UNIVERSITY OF TECHNOLOGY SYDNEY

Activity 4a: Enhancing the Reliability of Condition Assessment of Buried Large Diameter Water Mains

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UTS

Presentation Outline

1. Summary Current State of Affairs
2. In-Between Frameworks
   - The Role of Spatial Statistic Machine Learning
   - Case Study 1
3. In-Between Frameworks
   - The Role of Fusion
   - Case Study 2

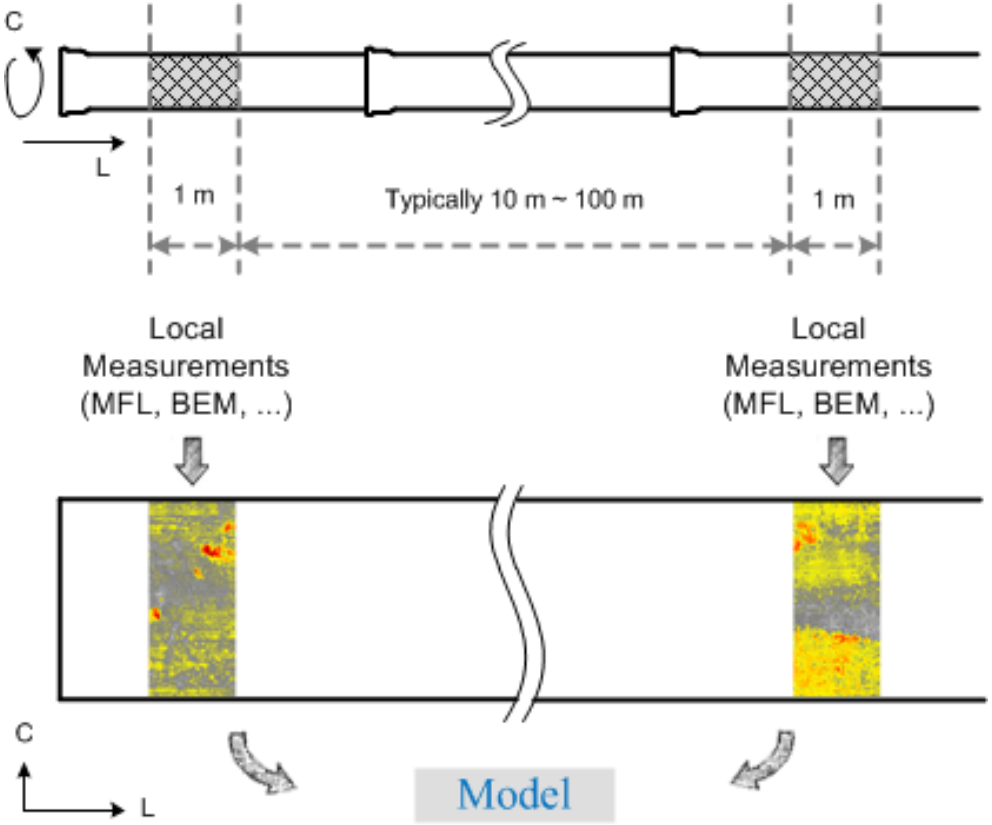
Summary Current State of Affairs and Latest Progress

1. UTS has developed two separate methodologies to estimate continuous geometry
    - One based on multivariate Gaussian distribution – more developed
    - Other based on probabilistic corrosion modelling – less developed

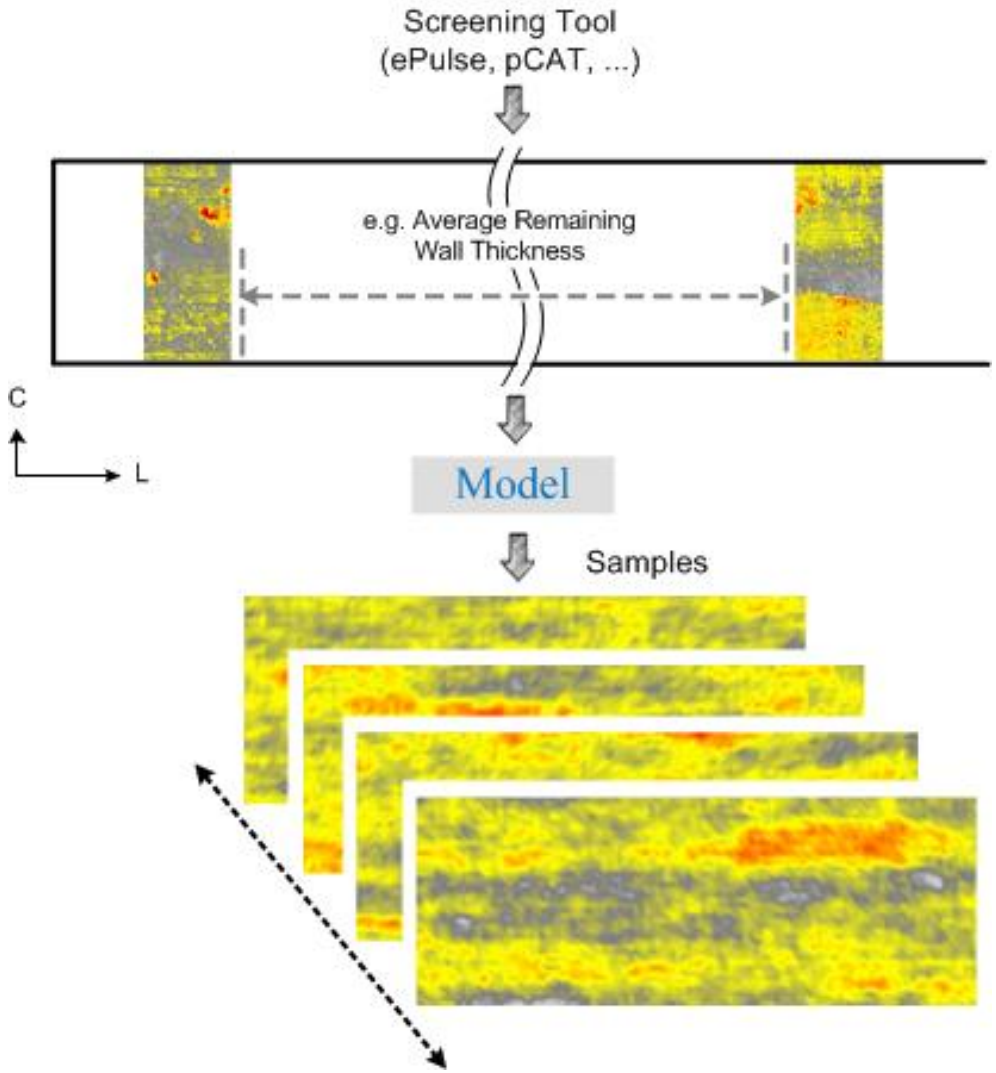
2. Moreover, the in-between framework has been enriched with a preliminary optimal condition assessment data fusion approach using an efficient sub-mapping strategy
    - Allows information from CA technologies at higher resolutions yet sparse sensing (such as MFL or RFT) to be incorporated
    - Technique also validated at highest possible resolution with outer pipe wall laser data

3. Validate with data collected from test bed: how good is the above using what is available, i.e. real CA data?

In-Between Prediction: The Framework



In-Between Prediction: The Framework



In-Between Prediction: The Model

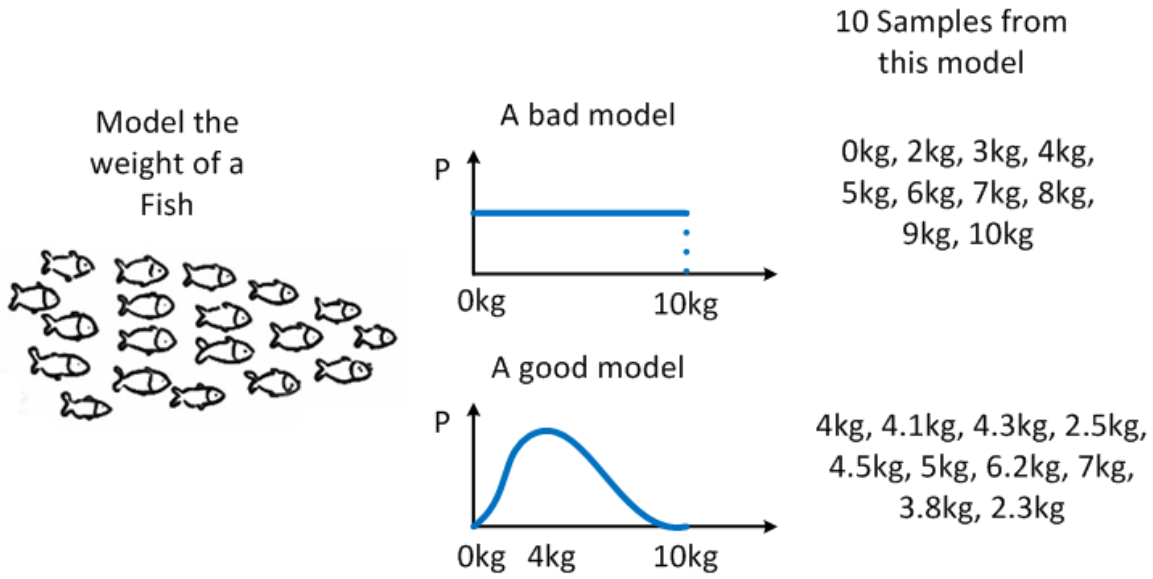
What it is?

An infinite-dimensional multivariate normal distribution

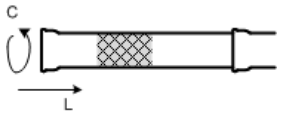
What it does?

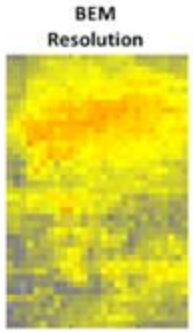
Generate infinite instances of arbitrary dimensions

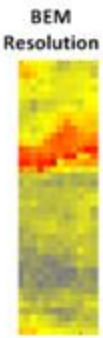
A good model has better chance to hit the truth

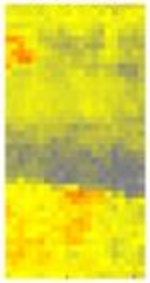


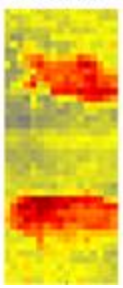
Case Study 1: Training Data





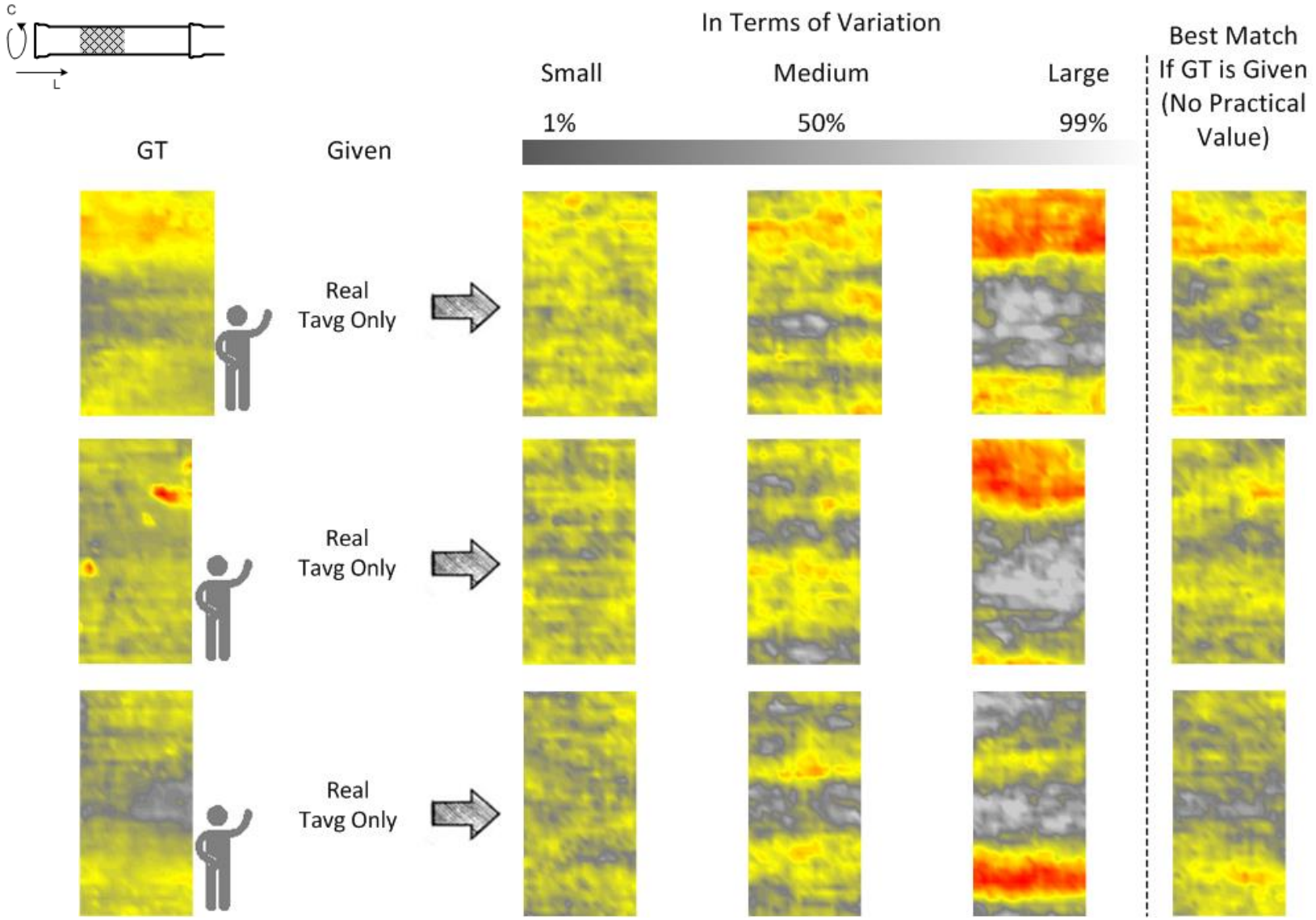






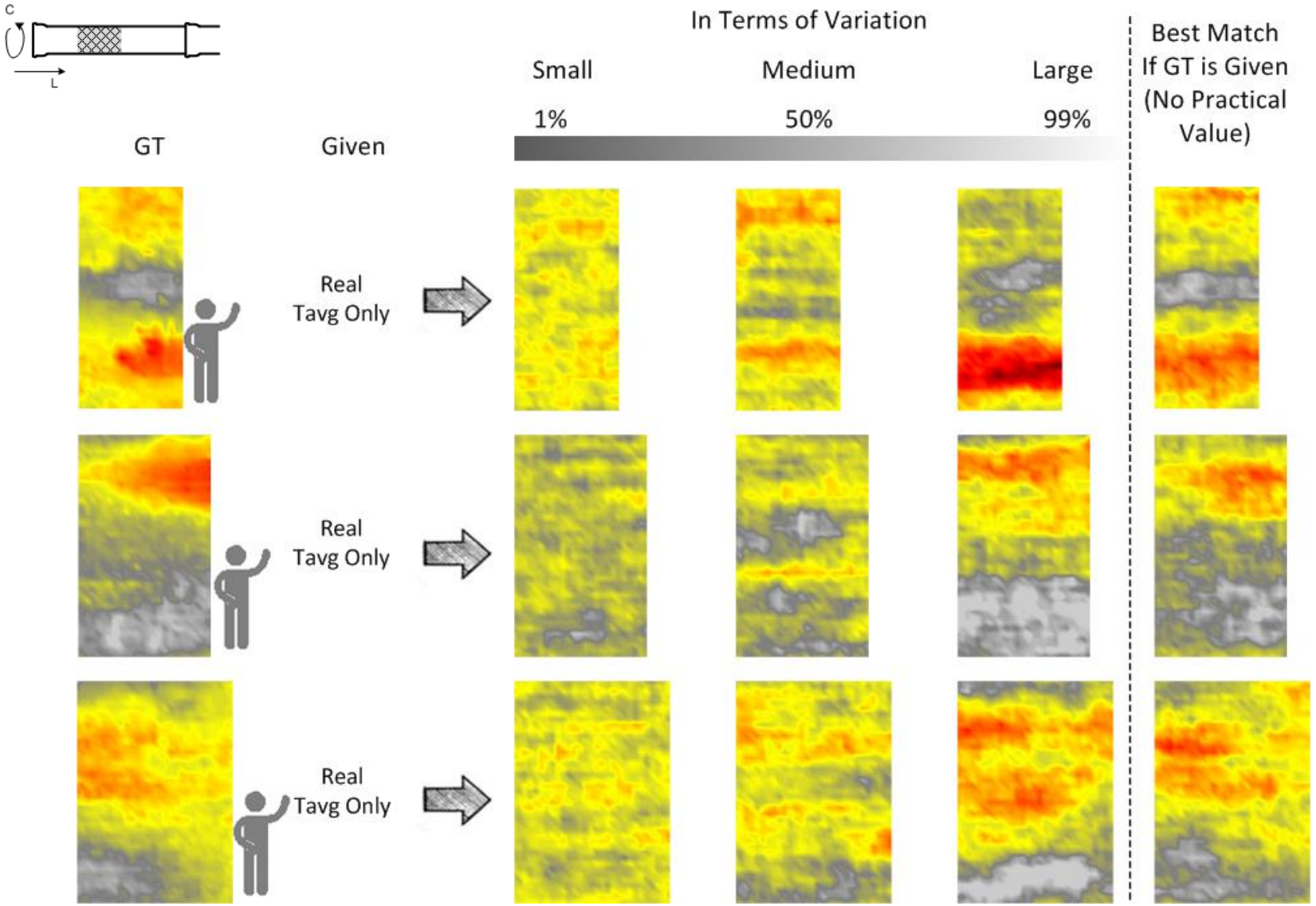
Pits labeled in RED are used for training given their relative condition attained from currently available synthesized screening results (Russell, epulse, LPR)

Case Study 1: Prediction Based on Tavg Only

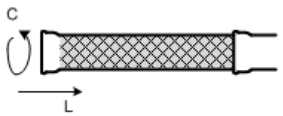


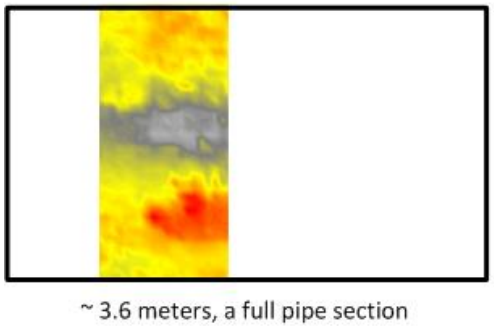
Additional measured data required to guide this decision

Case Study 1: Prediction Based on Tavg Only

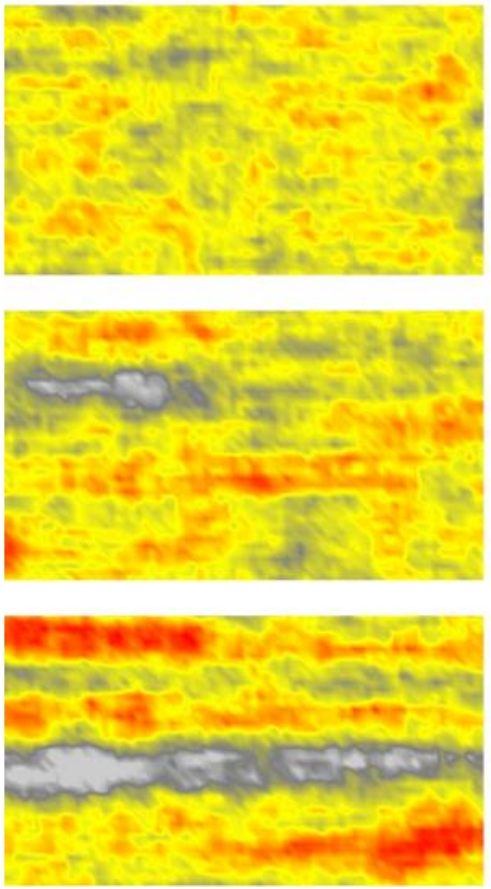


Case Study 1: Prediction Based on Tavg Only (arbitrary length*)





Real
Tavg Only



In Terms of Variation

Small

1%

Medium

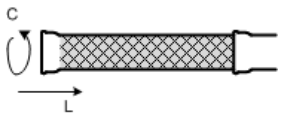
50%

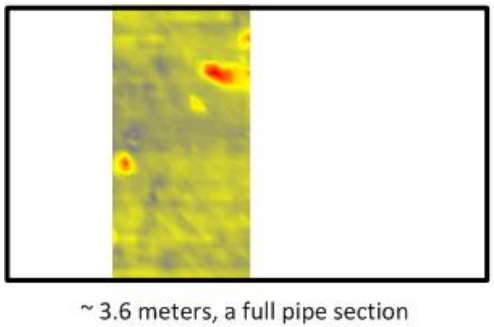
Large

99%

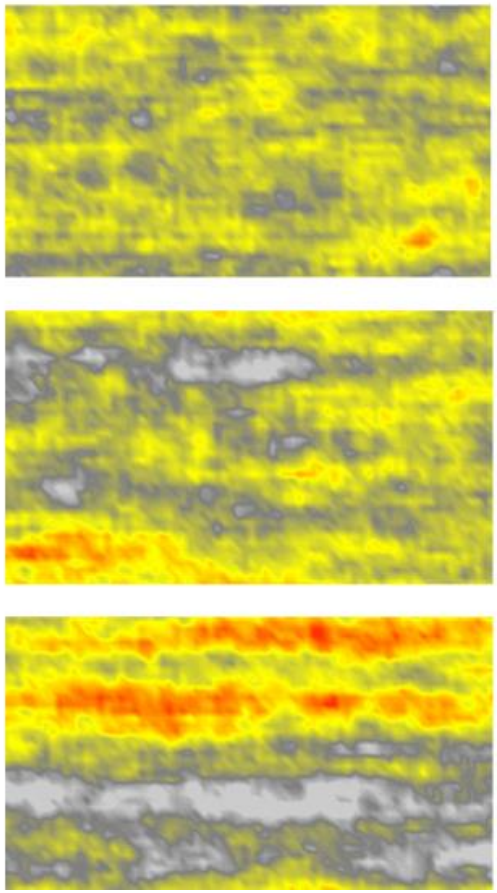
* The actual maximum length of a single instance is only limited by available computer memory

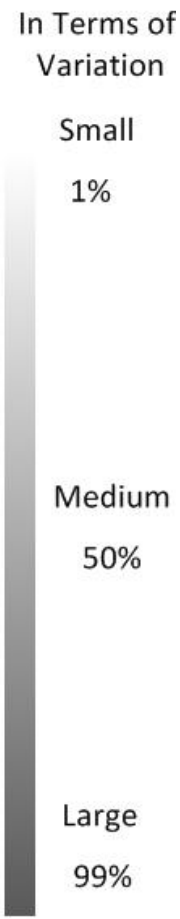
Case Study 1: Prediction Based on Tavg Only (arbitrary length*)





Real
Tavg Only





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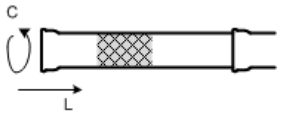
Case Study 1: Prediction Based on Tavg and Tmin



In Terms of Variation

Given	Small	Medium	Large
	1%	50%	99%

GT

Real Tavg Only

Real Tavg & Tmin

Hidden to highlight the worst case only

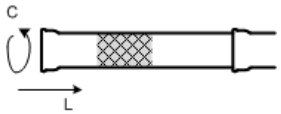
Hidden to highlight the worst case only

Hidden to highlight the worst case only

Hidden to highlight the worst case only

lower limit constraint helps to refine the prediction

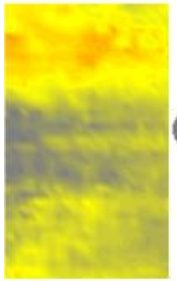
Case Study 1: Prediction Based on Tavg and Tmin



In Terms of Variation

	Small	Medium	Large
Given	1%	50%	99%

GT



Real Tavg Only

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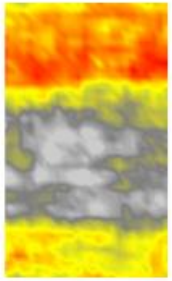

Real Tavg & Tmin

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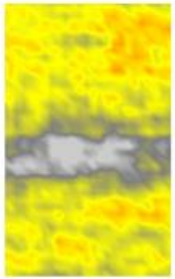
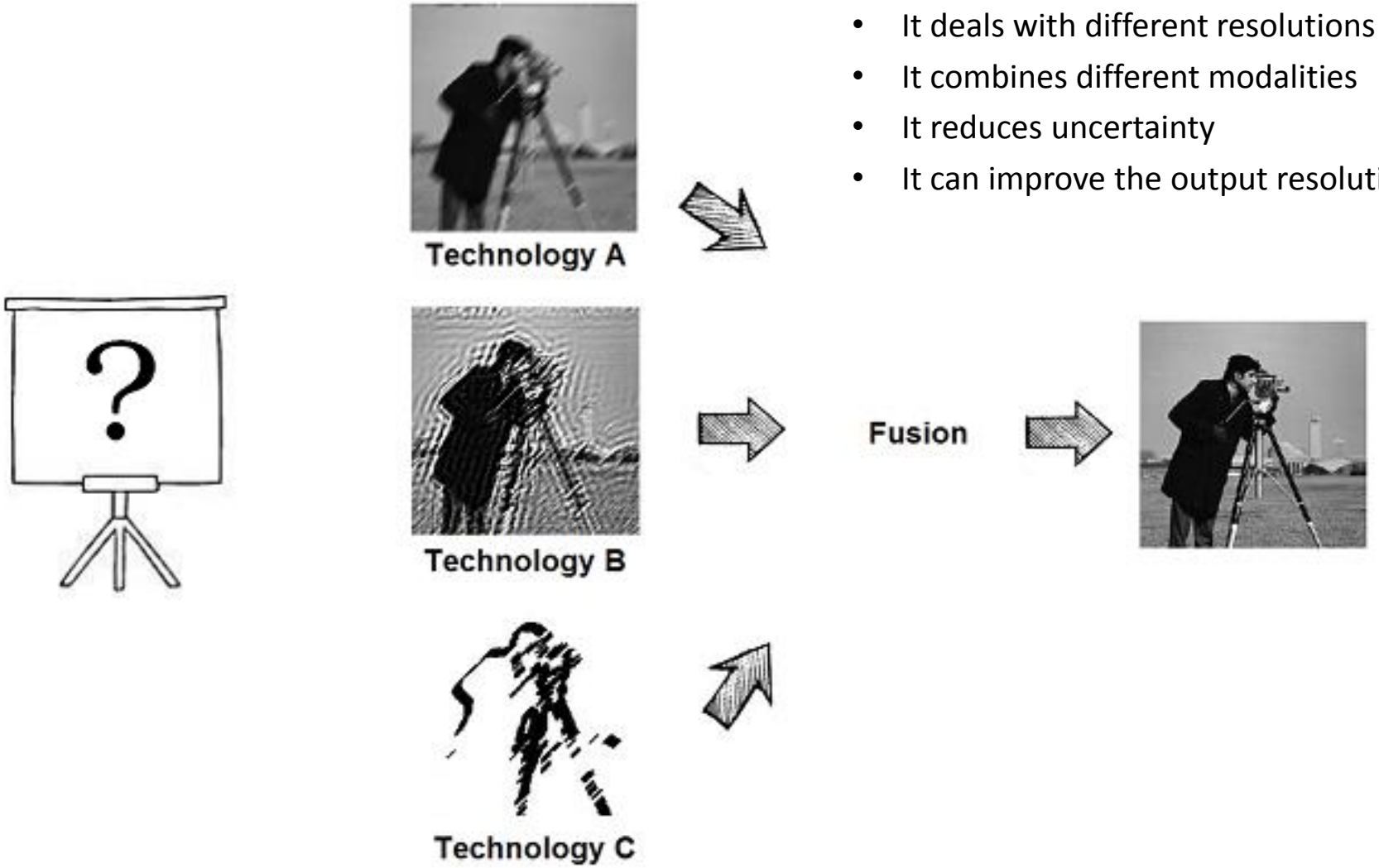


lower limit constraint helps to refine the prediction

Data Fusion



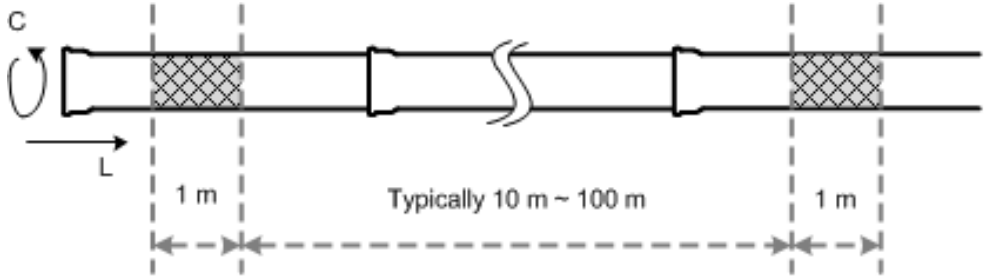
- It deals with different resolutions
- It combines different modalities
- It reduces uncertainty
- It can improve the output resolution

Data Fusion: Challenges

1. Data fusion can be a computationally expensive process in that relations between all the data points needs to be calculated and maintained throughout for most accurate results

2. A framework has been proposed in this work to partially overcome this challenge for in-between interpretations by use of sub-maps (see last TAC presentation, also list of publications)

In-Between Prediction:
Two-fold Role of Fusion - Local



Local Measurements (MFL, BEM, ...)

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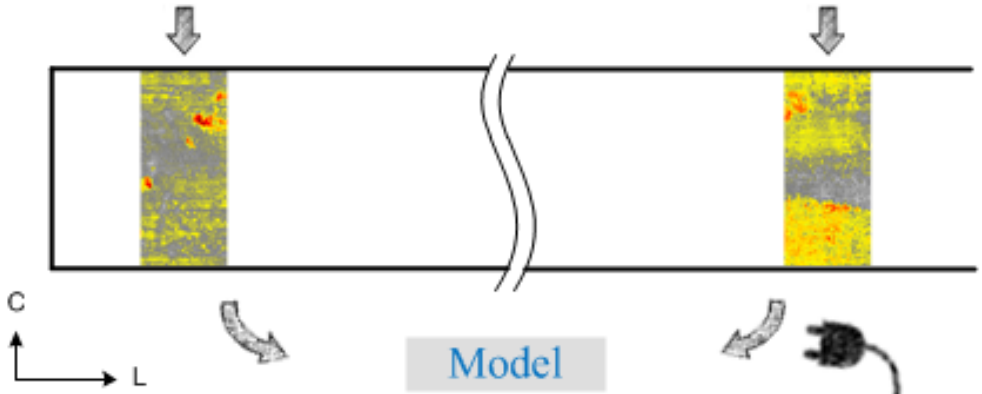
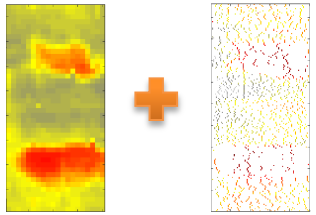


Model

Combine local measurements with different properties

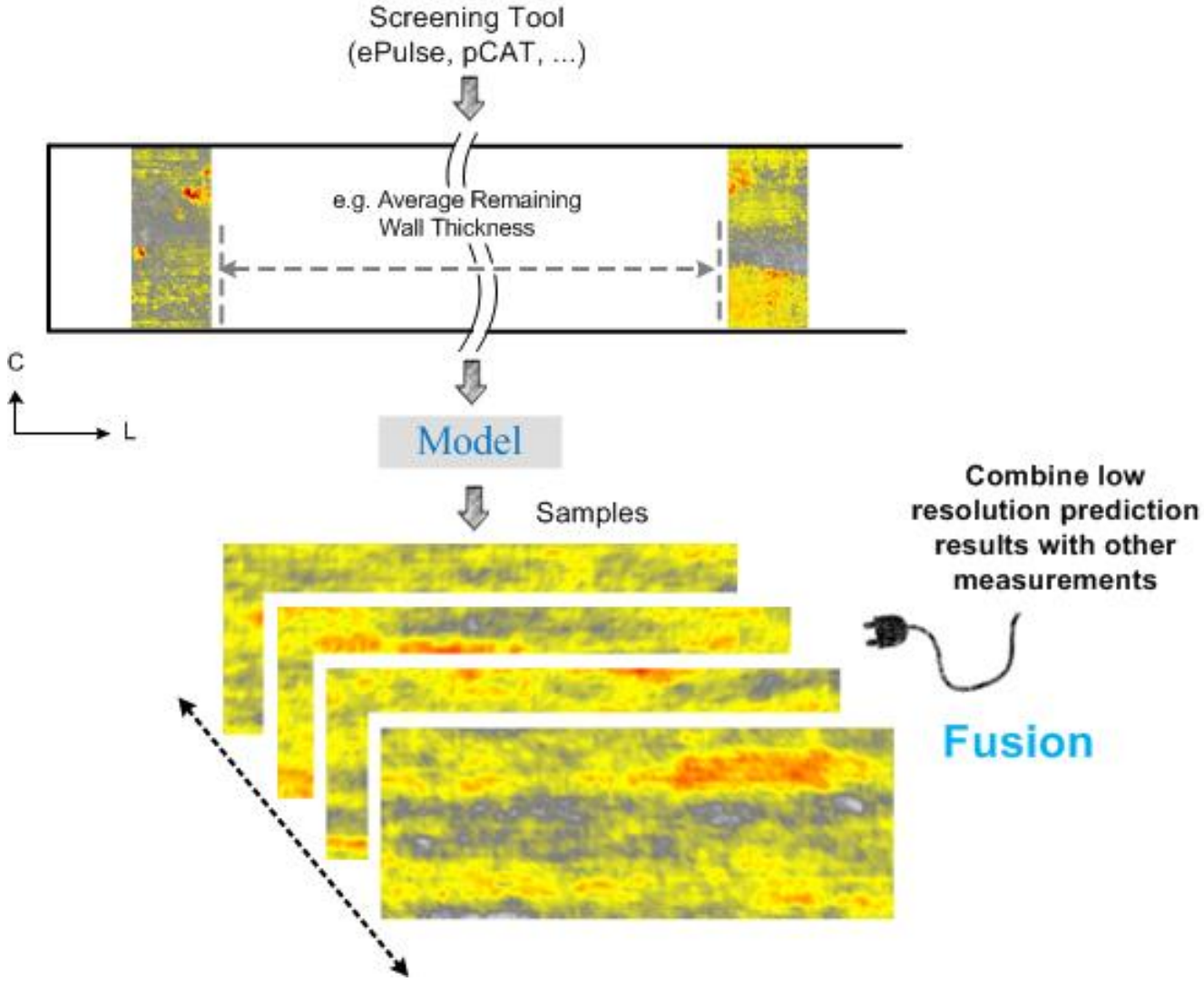
Fusion

For Example:



BEM data MFL data

In-Between Prediction:
Two-fold Role of Fusion - Refinement after Inference



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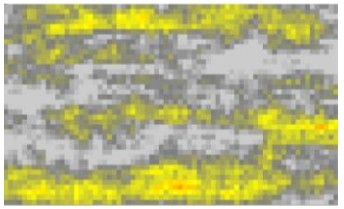
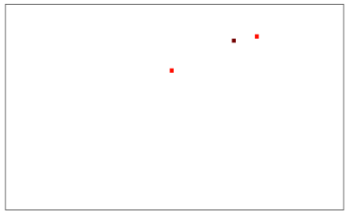
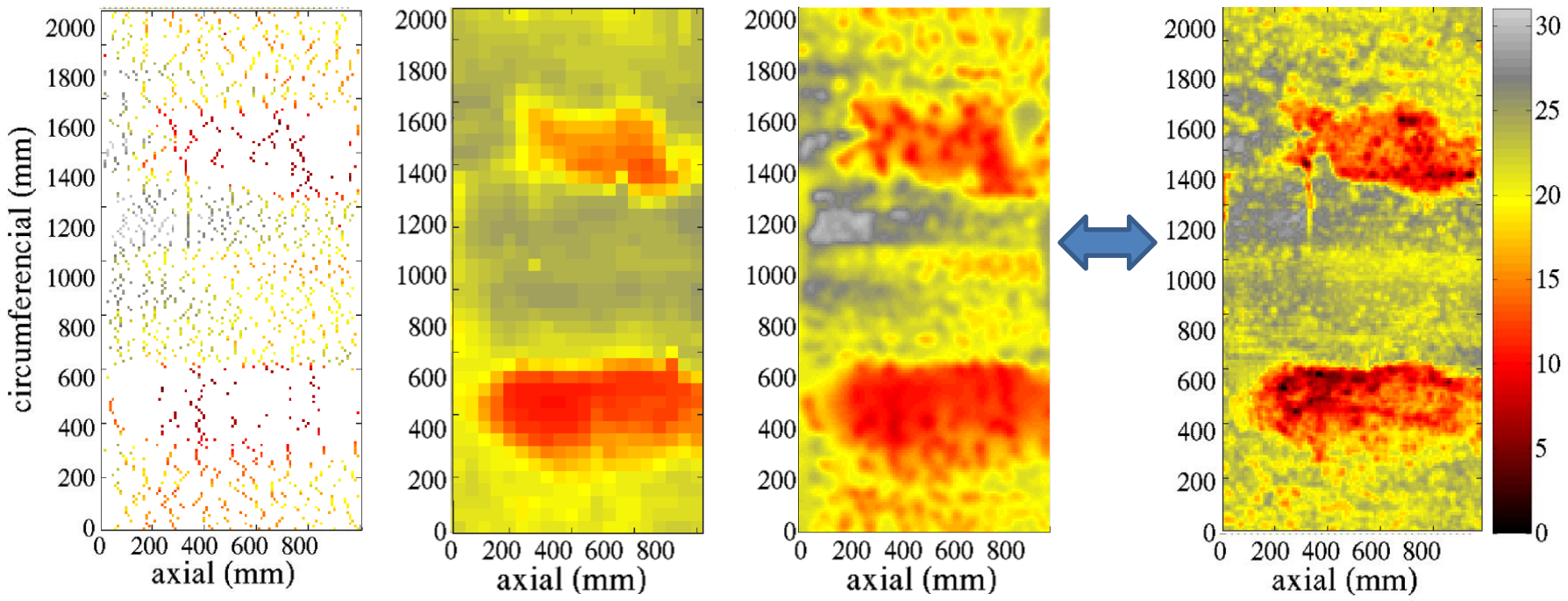


In-between Inference



Russell's 3 defects

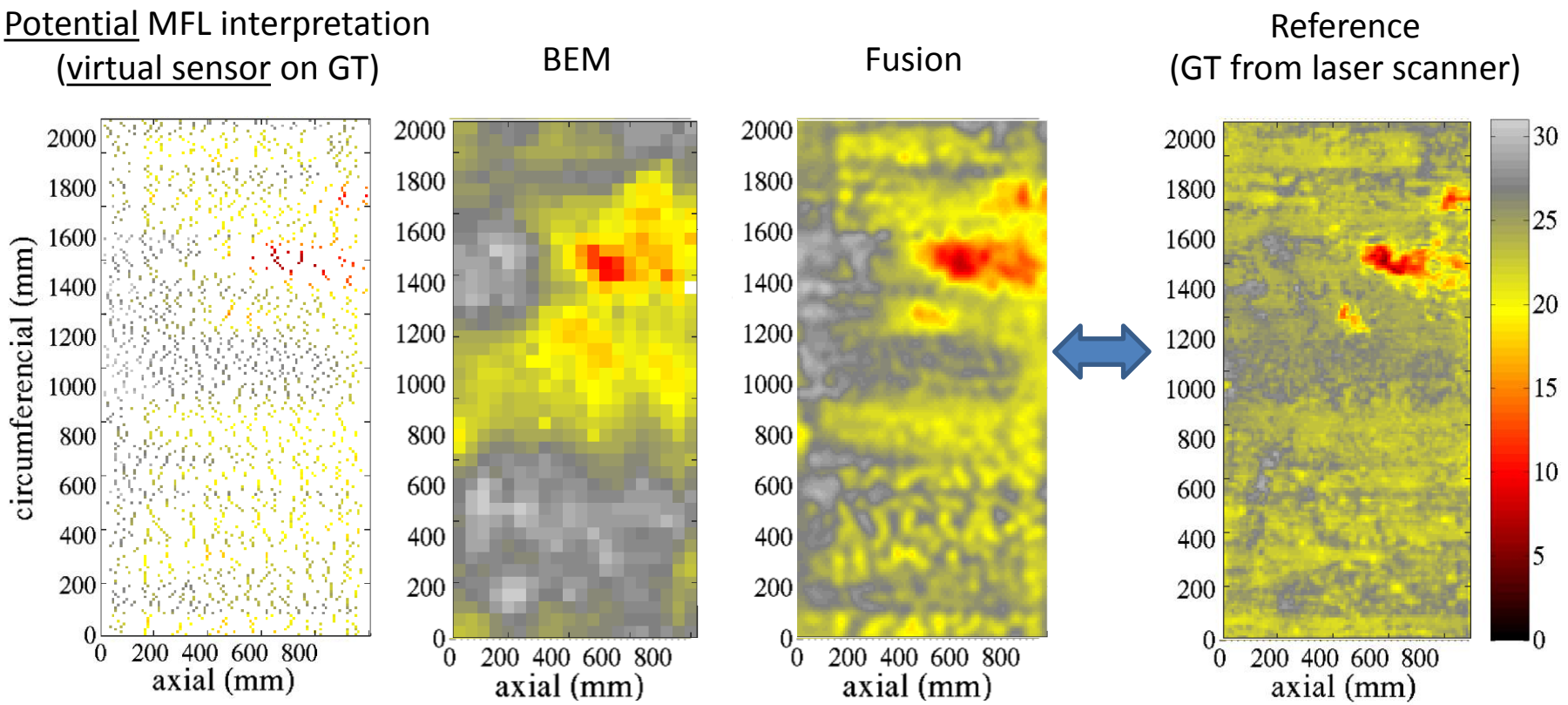
Case Study 2: More Detailed Local Fusion Models



RMSE*	3.69 mm	3.97 mm	2.88 mm

*Root Mean Squared Error

Case Study 2: More Detailed Local Fusion Models



RMSE*	2.70 mm	3.45 mm	2.16 mm

*Root Mean Squared Error

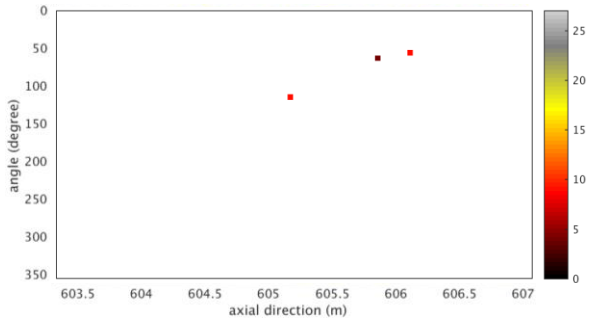
Case Study 2: Better In-between Inference

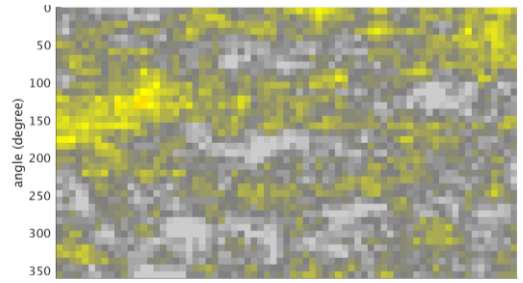
Russell (3 defects)

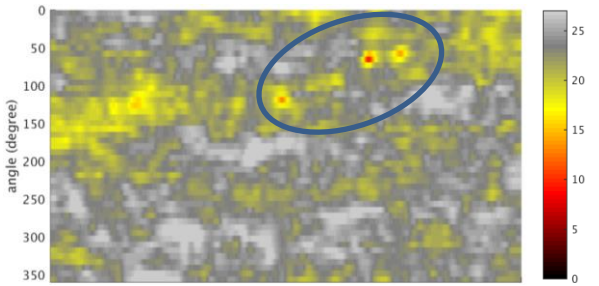
In-Between Inferences

Fusion

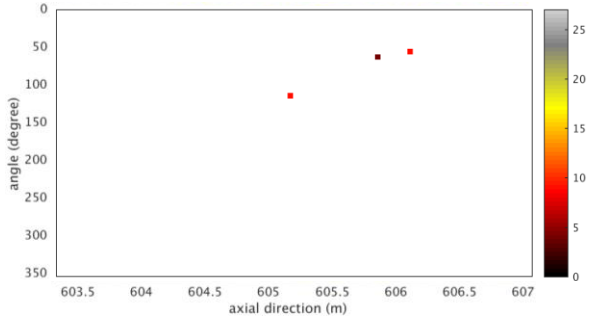
Condition A

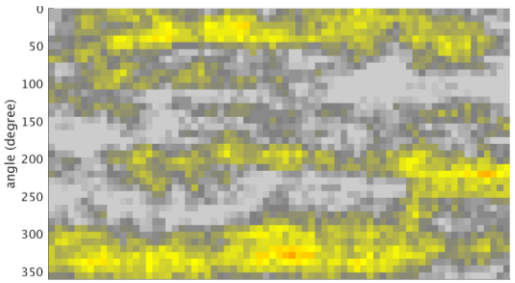


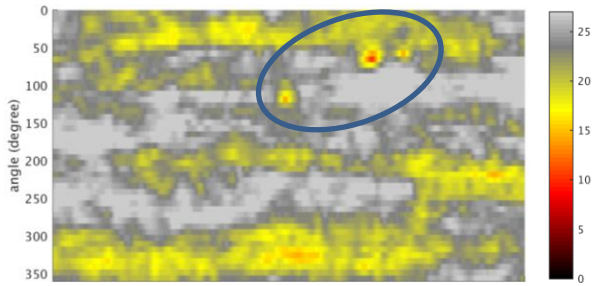




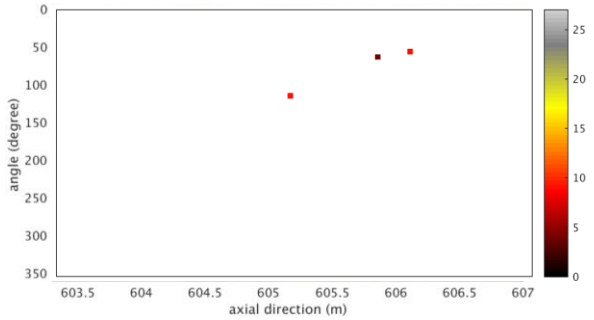
Condition B

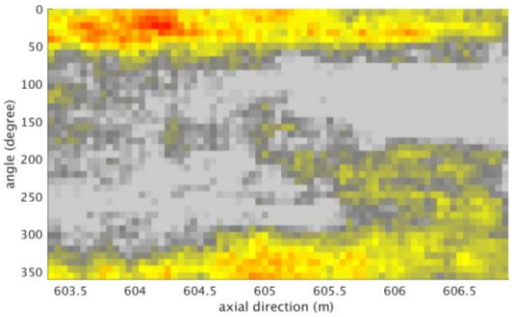


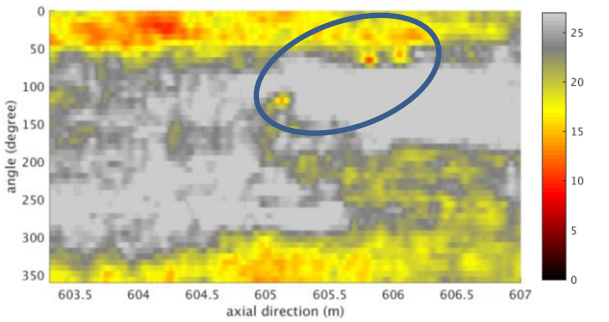




Condition C







Final Thoughts

1. Proposed Framework is flexible to allow for the variety of the scenarios presented to be readily incorporated

2. Understanding what current technologies and their interpretations can provide remains paramount for success and it is a key objective of the on-going efforts from this activity

3. Framework being put into practice on real test-bed data

4. Validation currently means digging up long sections of pipe, unfeasible. Alternatives are being pursued.

Current Progress and Future Goals

Goal	Status
Appointment of personnel and training Review of current practices and literature Signing agreements with technology providers/partners Establish framework to fuse data at varying resolutions Establish protocols for data collection	Completed
First pass at data fusion framework with simulated/numerical sensor data; Data collection runs completed; Preliminary evaluation of framework with real sensor data	In progress (70%)
Robust validation of framework with real data; Training (SWC/industry partners) and reporting	In progress (20%)