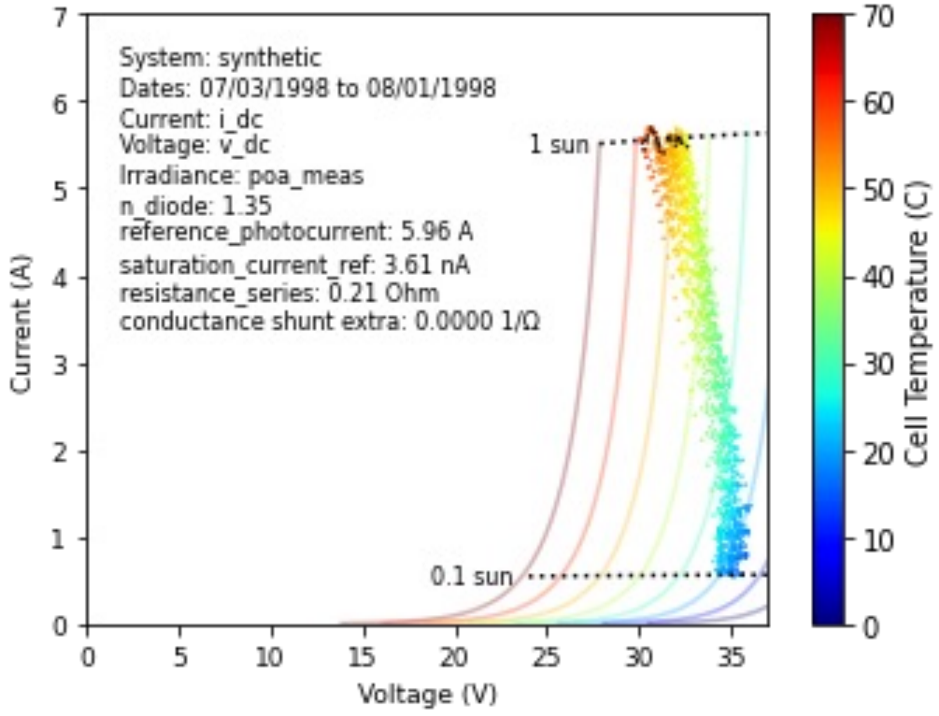
PVPRO uses 5 fit parameters:

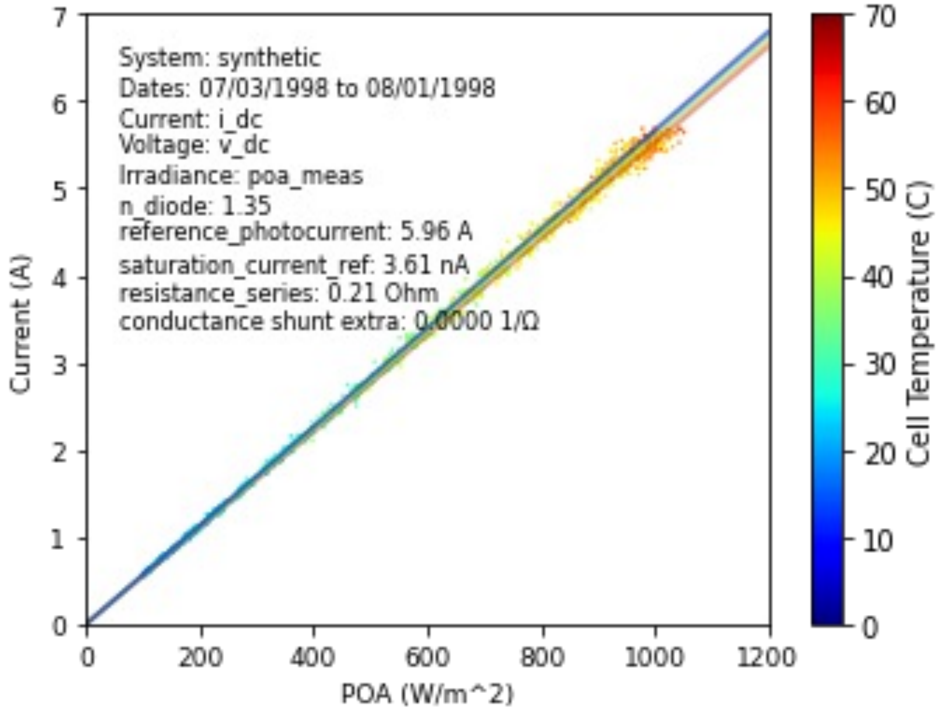
- Saturation current at reference conditions (Io)
- Photocurrent at reference conditions (IL)
- Series resistance (Rs)
- Extra shunt resistance (Rsh)
- Diode factor (n)



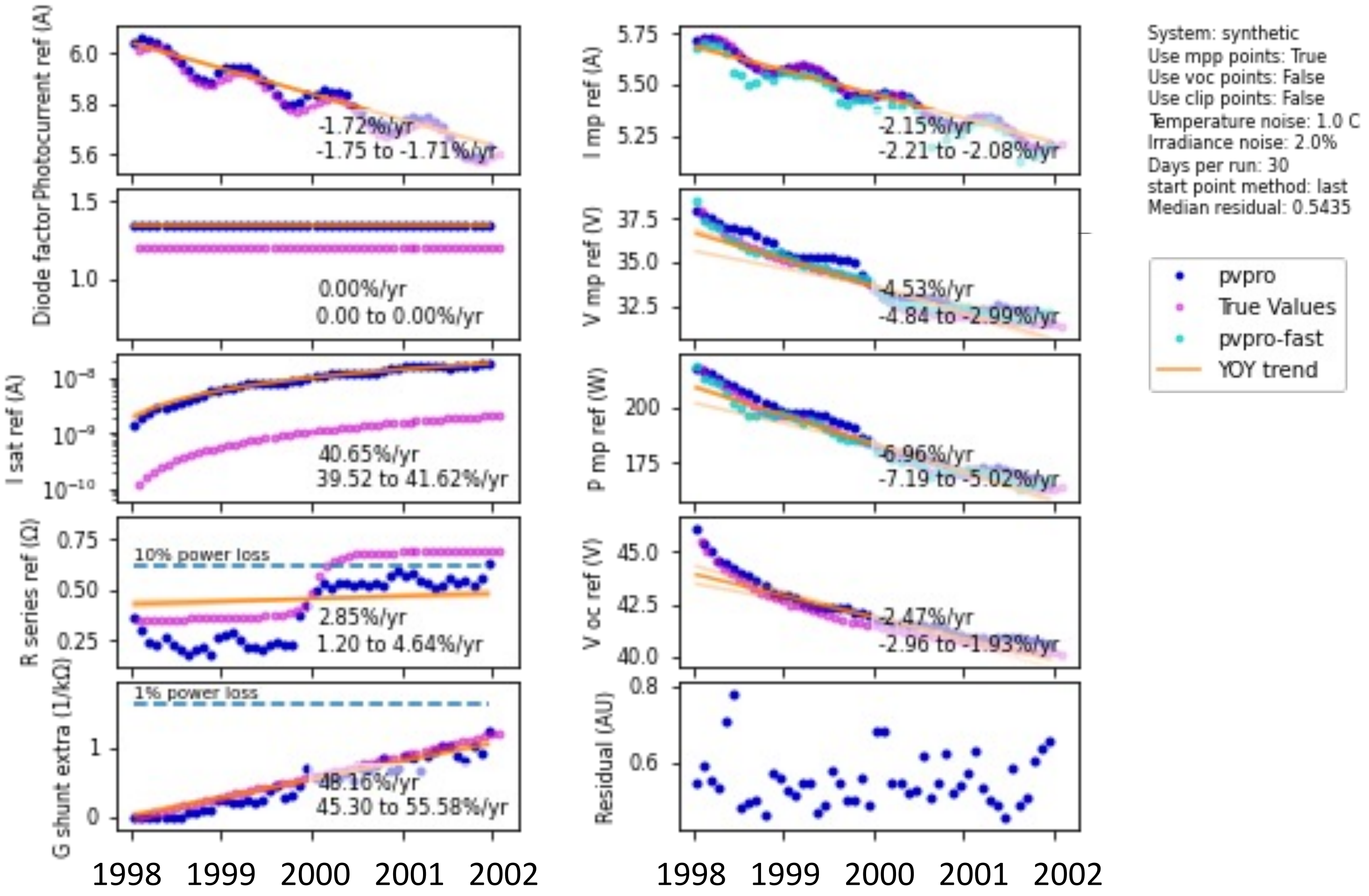
Application: Synthetic data

Data:
Simulate PV system over time with various parameter degradation using NSRDB weather data (https://nsrdb.nrel.gov/)
Irradiance sensor has multiplicative 2% error, temperature sensor has additive 1 C error, 15-minute data.

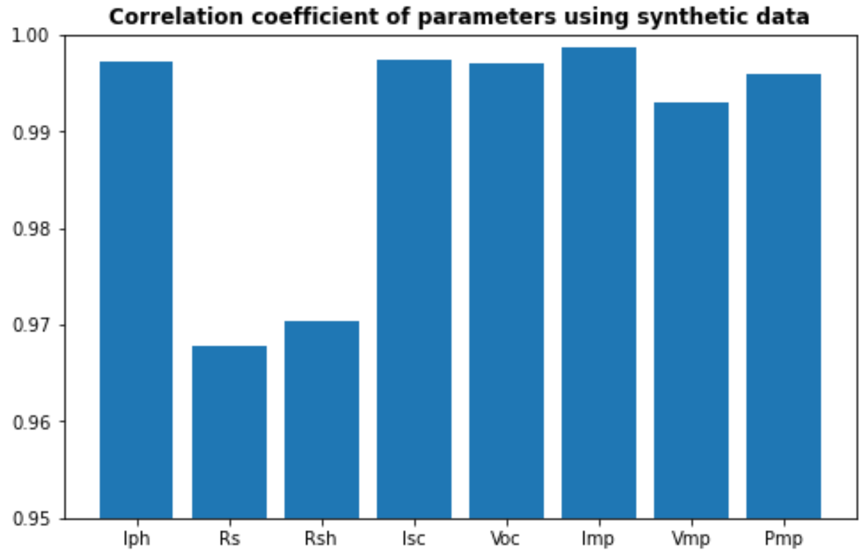




Application: Synthetic data



Correlation coefficient of parameters



Mean correlation coefficient = 0.99

Field data (NIST)

National Institute of Standards and Technology U.S. Department of Commerce

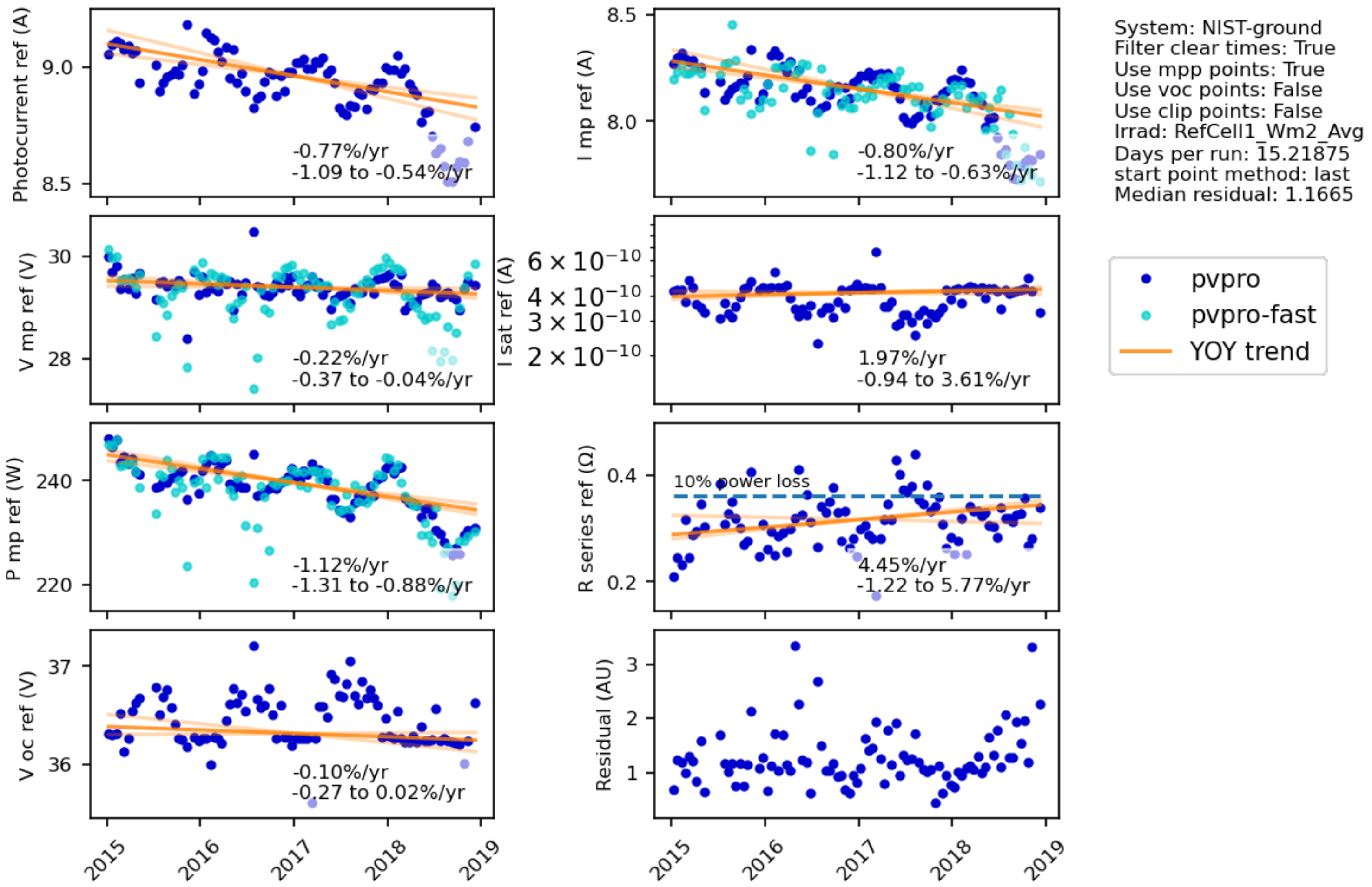
■ Ground dataset
- 1152 modules
- 271 kW

■ Canopy dataset
- 1032 modules
- 243 kW

■ Roof dataset
- 132 modules
- 73.3 kW

https://pvdata.nist.gov/

Results: Field data



- Reasonable and **clear seasonality trend** observed
- **Degradation rates** can be extracted for the SDM parameters

Ongoing:

- Get the **ground truth** (from indoor flashing test / reference module)
- Correlate the **data quality** with the variation of results

Ongoing: Connecting BOM with degradation

Bill of material files from PVEL

~90 Features (electrical, material, …)

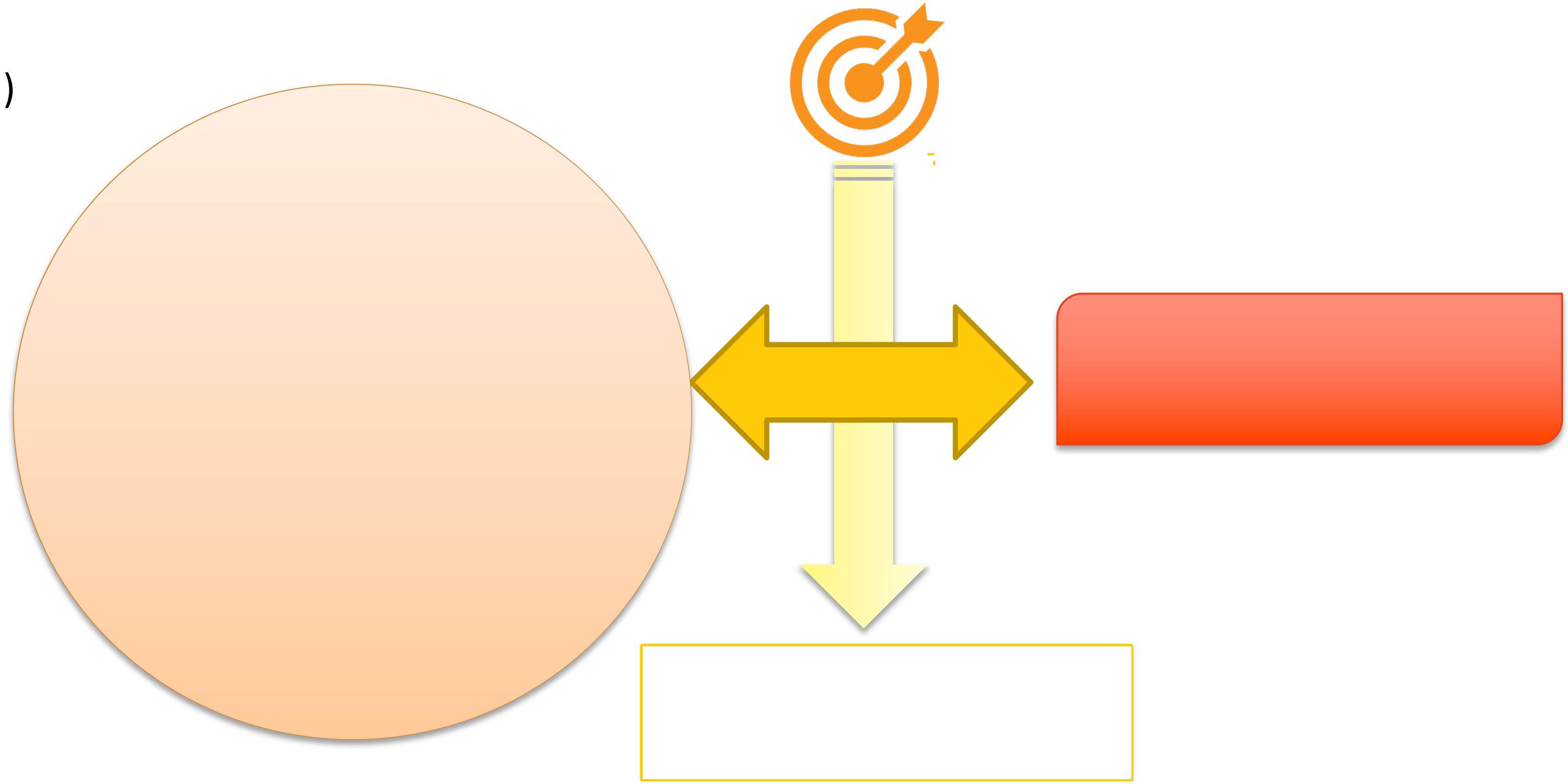
Materials 1 (%)

Materials 2 (%)

……

~500 data records

……



Summary

Conclusions:

- PVPRO provides an **automatic pipeline** including data cleaning, filtering, feature extraction and analysis.
- **Degradation patterns** of model parameters can be extracted by PVPRO using operation data
- Continued code development and tutorials on https://github.com/DuraMAT/pvpro

Future work:

- Determine **off-maximum power point** with PVPRO
- Refine the application of PVPRO on more **large-scale PV systems** and investigate the degradation

PV vision

PVPRO

Q&A and thank you!

PVPRO: T. Karin*, X. Chen, B. Li, A. Jain, C. Hansen, M. Deceglie, B. Meyers, L. Schelhas, B. King, D. Jordan, S. Moffitt

PV-Vision: X. Chen*, T. Karin, A. Jain, C. Libby, R. Sundaramoorthy, M. Deceglie, T. Silverman, N. Bosco, M. Owen-Bellini, E. Young, X. He, E. Bernhardt, P. Hacke, M. Bolen, D. Fregosi, W. Hobbs, PVEL company

DuraMAT Webinar

April 11, 2022