Trustworthy Machine Learning for Damage Identification in Composites

CAELIN MUIR

Advisors: Samantha Daly[1], Craig Smith[2]

Collaborators: Ashley Hilmas[3], Thao Gibson[3], Nikhil Tulshibagwale[1], Bhavana Swaminathan[1], Andrew Furst[1], Amjad Almansour[2], Michael Presby[2], James Kiser[2], Kathy Sevener[4]

[1] University of California, Santa Barbara

[2] NASA Glenn Research Center

[3] Air Force Research Laboratory

[4] University of Michigan, Ann Arbor

THIS RESEARCH IS SUPPORTED BY A NASA SPACE TECHNOLOGY RESEARCH FELLOWSHIP

Outline

Health monitoring of
ceramic matrix composites

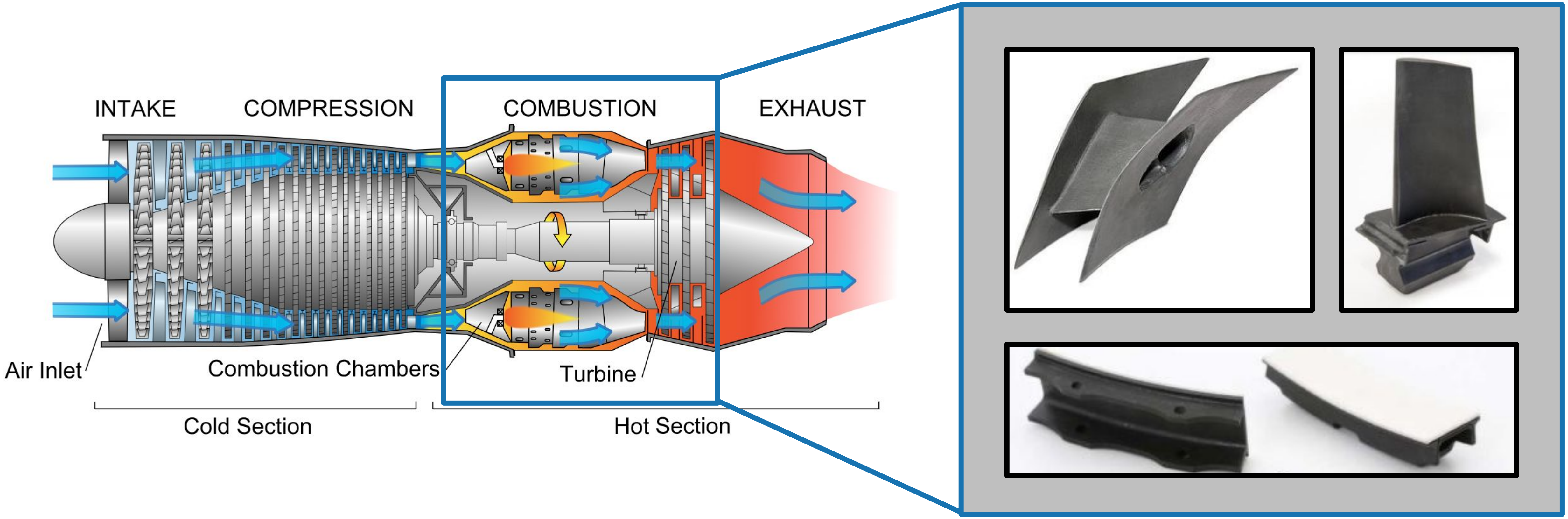
The spectral model

Quantitative benchmarking

Limitations of the spectral model

Conclusions

CMCs Are Next Generation Aerospace Materials



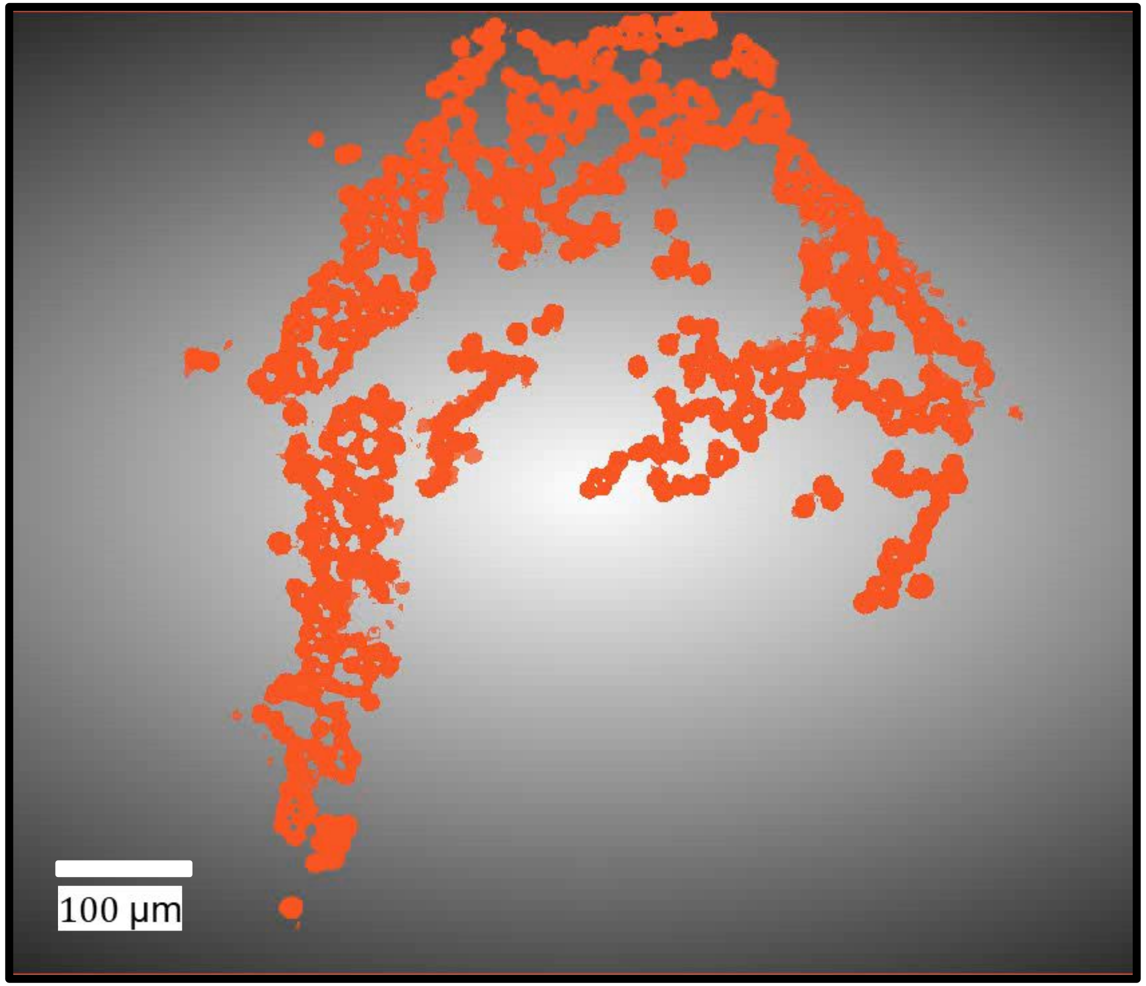
Kiser JD, Grady J, Bhatt RT, Wiesner V, Zhu D. Overview of CMC (Ceramic Matrix Composite) Research at the NASA Glenn Research Center. Proc. Ceram. Expo, 2016.

CMCs Exhibit High Damage Tolerance

Mechanical properties in extreme environments:

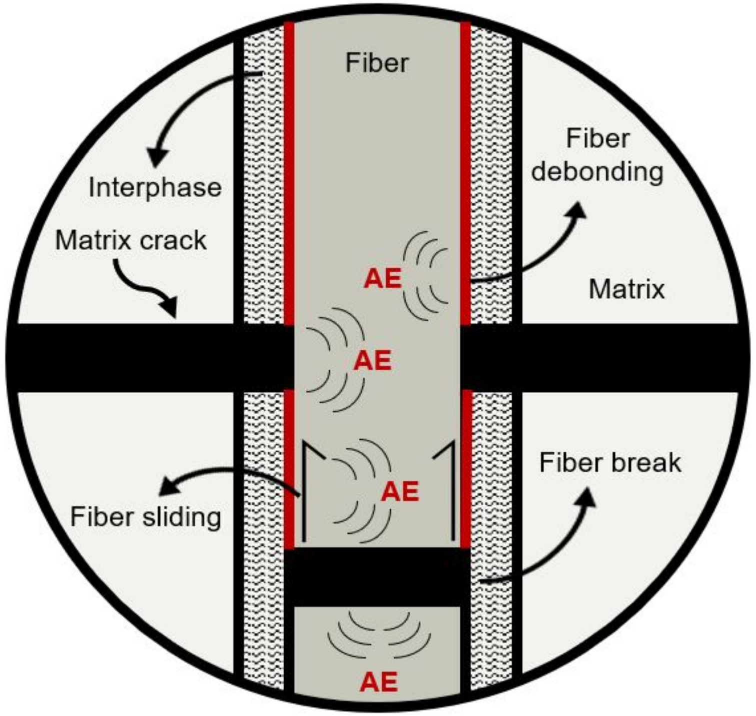
- Damage tolerant
- High strength
- Thermal stability
- Low density

Safety-critical applications require trustworthy health monitoring

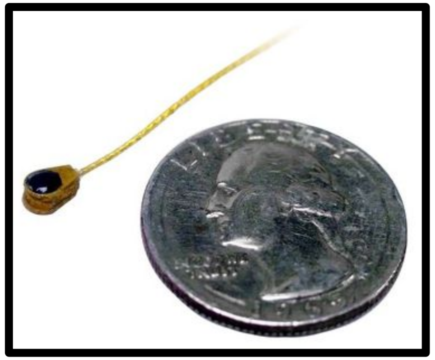


Damage Mechanism Identification is Critical to Health Monitoring

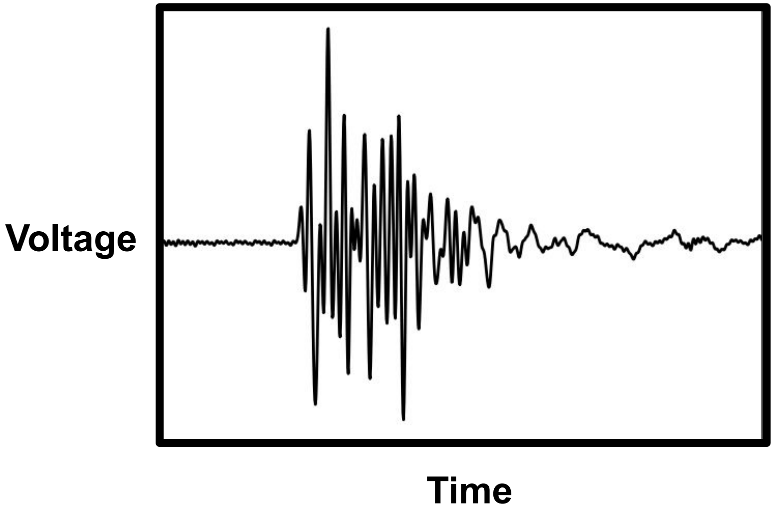
Bulk damage



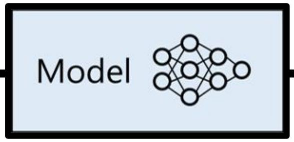
Piezoelectric sensor



Collected waveform

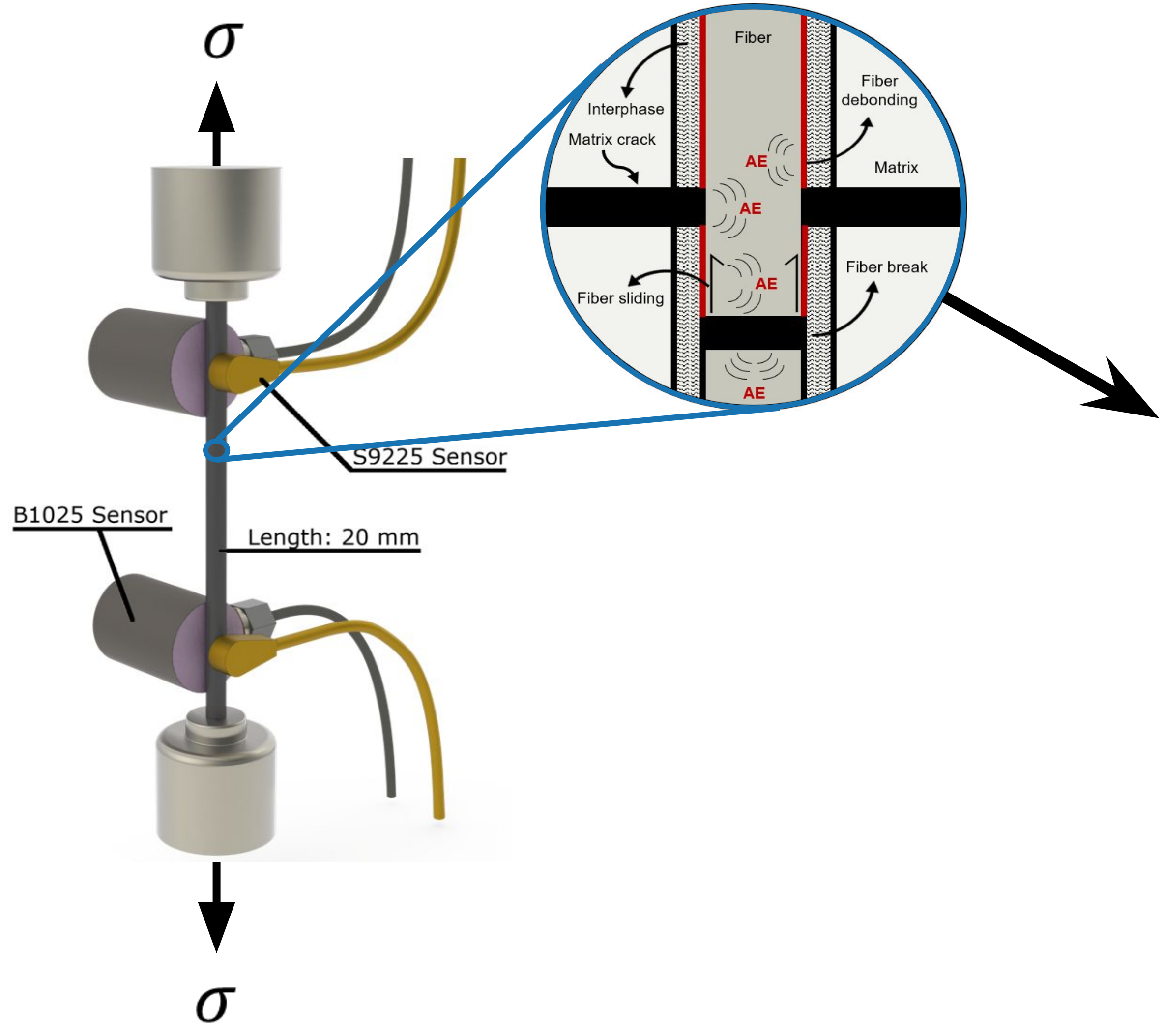


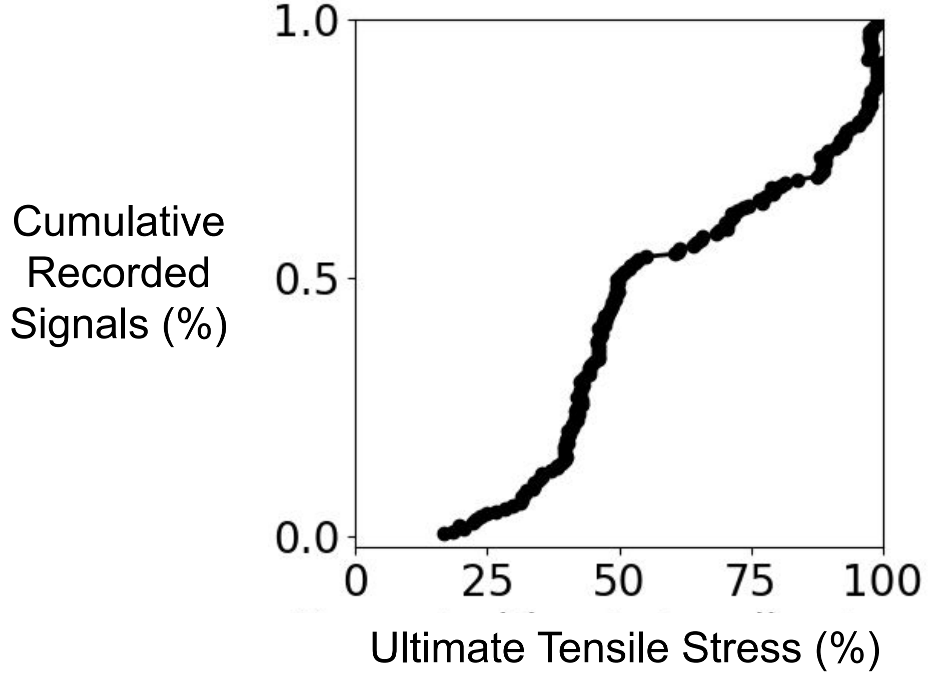
Correlate to mechanism



Muir, C *et al. npj Comput Mater* **7**, 95 (2021a).
https://doi.org/10.1038/s41524-021-00565-x

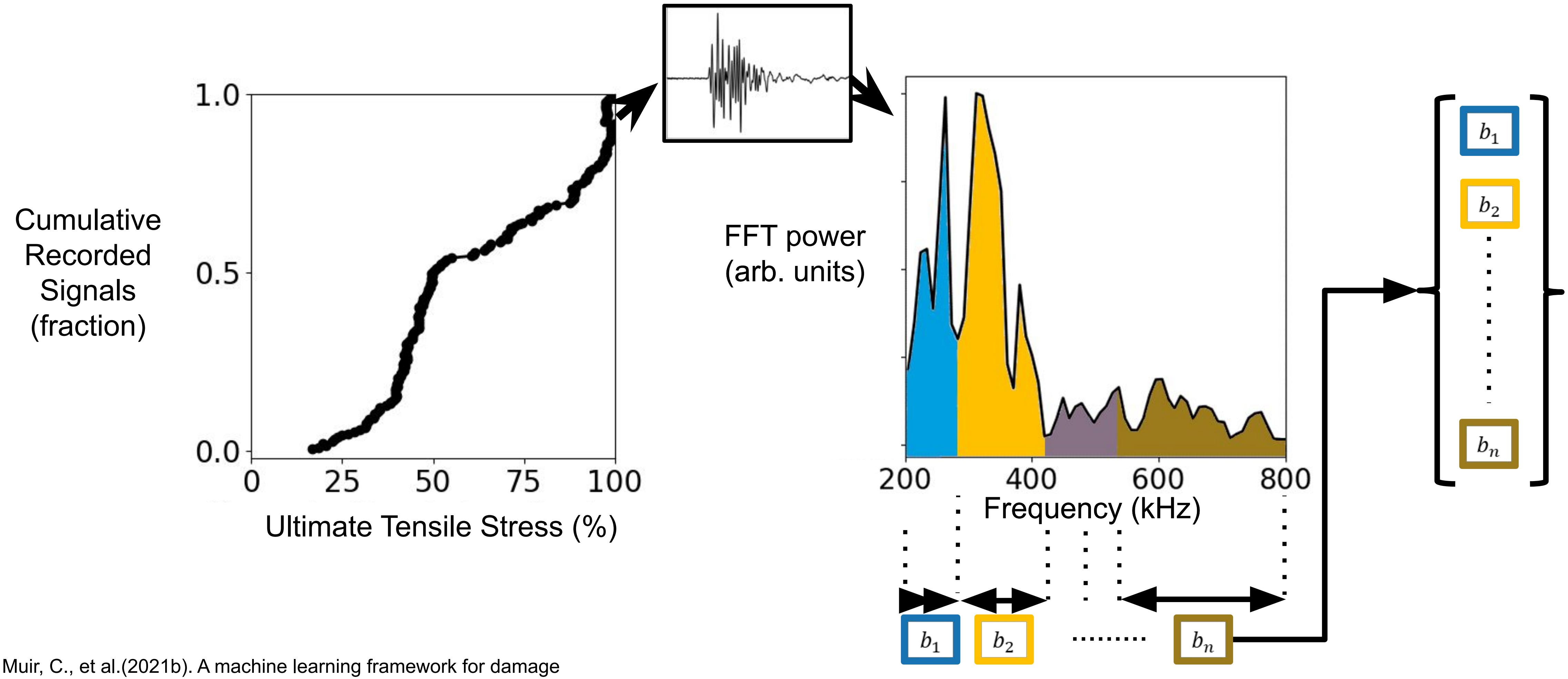
Anatomy of the Spectral Model





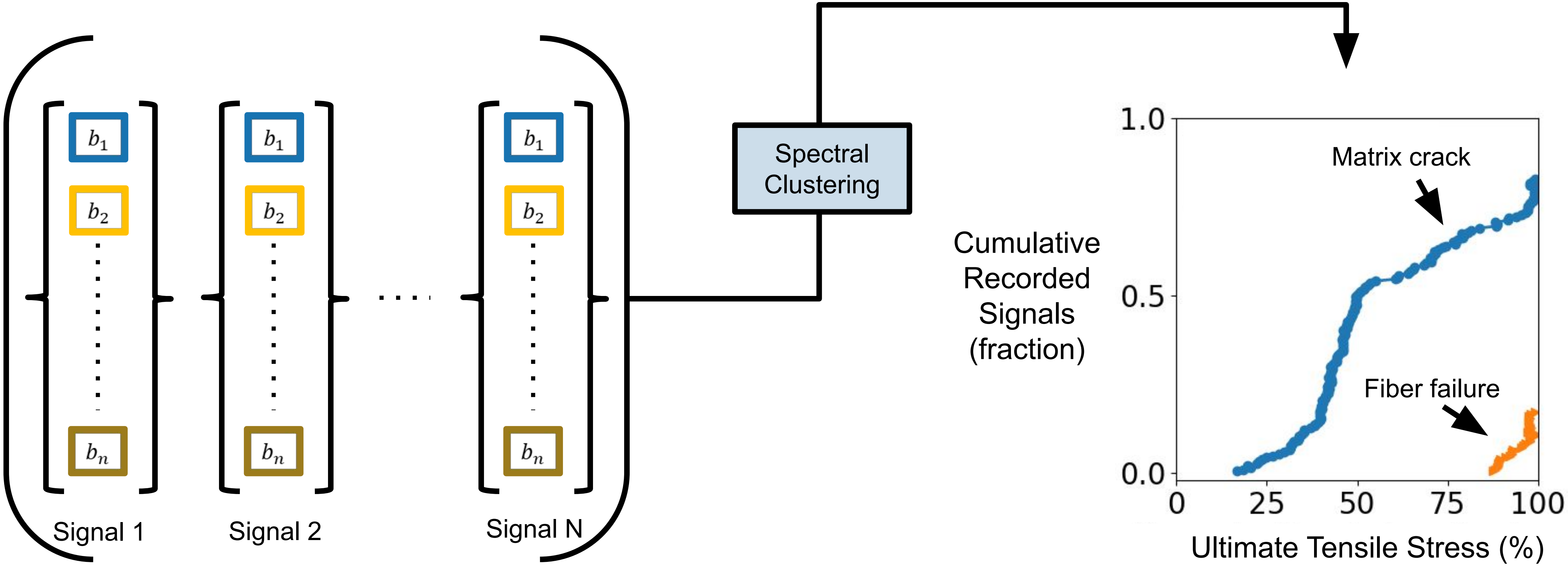
Muir, C., et al.(2021b). A machine learning framework for damage mechanism identification from acoustic emissions in unidirectional SiC/SiC composites. *Npj Computational Materials*, *7*(1), 1–10.

Waveforms are Encoded in Frequency Domain



Muir, C., et al.(2021b). A machine learning framework for damage mechanism identification from acoustic emissions in unidirectional SiC/SiC composites. *Npj Computational Materials*, *7*(1), 1–10.

Spectral Clustering Sorts Signals Based on Mechanism



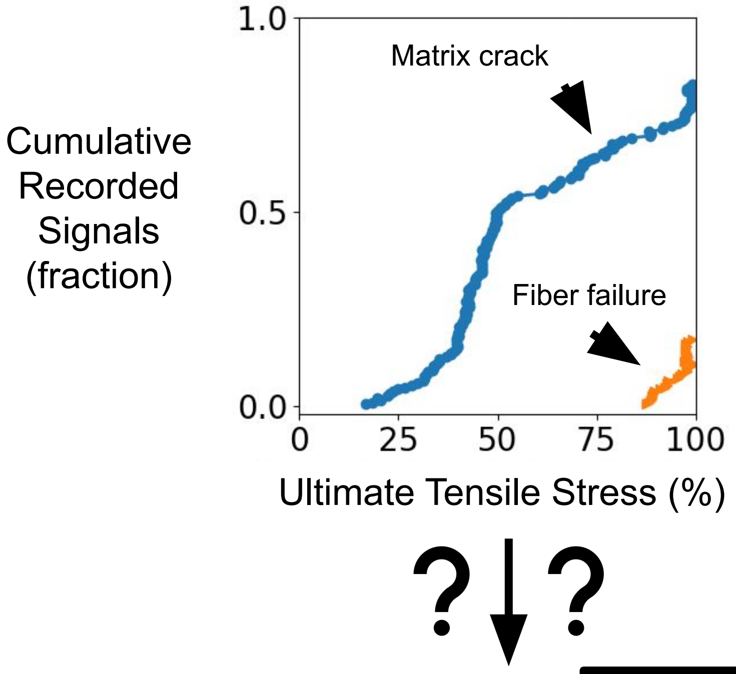
Muir, C., et al.(2021b). A machine learning framework for damage mechanism identification from acoustic emissions in unidirectional SiC/SiC composites. *Npj Computational Materials*, *7*(1), 1–10.

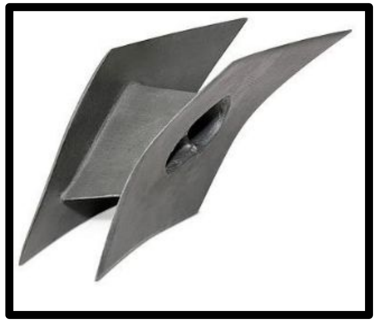
Need to Ensure Spectral Model is Trustworthy

1. Clear Objective
   - Definition of success must be defined

2. Quantifiable Evaluation
   - Characterize expected error
   - Benchmark against other approaches

3. Establish Extensibility
   - Find the space where the model a capable predictor
   - Establish procedures for generalization

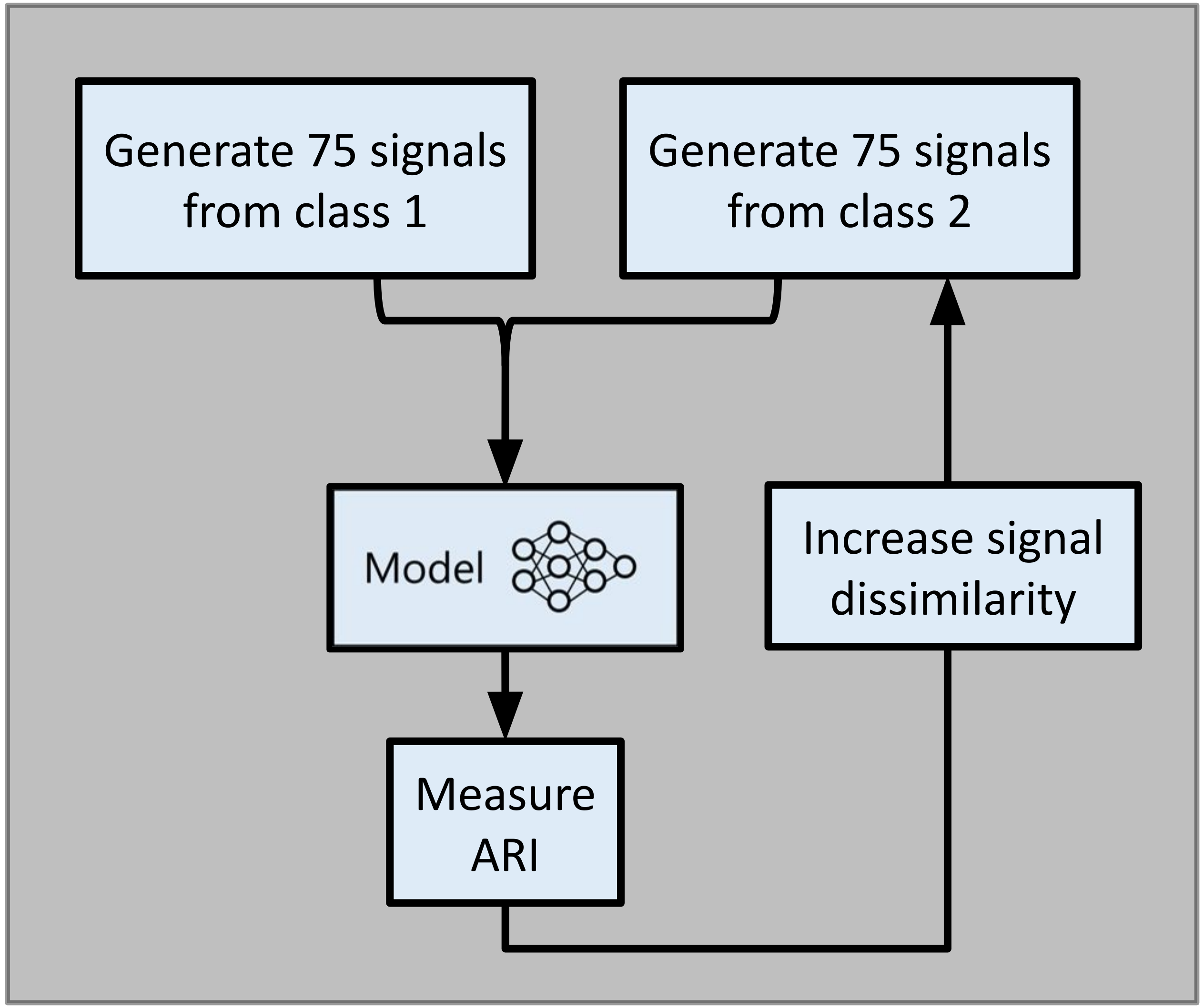


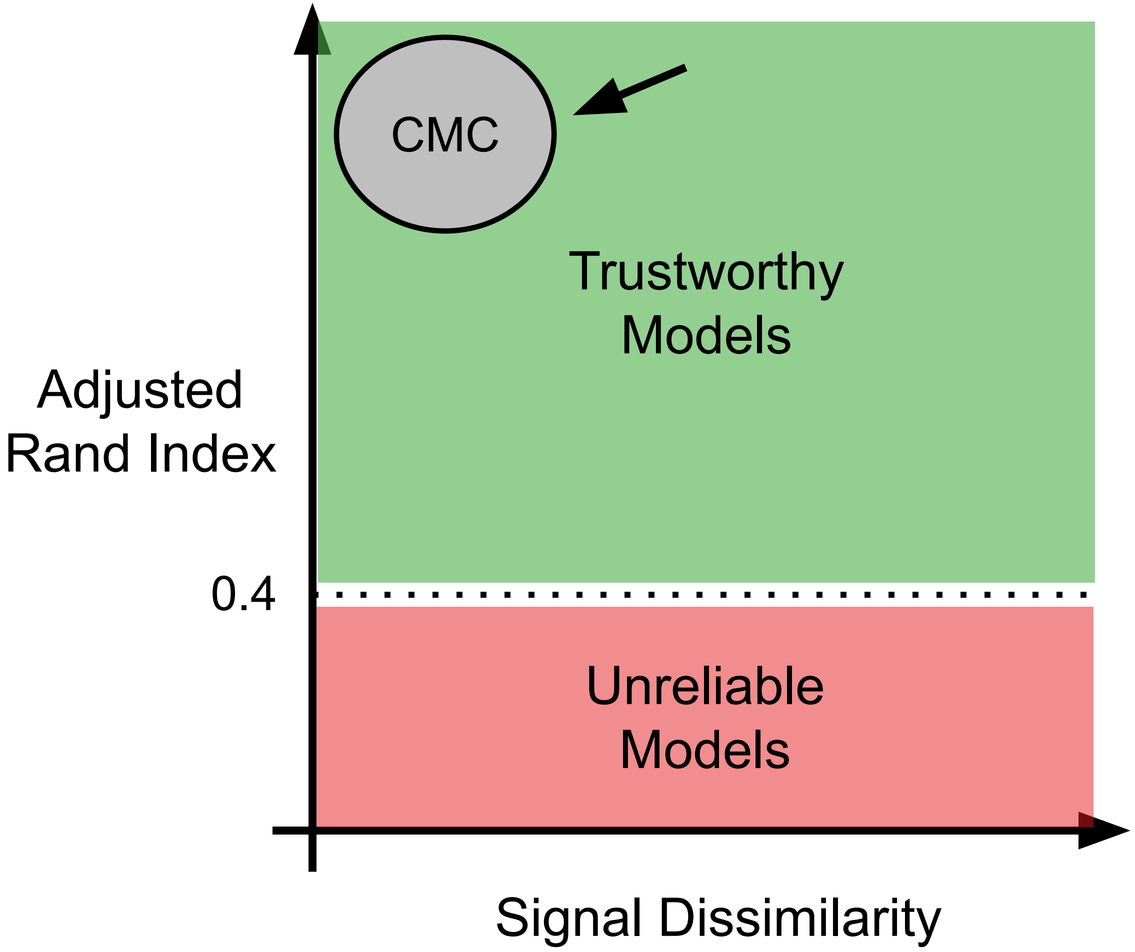


Brodnik, N. R., Muir, C., Tulshibagwale, N., et al. (2023). Perspective: Machine learning in experimental solid mechanics. *Journal of the Mechanics and Physics of Solids*, *173*, 105231.

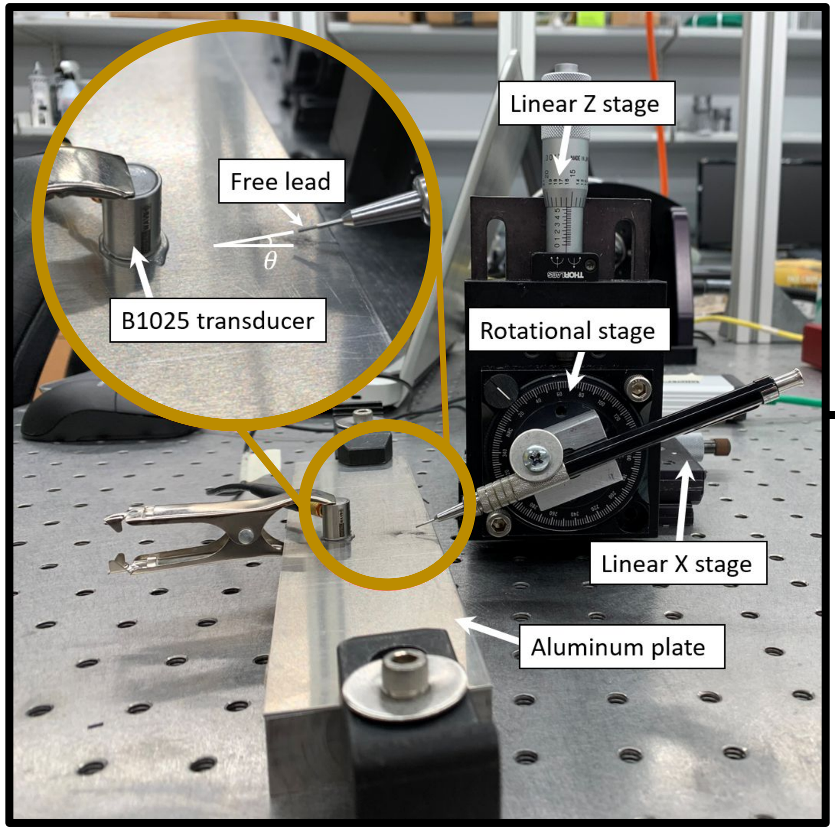
Kiser JD, Grady J, Bhatt RT, Wiesner V, Zhu D. Overview of CMC (Ceramic Matrix Composite) Research at the NASA Glenn Research Center. Proc. Ceram. Expo, 2016.

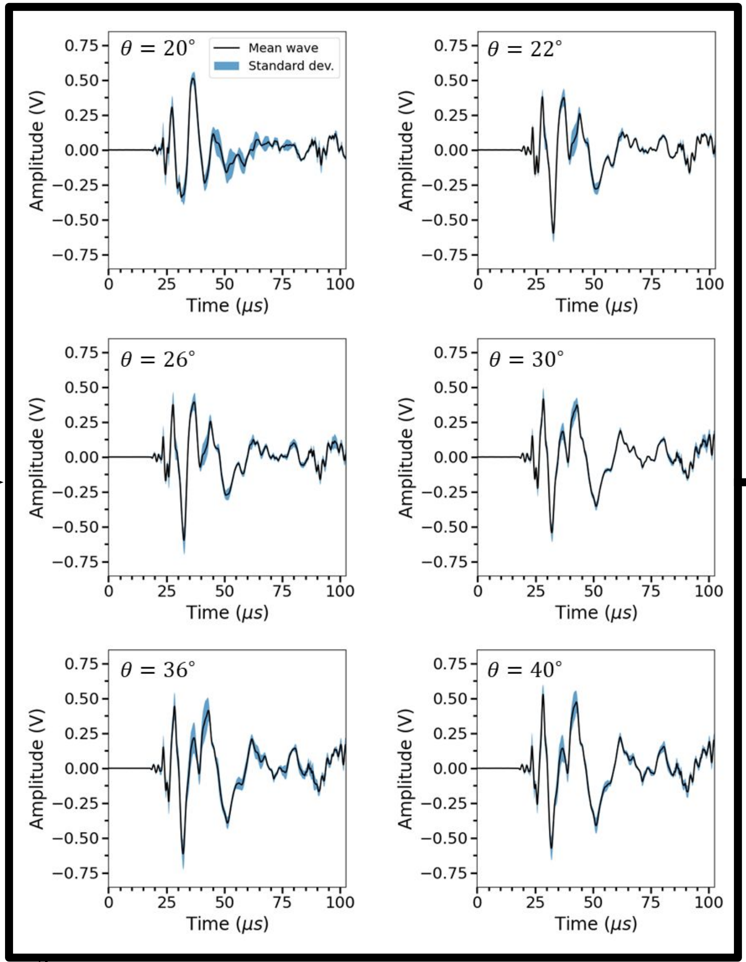
Models Are Evaluated With the Adjusted Rand Index

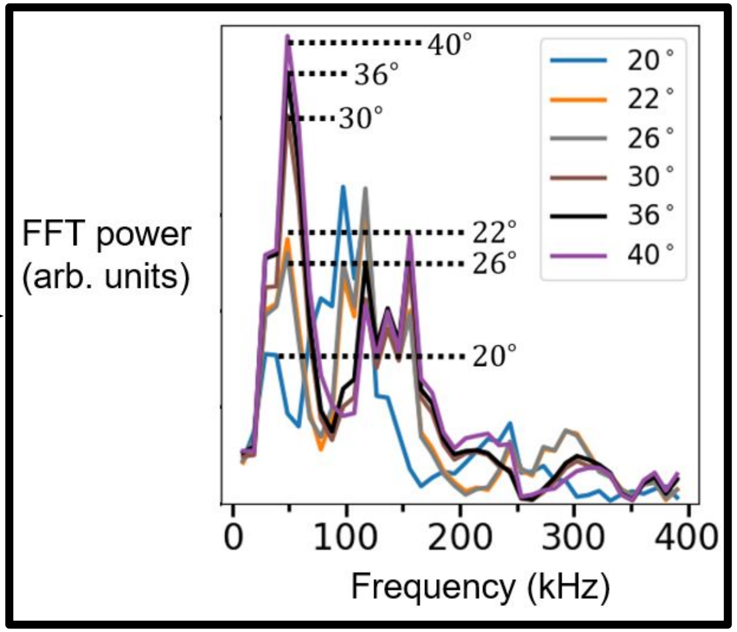




Pencil Lead Breaks Allow Precise Control of Dissimilarity







Muir, C., Tulshibagwale, N., et al. (2023). Quantitative Benchmarking of Acoustic Emission Machine Learning Frameworks for Damage Mechanism Identification. *Integrating Materials and Manufacturing Innovation*, *12*(1), 70–81.

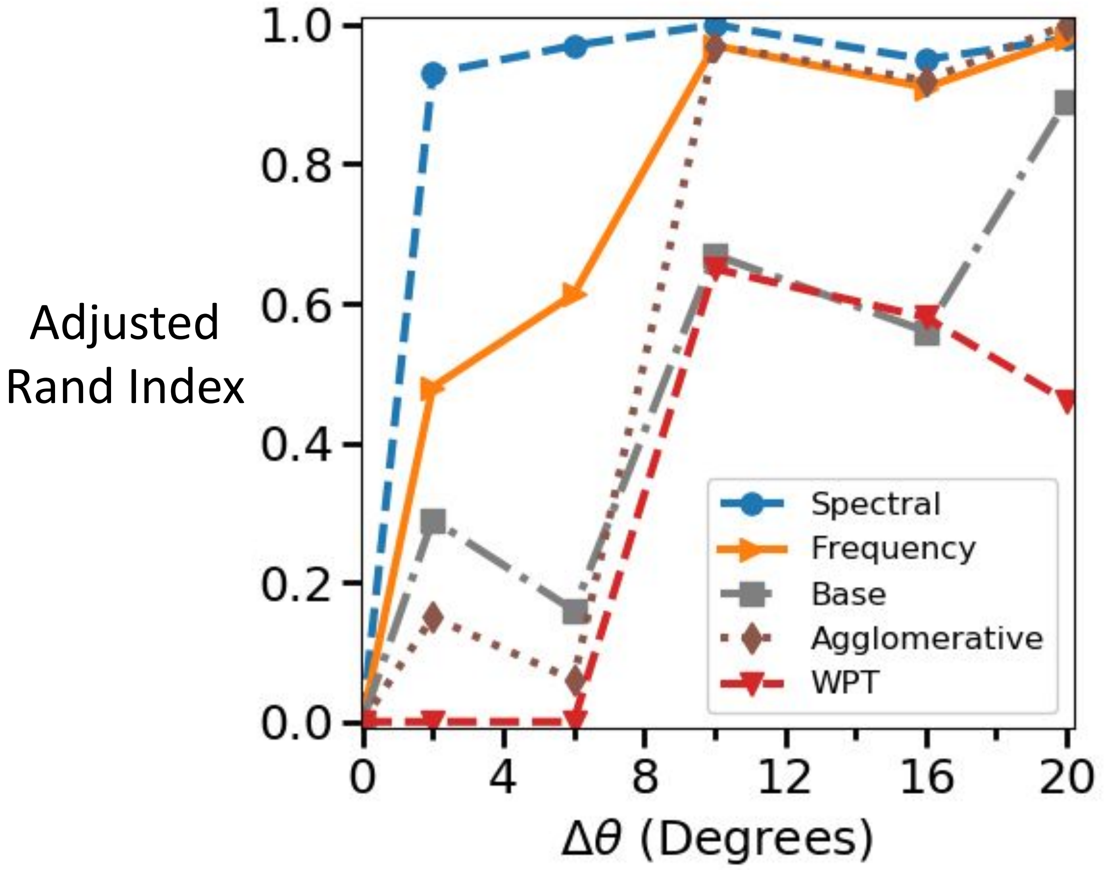
Benchmarking Used to Identify Trustworthy Models

- Identify strengths and weaknesses
  - Frequency based models are most reliable

- Direct characterization of performance allows improvement strategies
  - Identify ideal signal encoding schemes
  - Define how experimental factors impact signal features

- Quantify relative accuracy of models

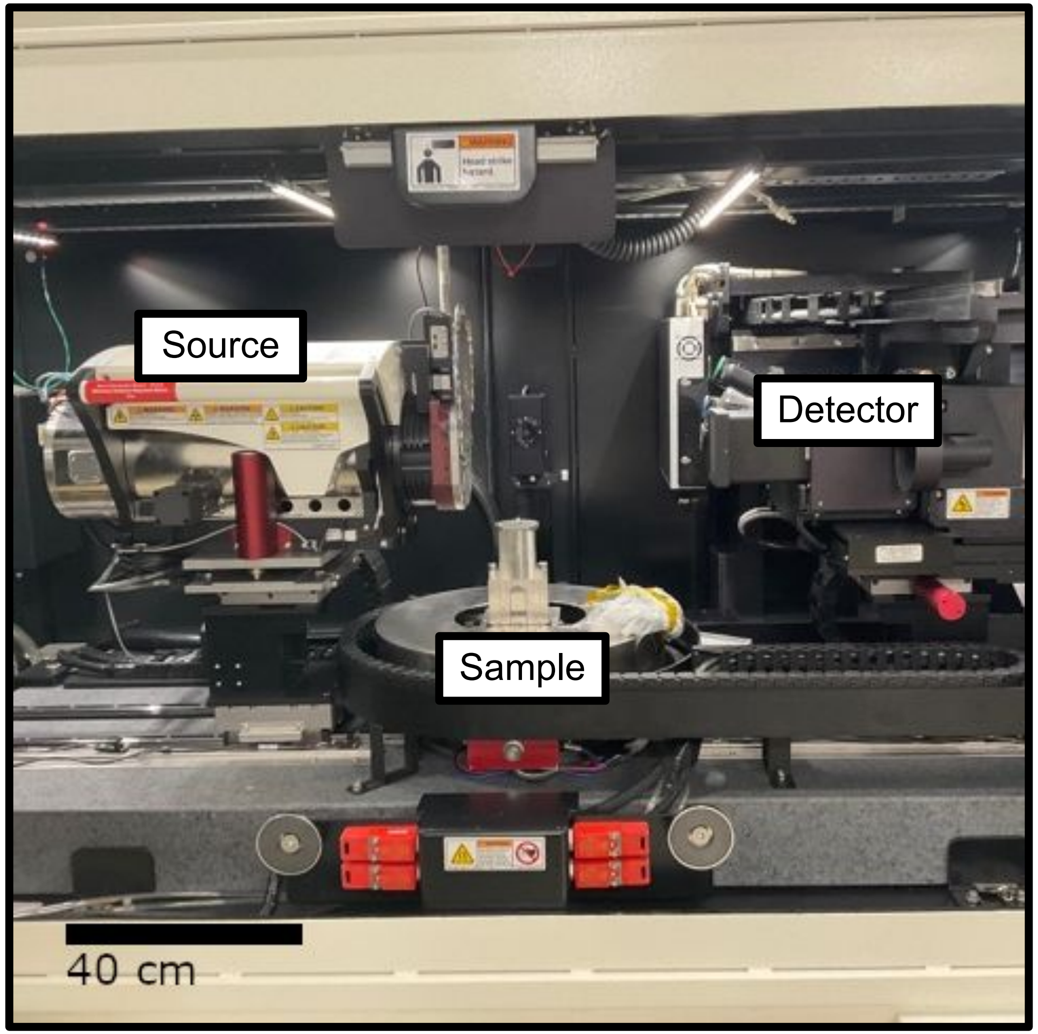
- Confirm new models work as expected



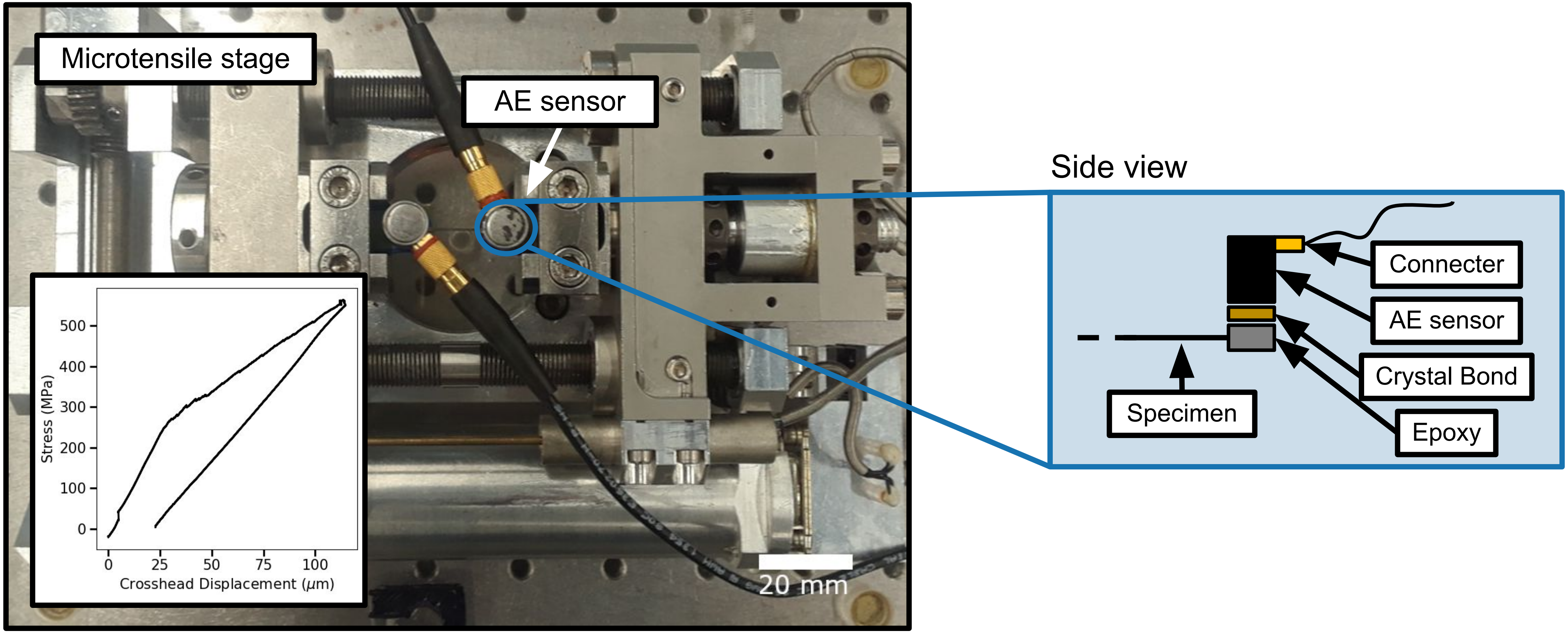
Muir, C., Tulshibagwale, N., et al. (2023). Quantitative Benchmarking of Acoustic Emission Machine Learning Frameworks for Damage Mechanism Identification. *Integrating Materials and Manufacturing Innovation*, *12*(1), 70–81.

Model Extensibility Characterized with XCT

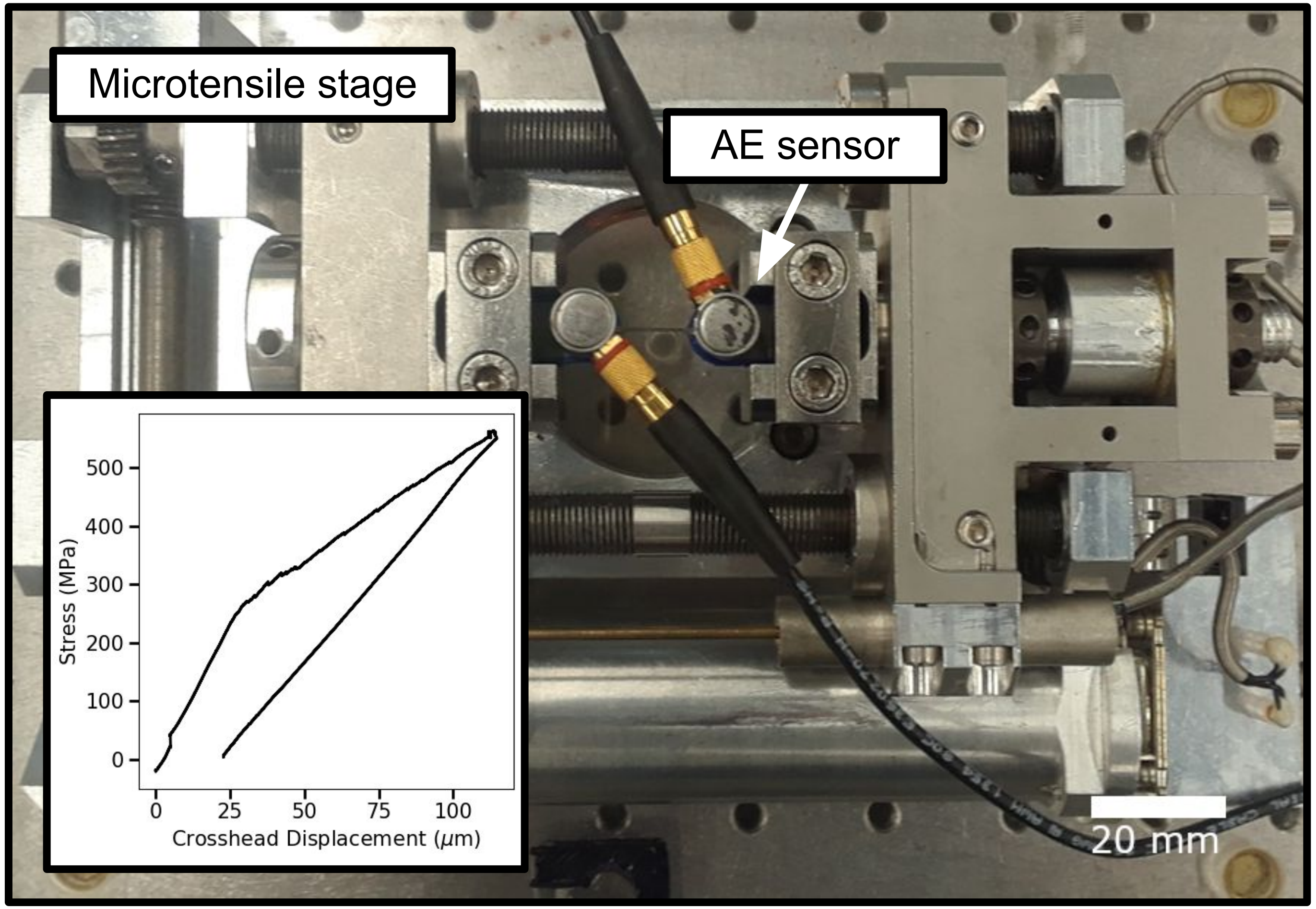
- Need to identify limitations of mechanism identification model
- X-ray computed tomography (XCT) allows bulk microstructural observations
- Allows us to correlate specific damage mechanisms to load-states



Sample Loaded Ex-Situ and Transferred to XCT Load Stage

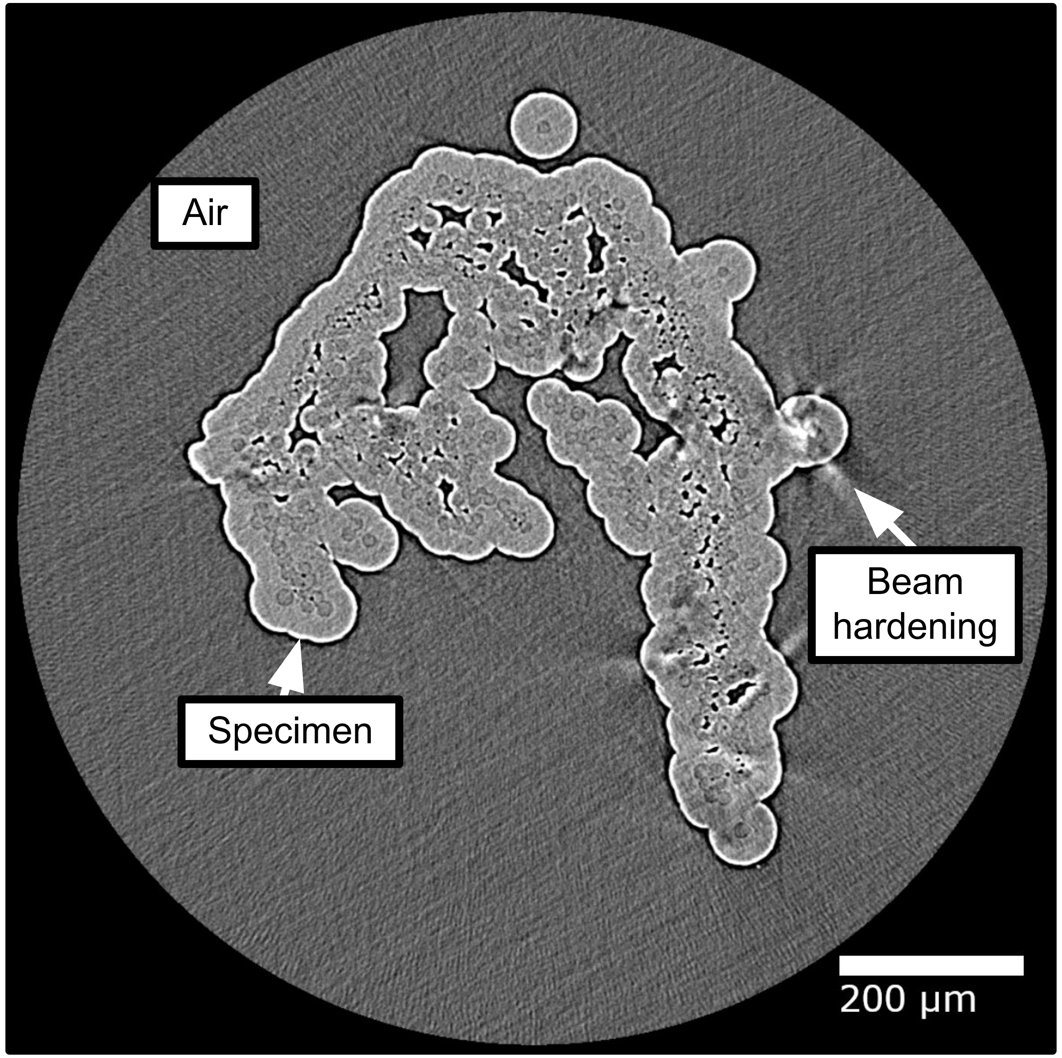


Sample Loaded Ex-Situ and Transferred to XCT Load Stage

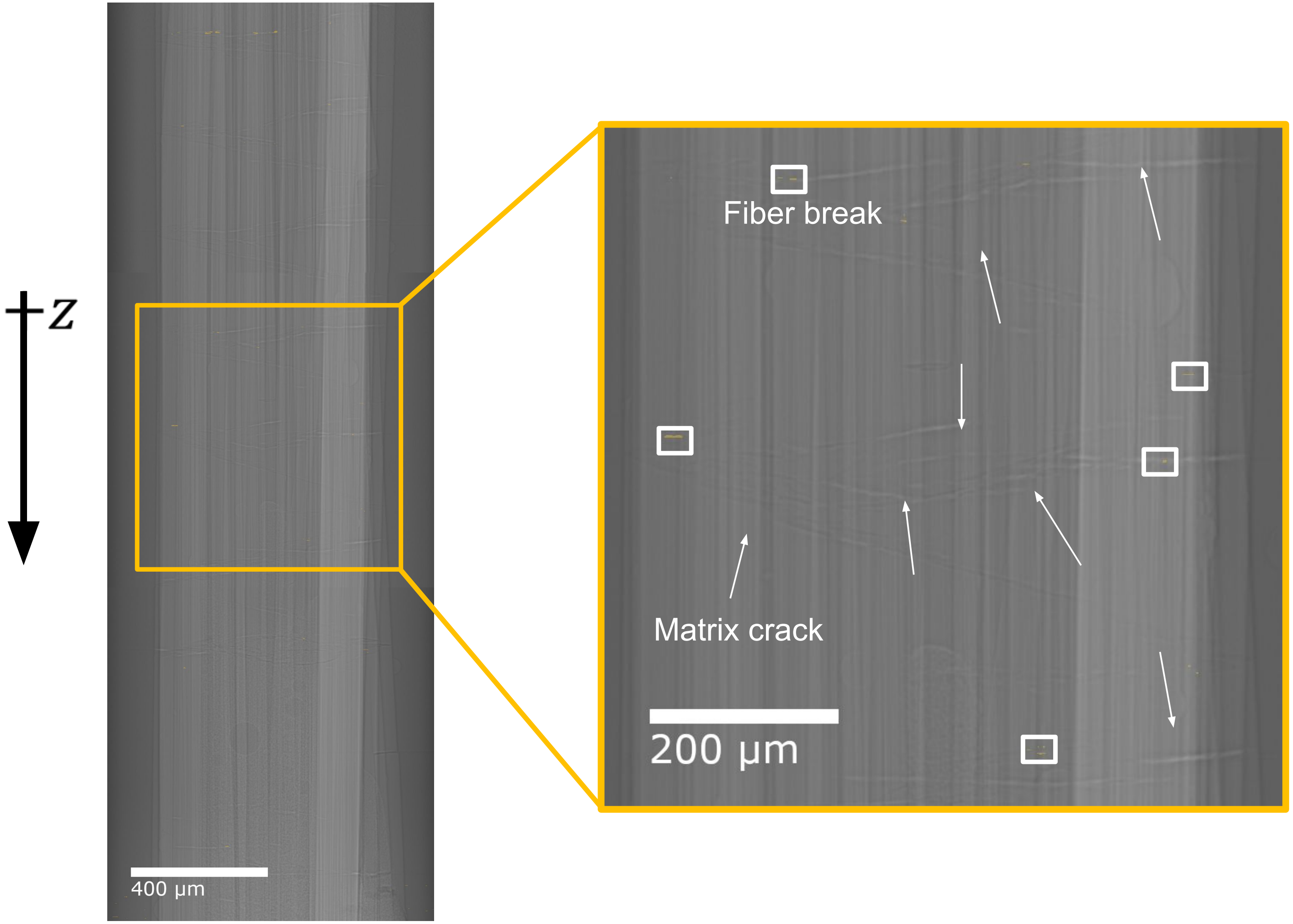


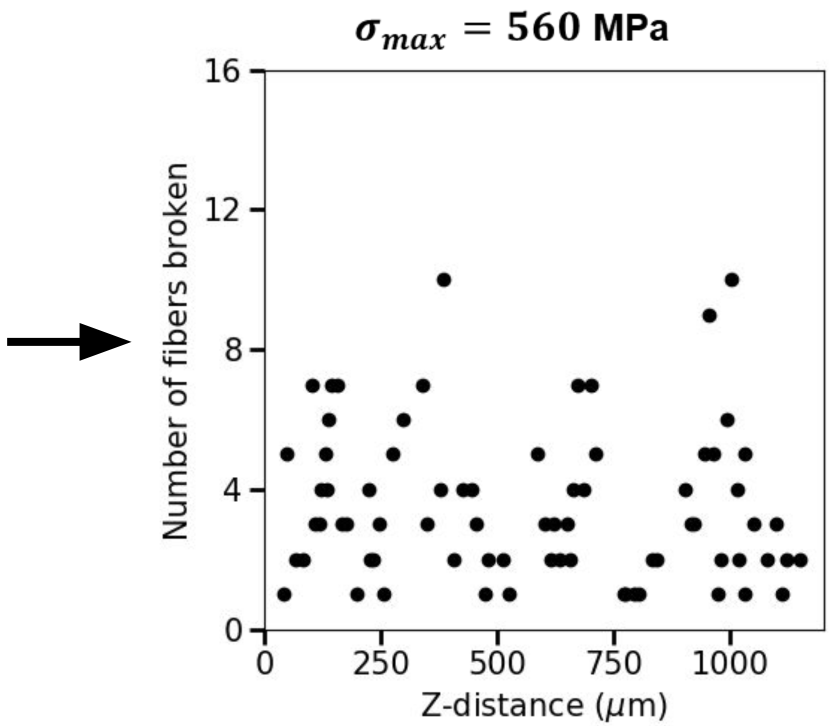
ML Segmentation Allows Damage Identification

- Minicomposite is imaged over 2.5mm length
  - Voxel size of 1.16 µm
- Matrix and fiber damage is identified assisted by ML segmentation
  - Allows high throughput identification
- Minimum expected crack opening at the image stress is 1.5-2 µm
  - Sufficient resolution for identifying existence/location of damage

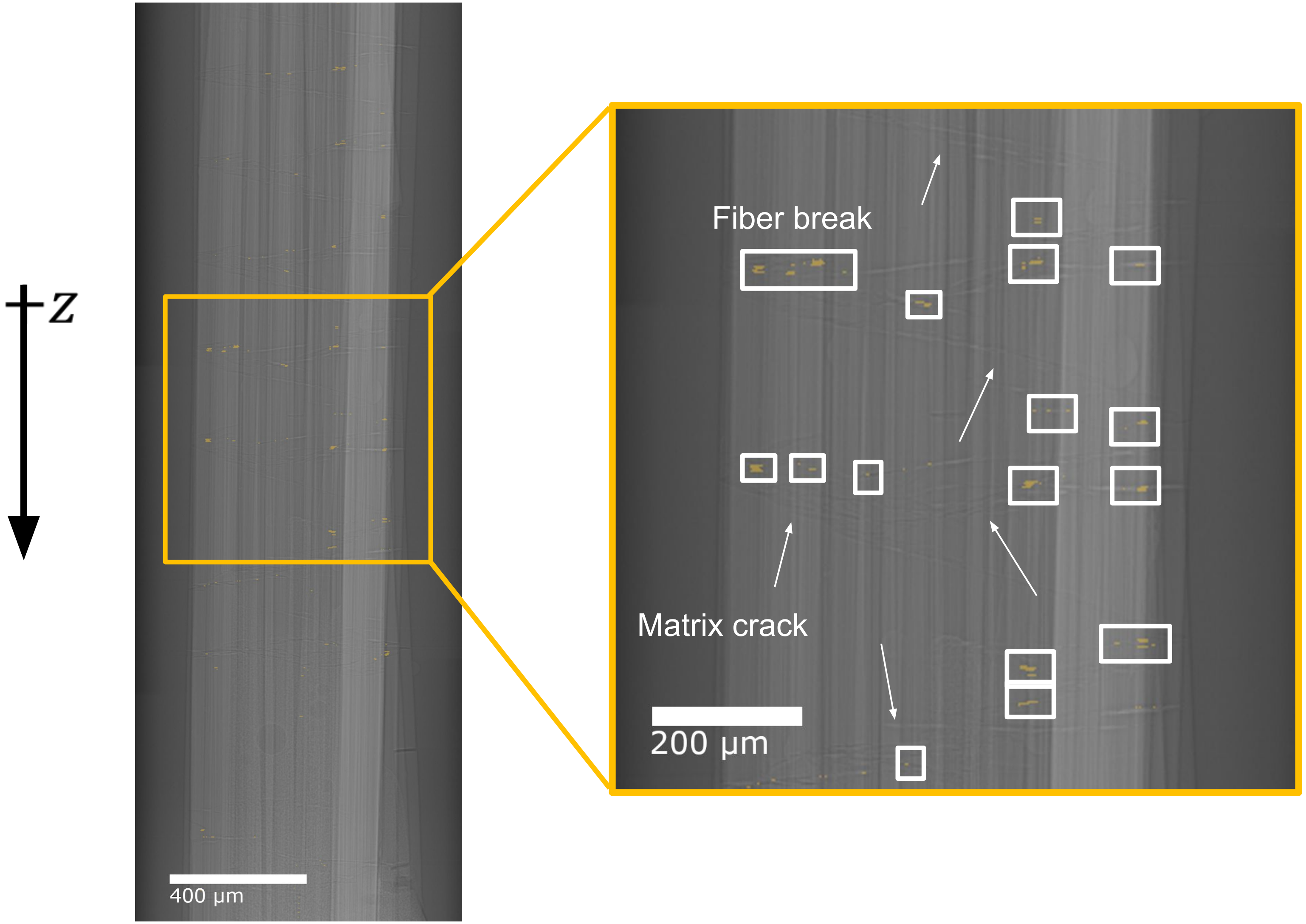


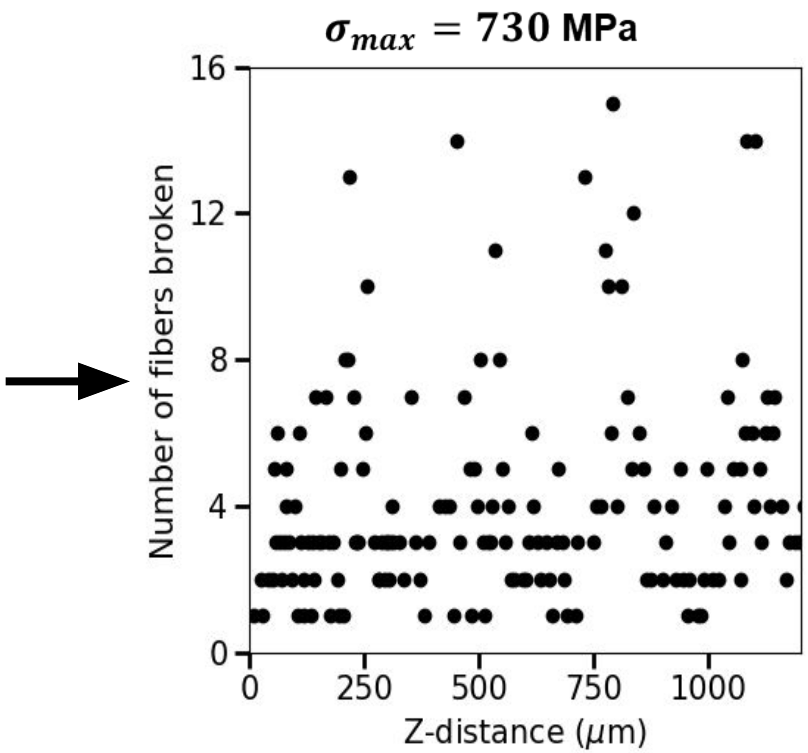
Fiber Breaks are Limited Below 560 MPa





Fiber Break Activity Increases Above 560 MPa





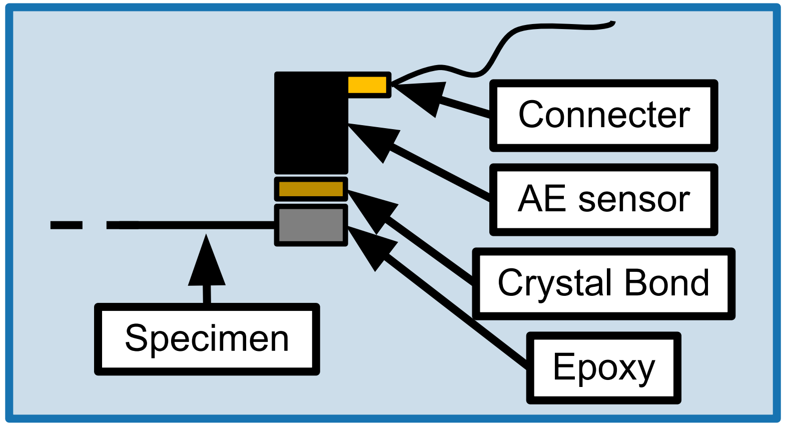
Model Must be Calibrated to Each Environment

- Model must be calibrated before use in new experimental settings

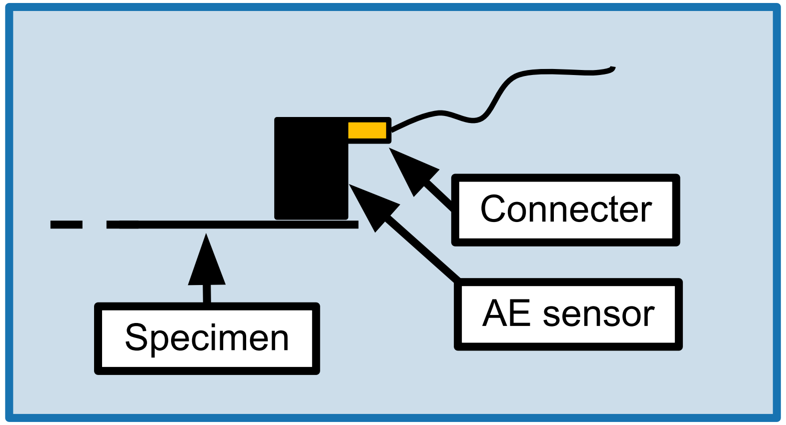
- Thick (>1-2mm) couplings attenuate high frequency components
  - High frequency information is lost
  - Spectral model must be adjusted to prioritize low frequencies

- Post-calibration, the spectral model correctly correlates acoustic signals to damage mechanisms

XCT coupling

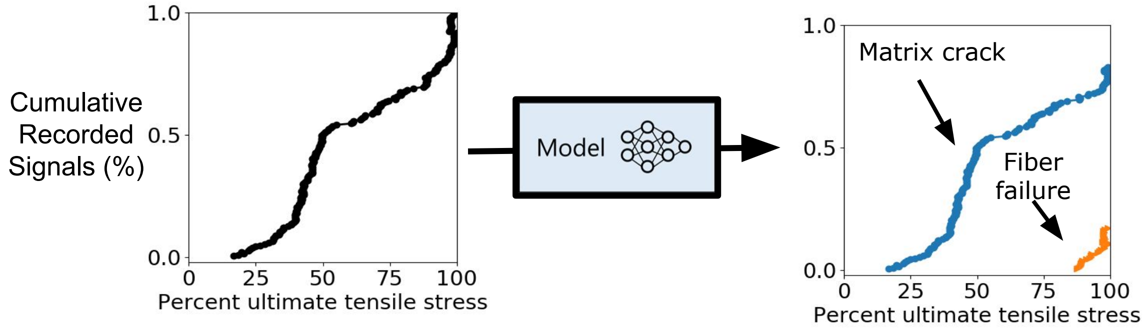


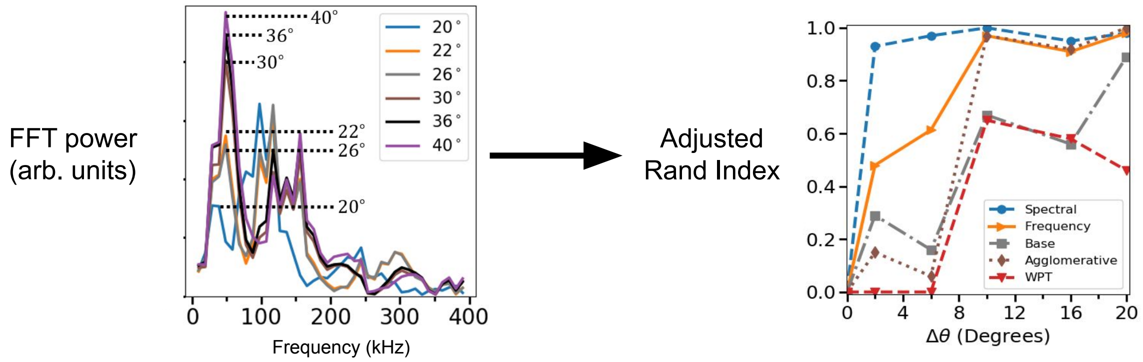
Standard coupling

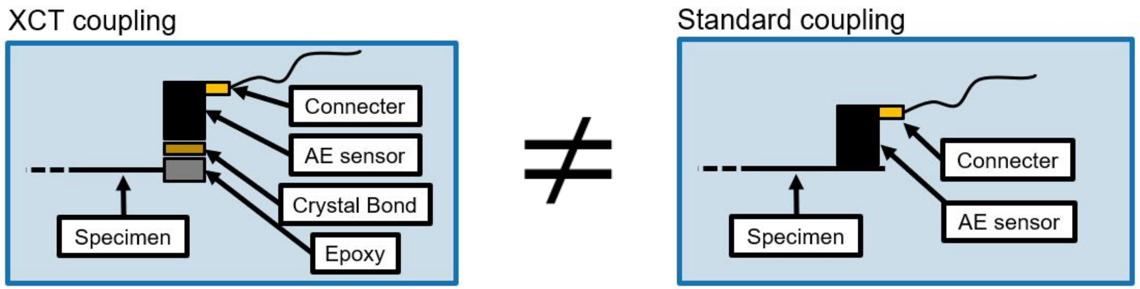


Conclusions

- Have created a trustworthy model to identify damage mechanisms from AE
- Benchmarking datasets were used to identify trustworthy models
- Models must be re-calibrated before use in new experimental or environmental conditions







Questions