

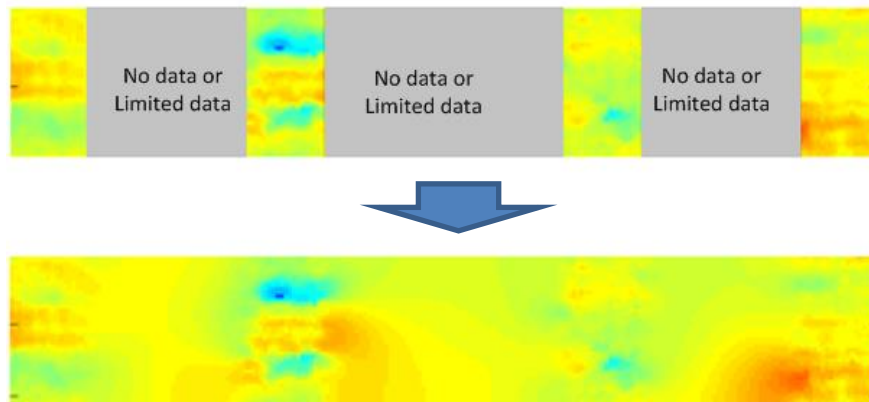
Activity 4a: Enhancing the Reliability of Condition Assessment of Buried Large Diameter Water Mains

Activity Co-leaders: A/Prof. Jaime Valls Miro, Prof. Gamini Dissanayake
UTS

Scope Activities 4a: In-Between Interpretation

Key Expected Outcomes:

1. Framework to assess in-between interpretations of pipeline condition from limited inspections



Activity 4 – UTS Team

Academics (x5):

- Prof Gamini Dissanayake (Co-activity leader)
- A/Prof Jaime Valls Miro (Co-activity leader)
- A/Prof Sarath Kodagoda (Sensor modelling, MFL)
- Dr Alen Alempijevic (Sensor modelling, BEM)
- Dr Teresa Vidal Calleja (Data interpretation, machine learning, estimation theory)

Fully dedicated (funded from project) personnel (x3):

- Dr Lei Shi (Leo)
 - In-between, Upcoming Technologies, LPR ML
- Ms Liye Sun (PhD candidate)
 - Multimodal Information Fusion for Advance Condition Assessment of Ageing Infrastructure
- David Hunt (Technical Assistant, Sept'15 – Mar'16)

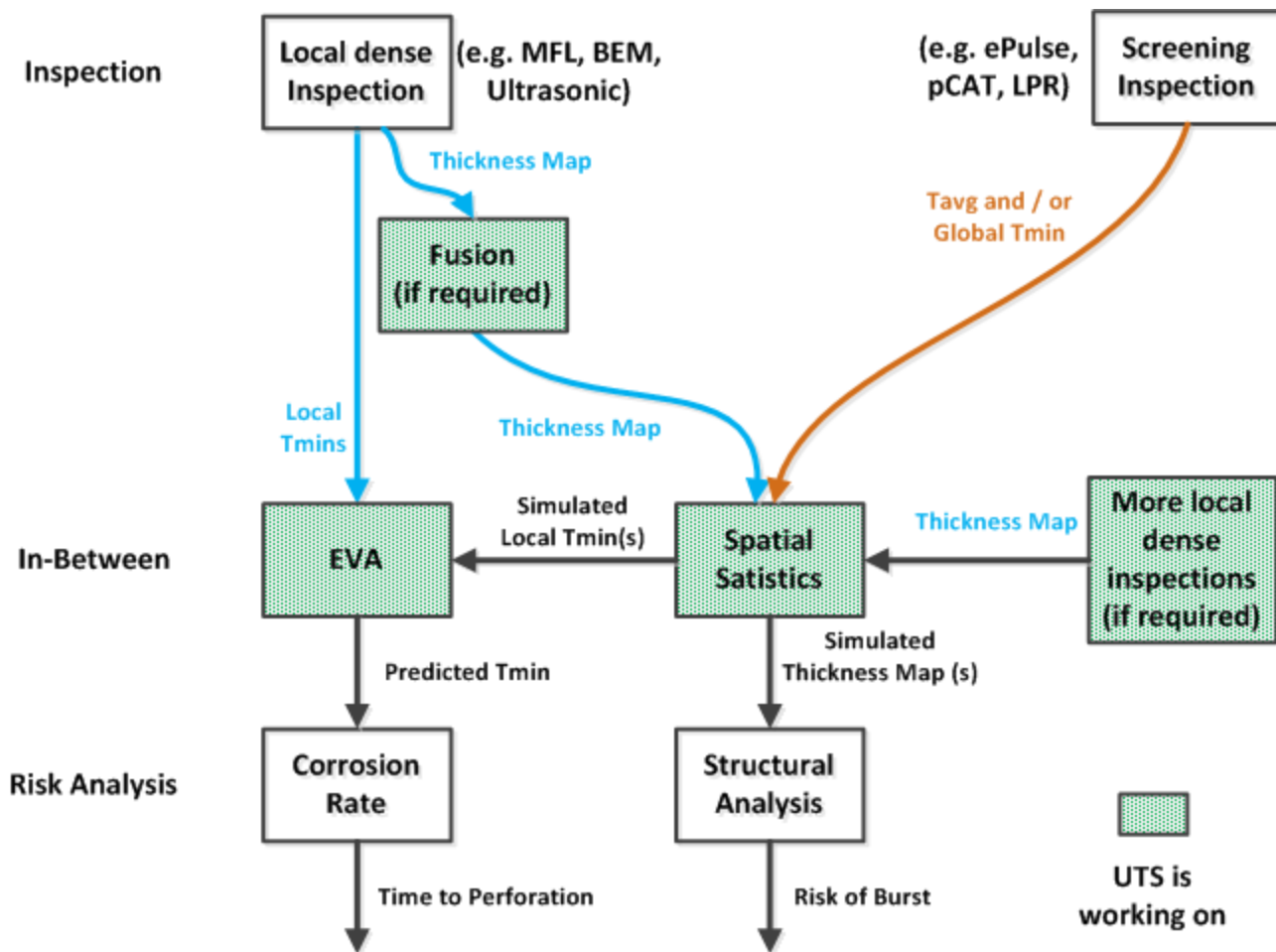
Presentation Outline

1. Summary Current State of Affairs
2. In-Between Framework
 - The Role of Spatial Statistic Machine Learning
 - Review
 - Quantitative Evaluation
 - Application in Sampling Inspection
3. In-Between Framework
 - The Role of Fusion
 - Challenges

Summary Current State of Affairs and Latest Progress

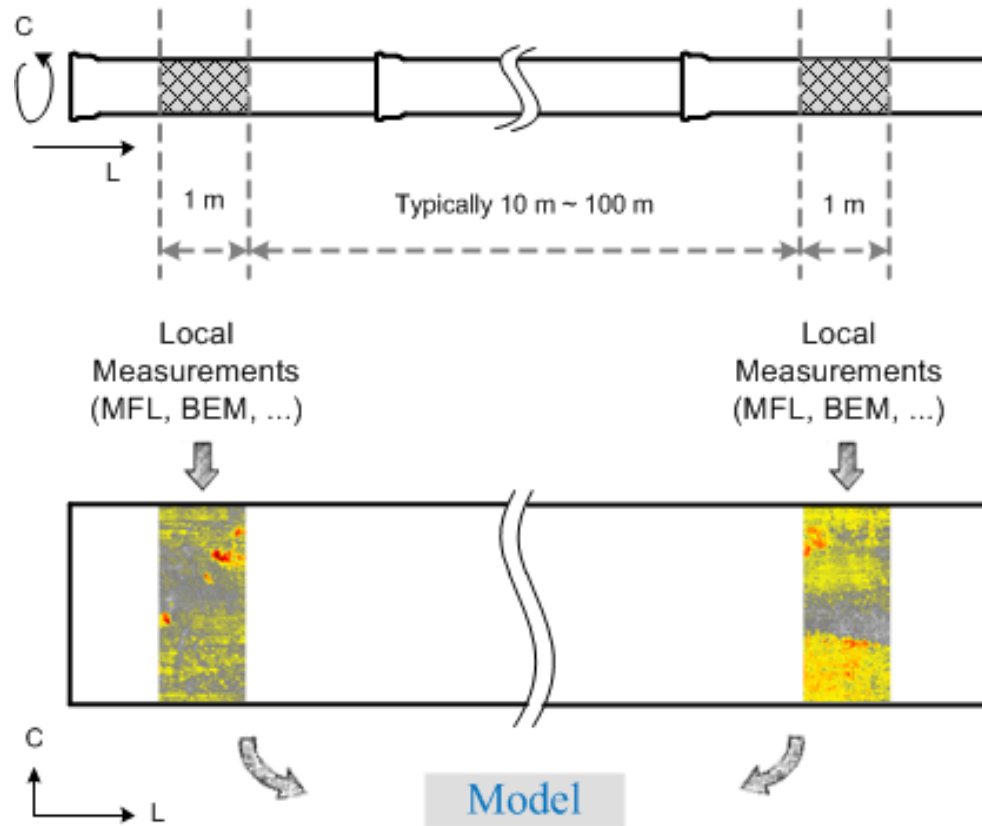
1. UTS has developed a methodology based on spatial statistics (Gaussian Processes) to estimate continuous geometry
2. A data fusion approach has been developed to combine different sources of information using an efficient sub-mapping strategy
 - Allows fusing MFL (high res) with BEM (low res)
 - Allows fusing in-between interpretations (low res) with RFT (higher res)
3. Validation with data collected from test bed: how good is the above using what is available, i.e. real CA data?

The Big Picture



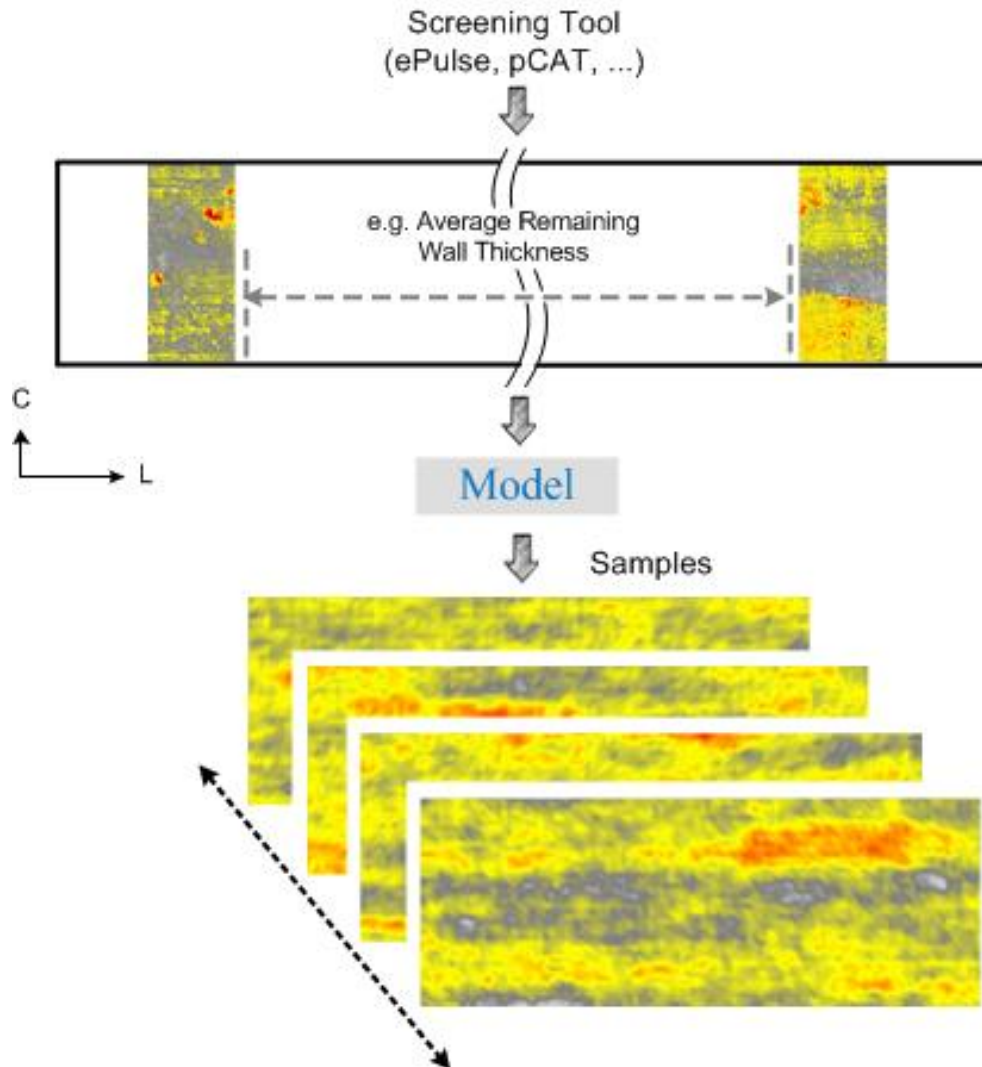
Reminder: In-Between Prediction

The Framework



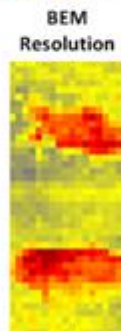
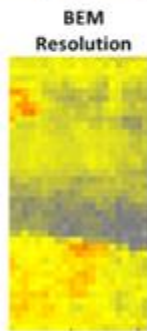
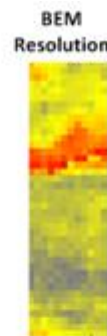
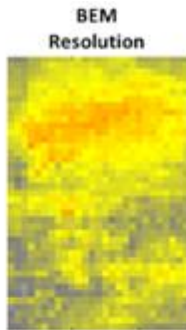
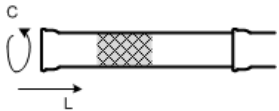
Reminder: In-Between Prediction

The Framework



Reminder: Case Study 1 from Last TAC

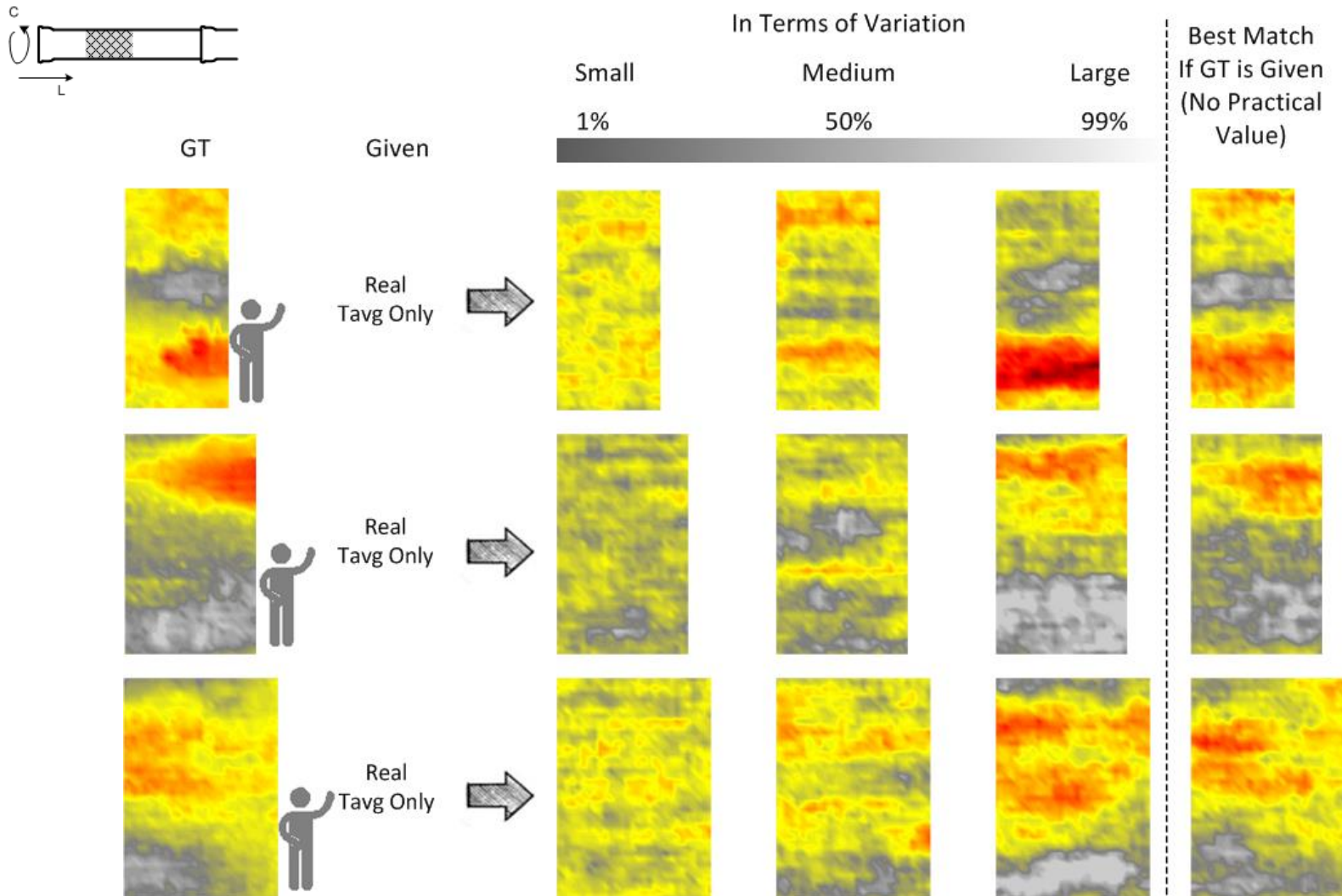
Training / Test Data



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

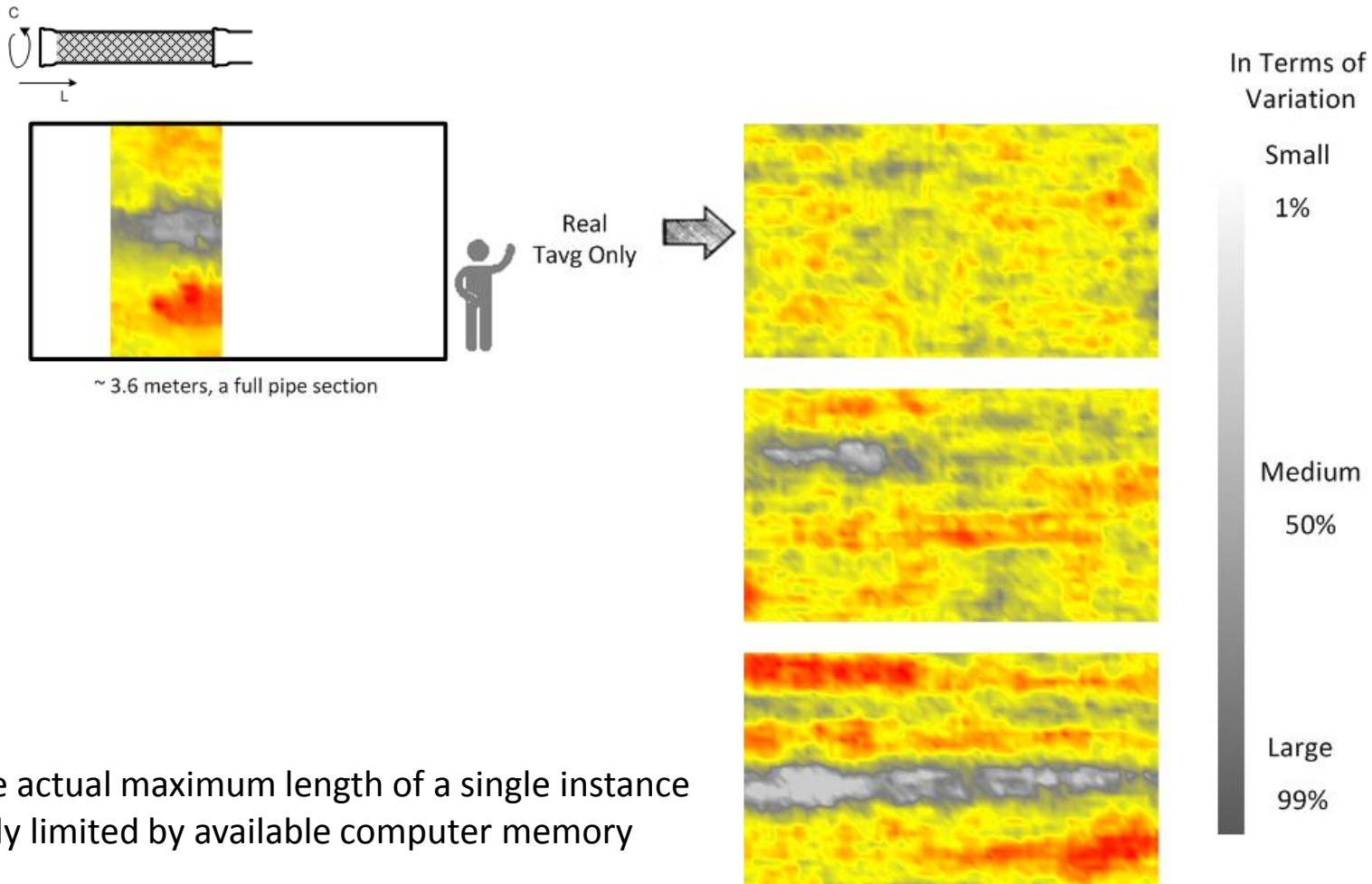
Reminder: Case Study 1 from Last TAC

Prediction Based on **Tavg Only**



Reminder: Case Study 1 from Last TAC

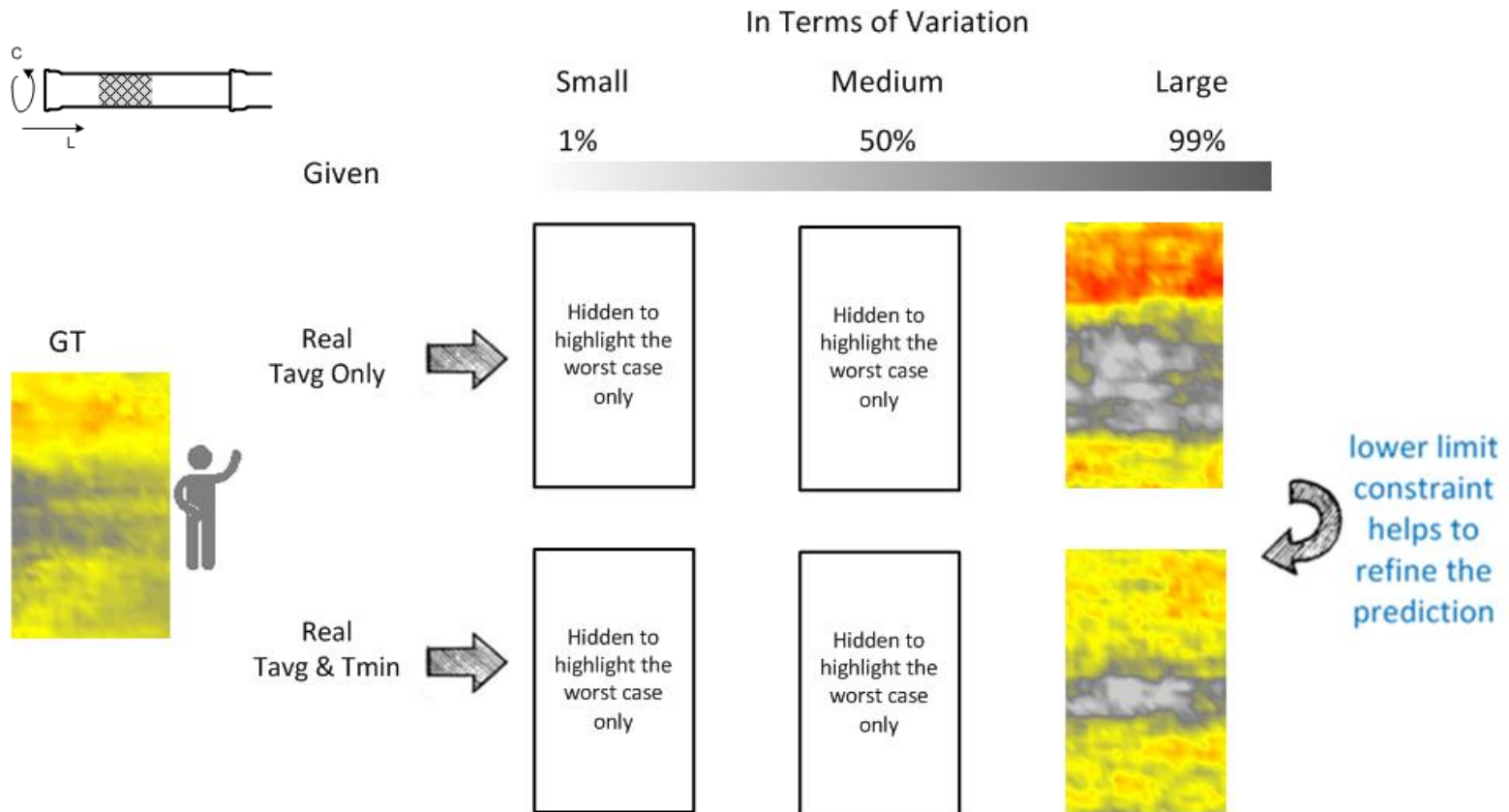
Prediction Based on Tavg Only (arbitrary length*)



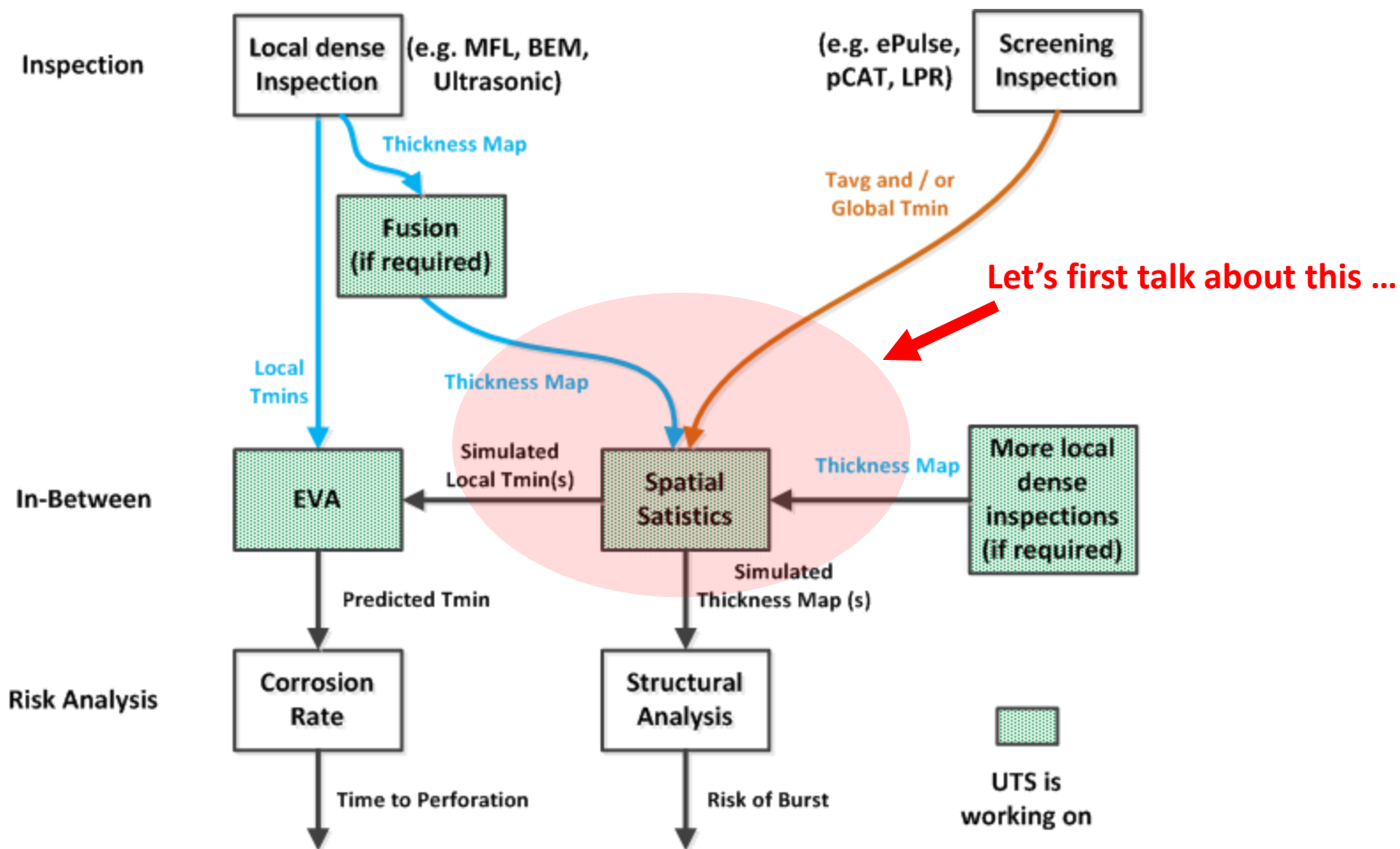
* The actual maximum length of a single instance is only limited by available computer memory

Reminder: Case Study 1 from Last TAC

Prediction Based on **Tavg** and **Tmin**

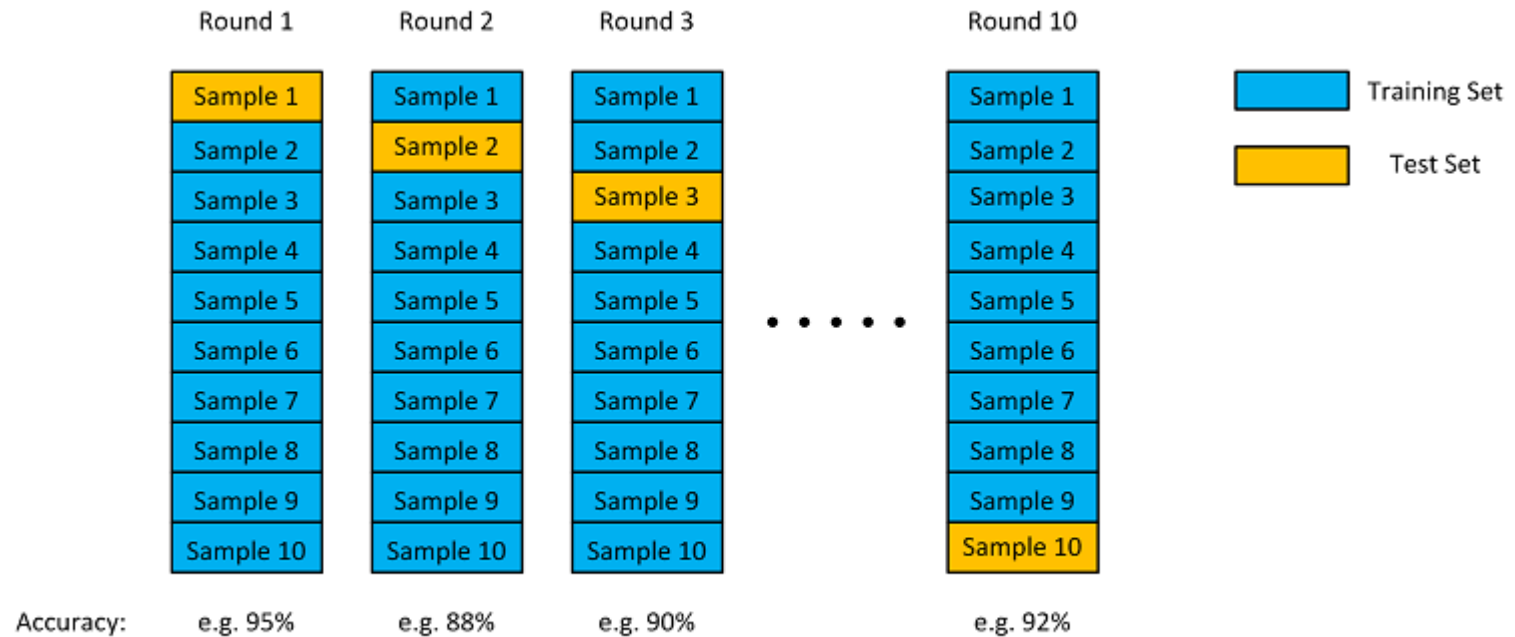


The Big Picture



Quantitative Evaluation of In-Between Framework

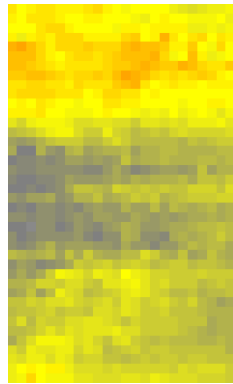
Methodology: Cross-Validation



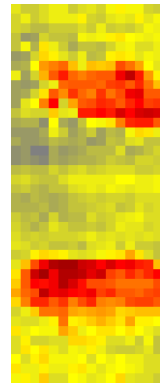
Final Accuracy = Average (Round 1, Round 2, ... Round 10)

Quantitative Evaluation of In-Between Framework

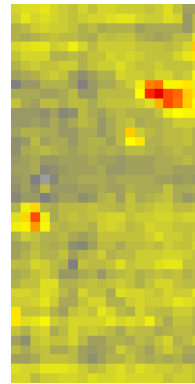
Methodology: Cross-validation



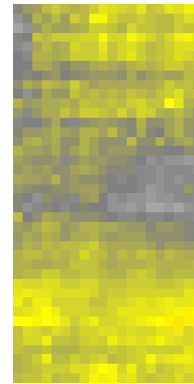
T2P1 (S1)



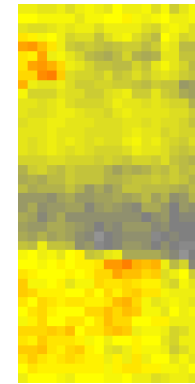
T2P2 (S2)



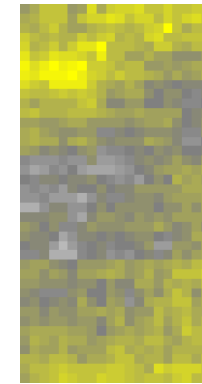
T2P3 (S3)



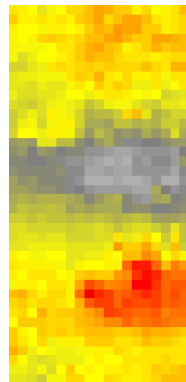
T2P4 (S4)



T3P1 (S5)



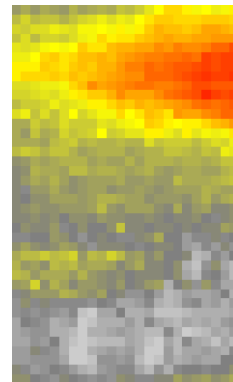
T3P2 (S6)



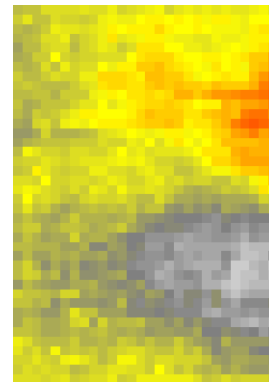
T3P3 (S7)



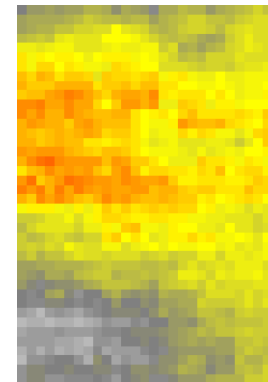
T3P4 (S8)



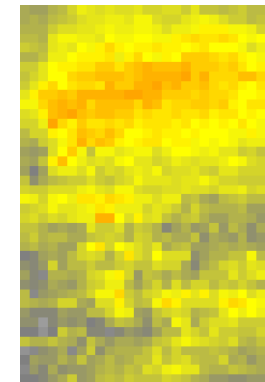
T3P5 (S9)



T5P11 (S10)



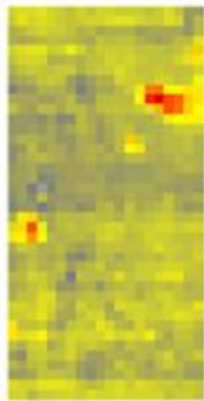
T5P12 (S11)



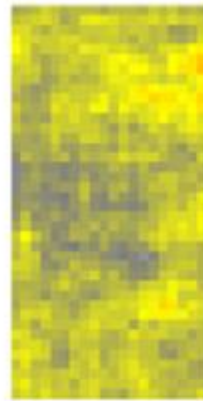
T5P13 (S13)

Quantitative Evaluation of In-Between Framework

Experimental Results: 2 Examples



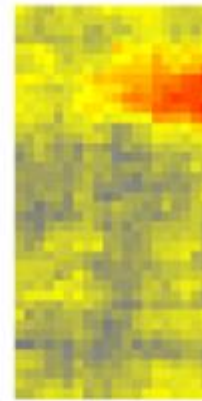
Ground Truth



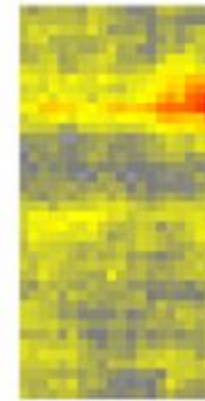
Nothing Given



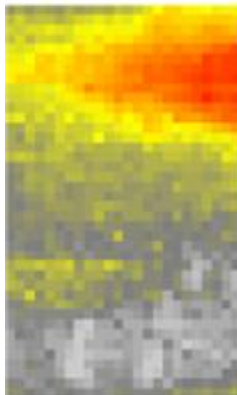
Tavg Given



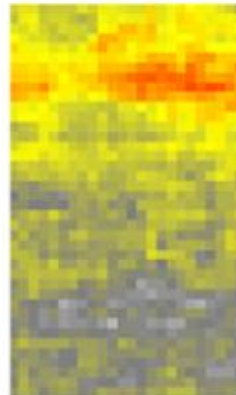
Tmin Given



Tavg & Tmin
Given



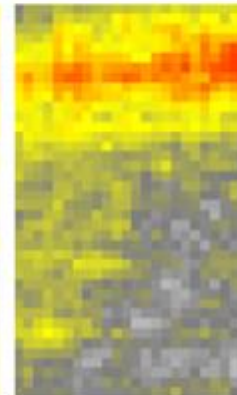
Ground Truth



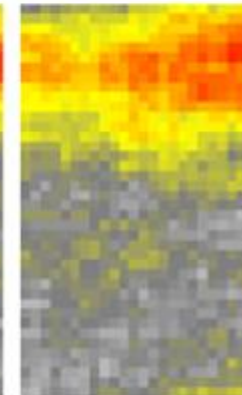
Nothing Given



Tavg Given



Tmin Given



Tavg & Tmin
Given

Quantitative Evaluation of In-Between Framework

Conclusions So Far

- Performance evaluated in terms of RMSE:

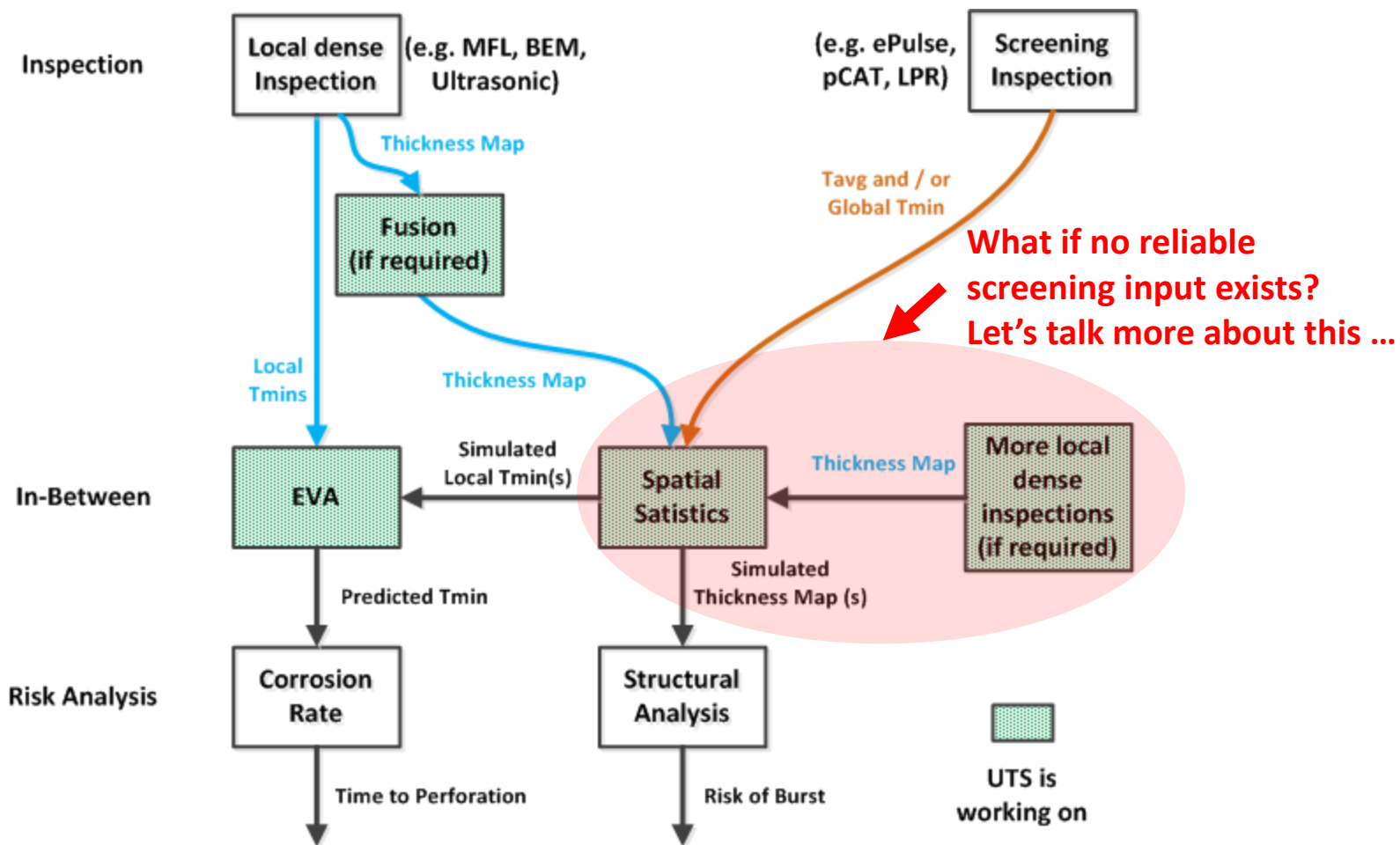
Mean Given > Nothing Given

Min Given > Nothing Given

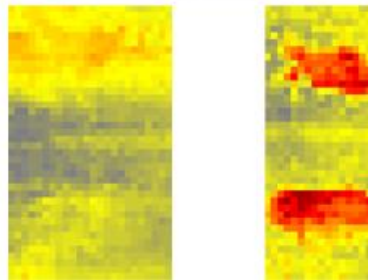
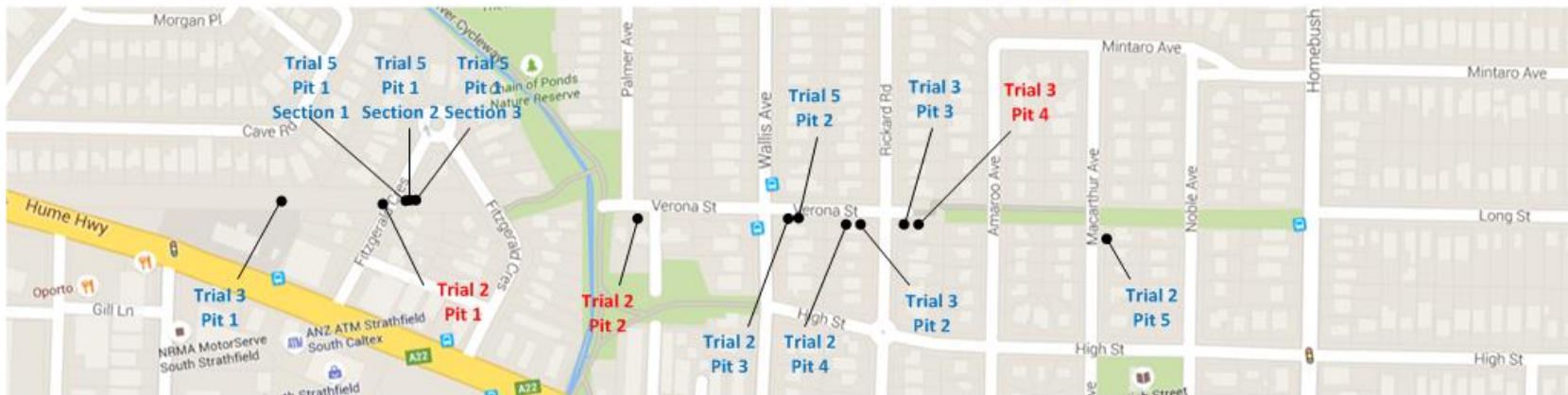
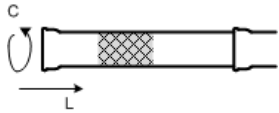
Mean and Min Given > Nothing Given

- The framework has been proven to be able to meaningfully incorporate mean/min/mean+min as constraints
- Generally speaking, more information gives more reliable prediction

The Big Picture



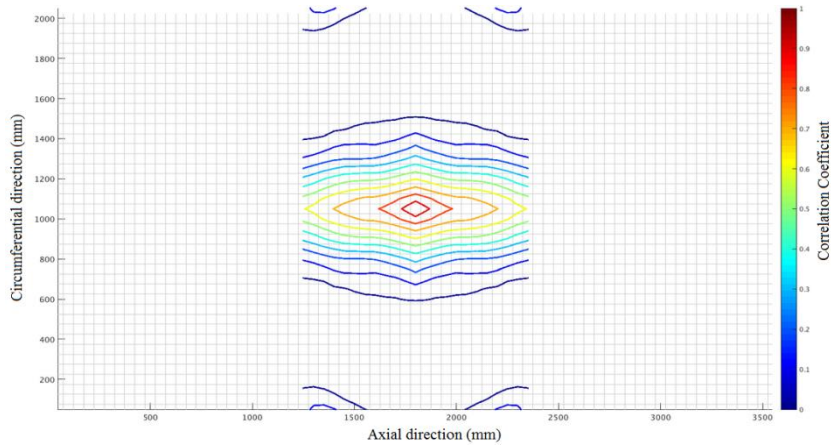
Sampling Inspection Training / Test Data



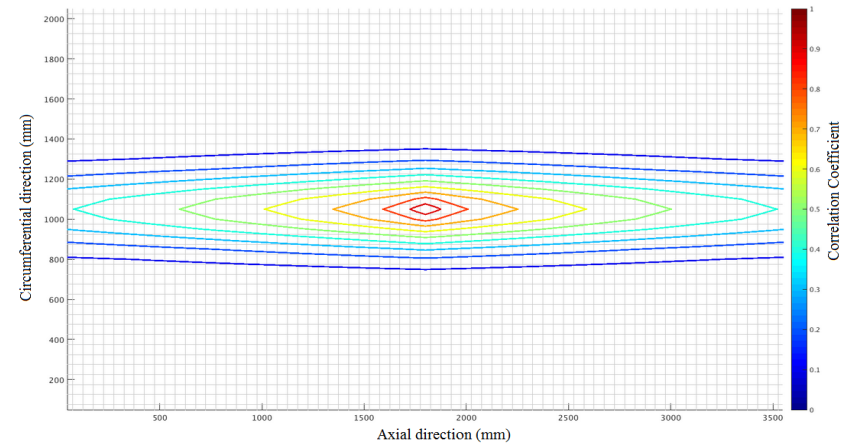
Pits labeled in **RED** are used for training

Sampling Inspection

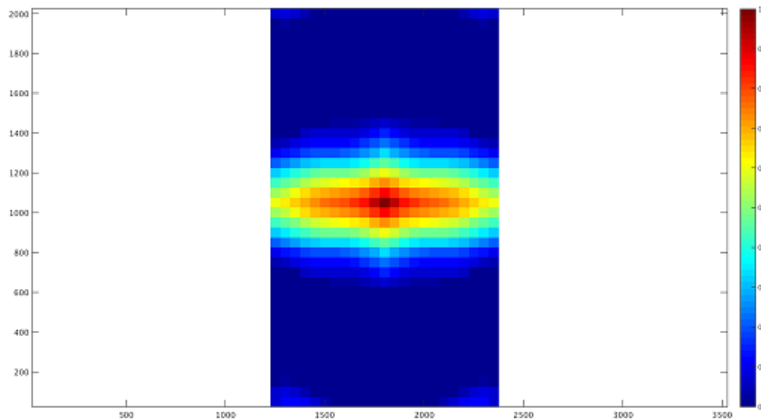
Correlation Maps



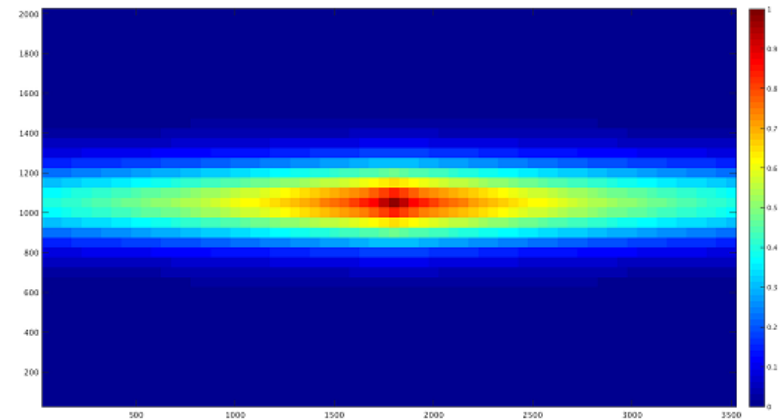
From statistics (Contour Map)



From the model (Contour Map)



From statistics (Colour Map)

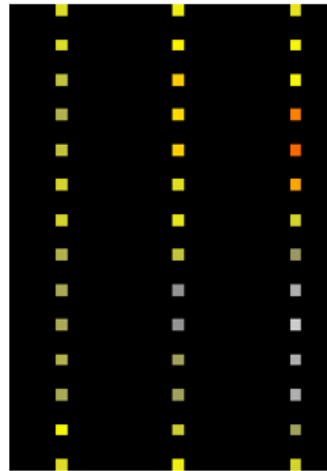
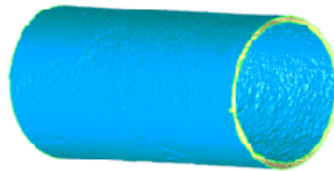


From the model (Colour Map)

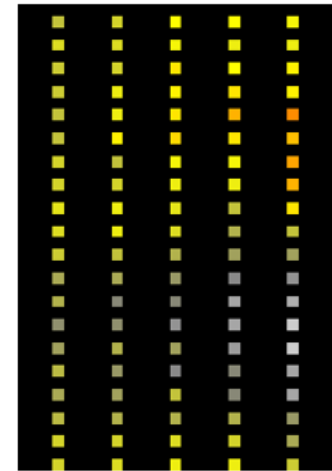
Sampling Inspection

Experimental Results

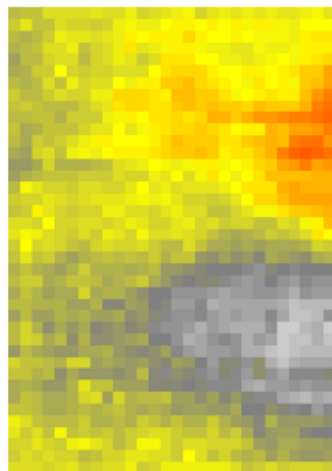
* Black -
uninspected area



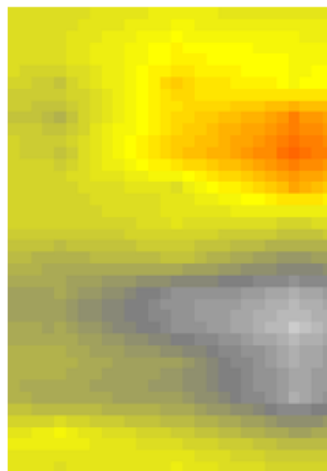
Inspection Pattern A
($r > 0.7$, use 3.33% of data)



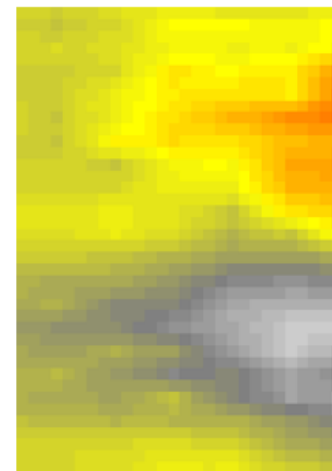
Inspection Pattern B
($r > 0.8$, use 10% of data)



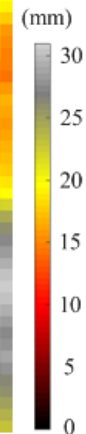
Ground-truth



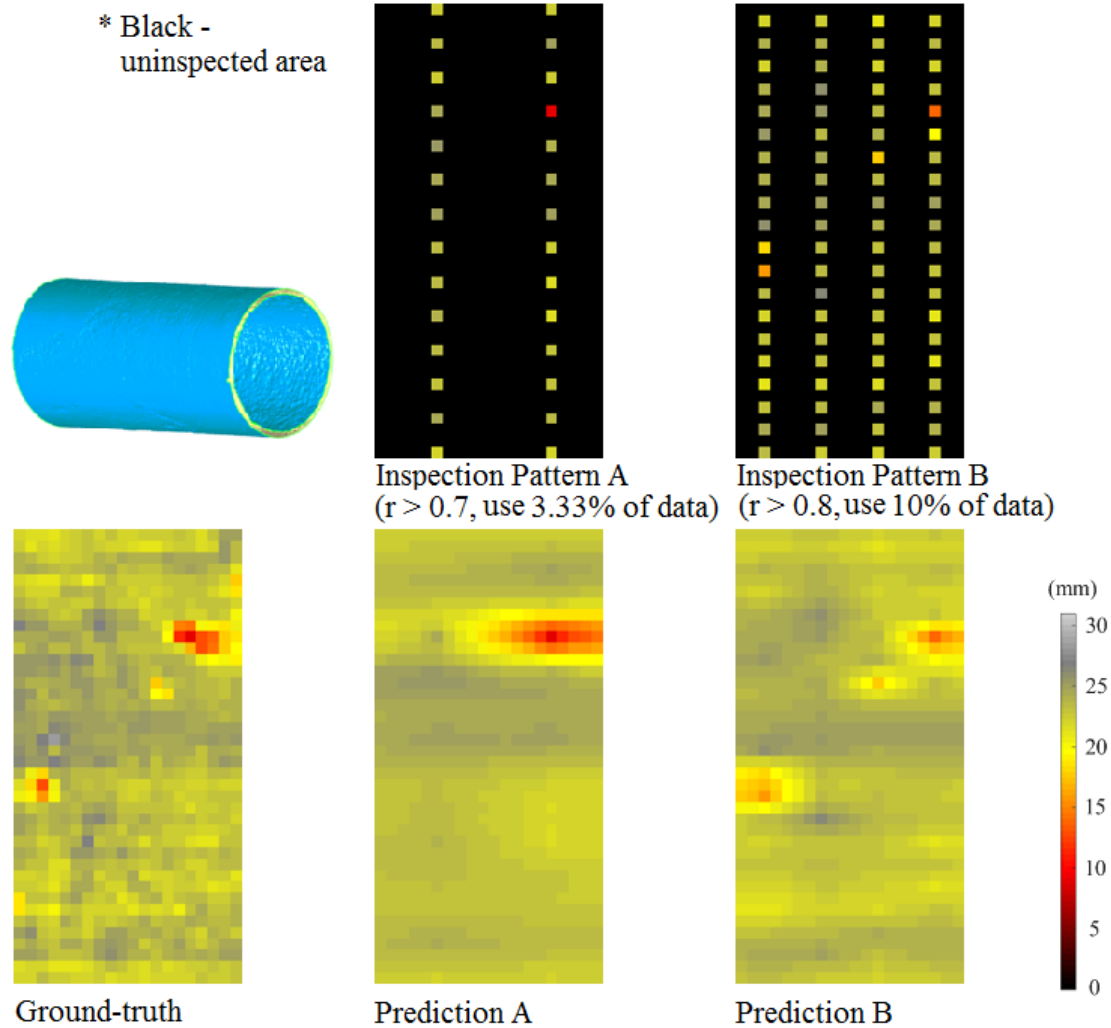
Prediction A



Prediction B



Sampling Inspection Experimental Results

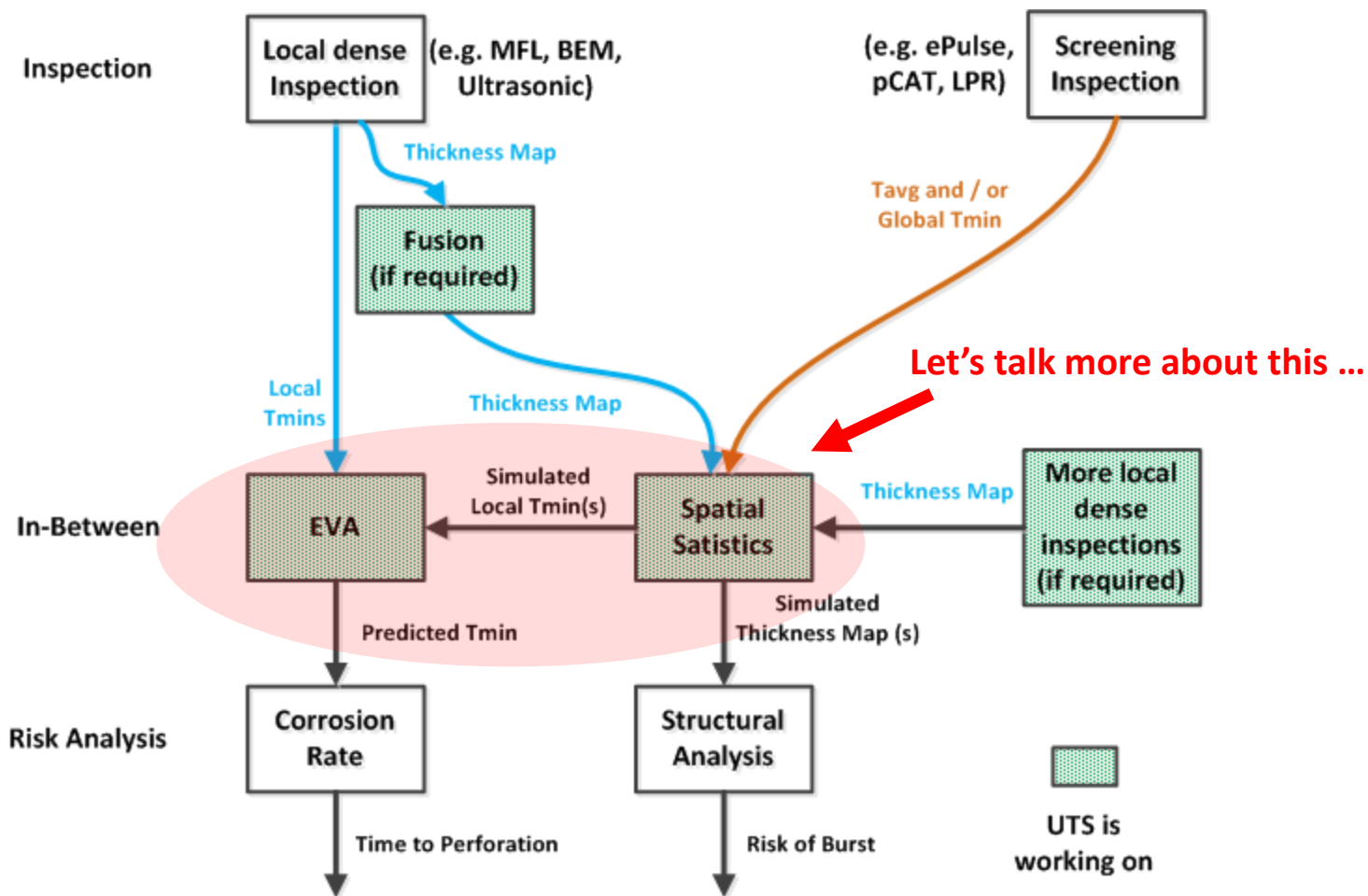


Sampling Inspection

Conclusions

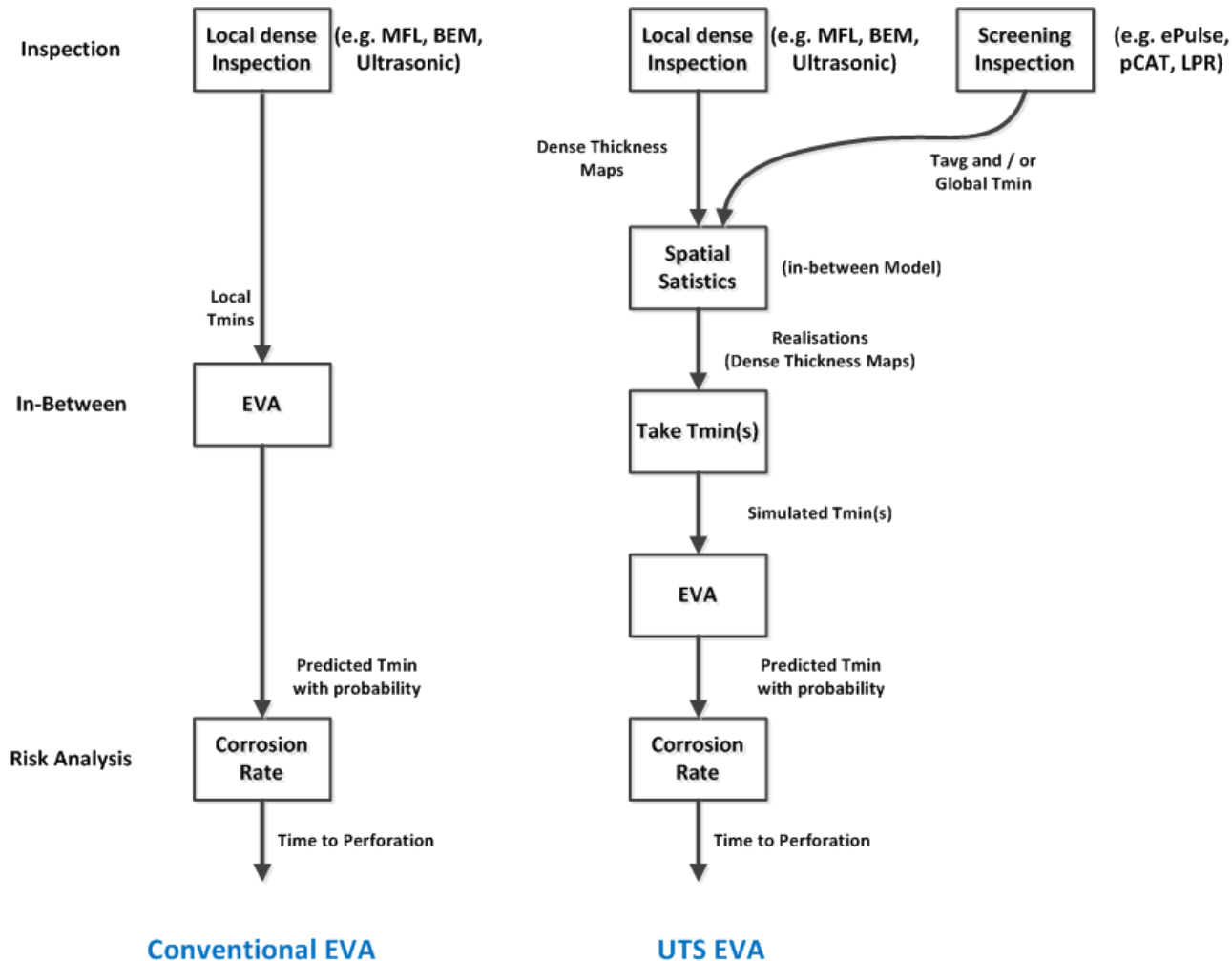
- Correlation pattern is anisotropic
- 10% of samples appear to represent the full thickness map well
- Extreme values could be missed out, but prediction can be provided

The Big Picture



UTS EVA

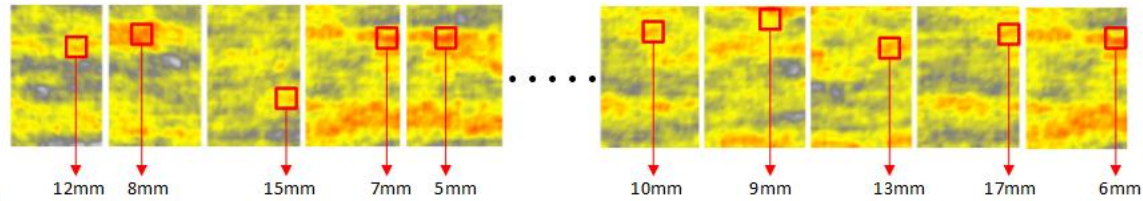
Improving Current Prediction Practices



UTS EVA

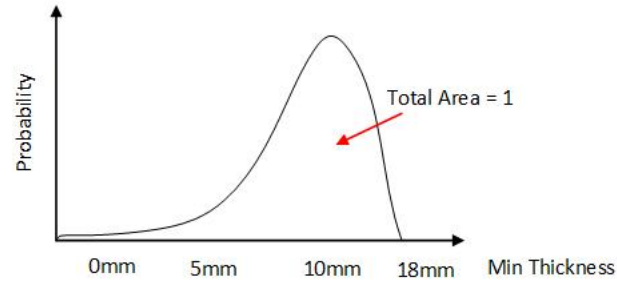
Gaussian Processes Model

Realisations for
Length = 1m
 $T_{avg} = 25\text{mm}$



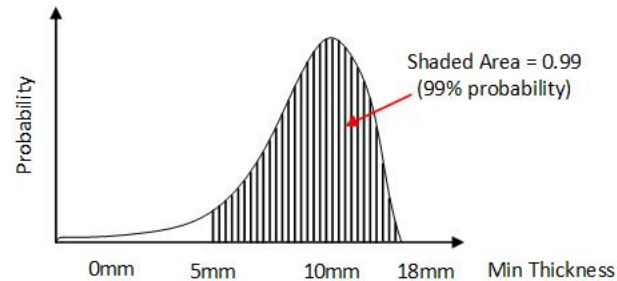
Minimums

Extreme Value Distribution



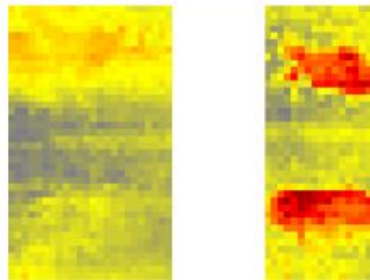
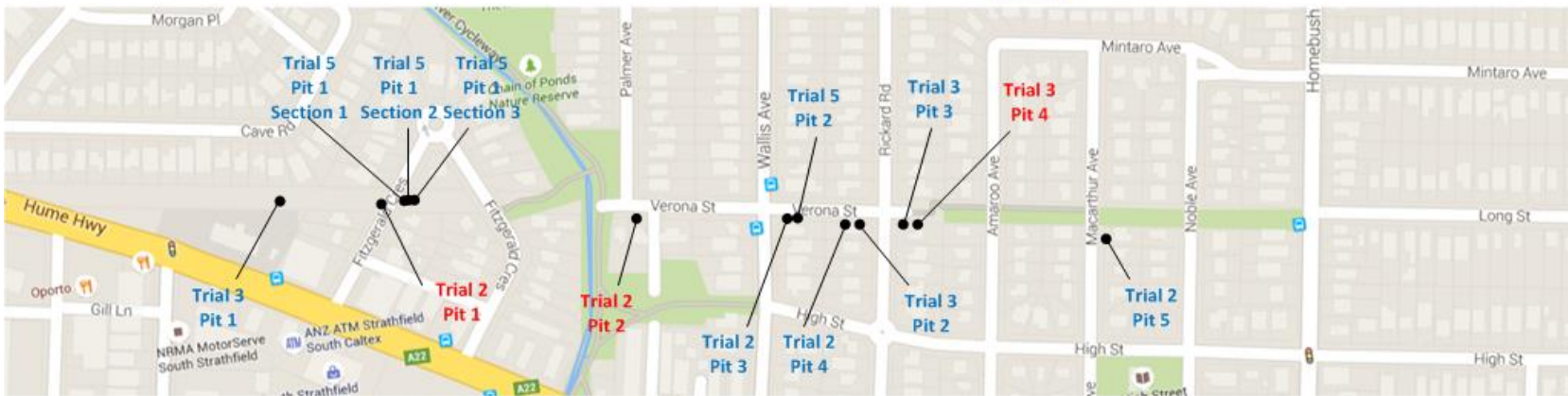
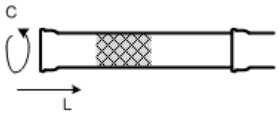
Question: where is your 99% confidence that the minimum > n?

Answer: $n = 5\text{mm}$, i.e. in 99% chance that the minimum > 5mm



UTS EVA

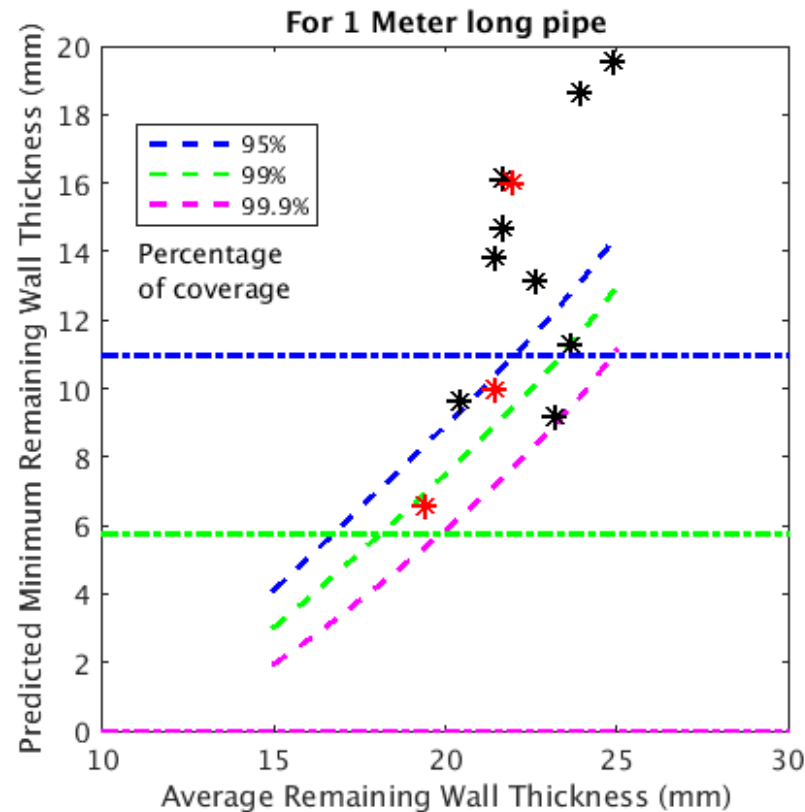
Training / Test Data



Pits labeled in **RED** are used for training

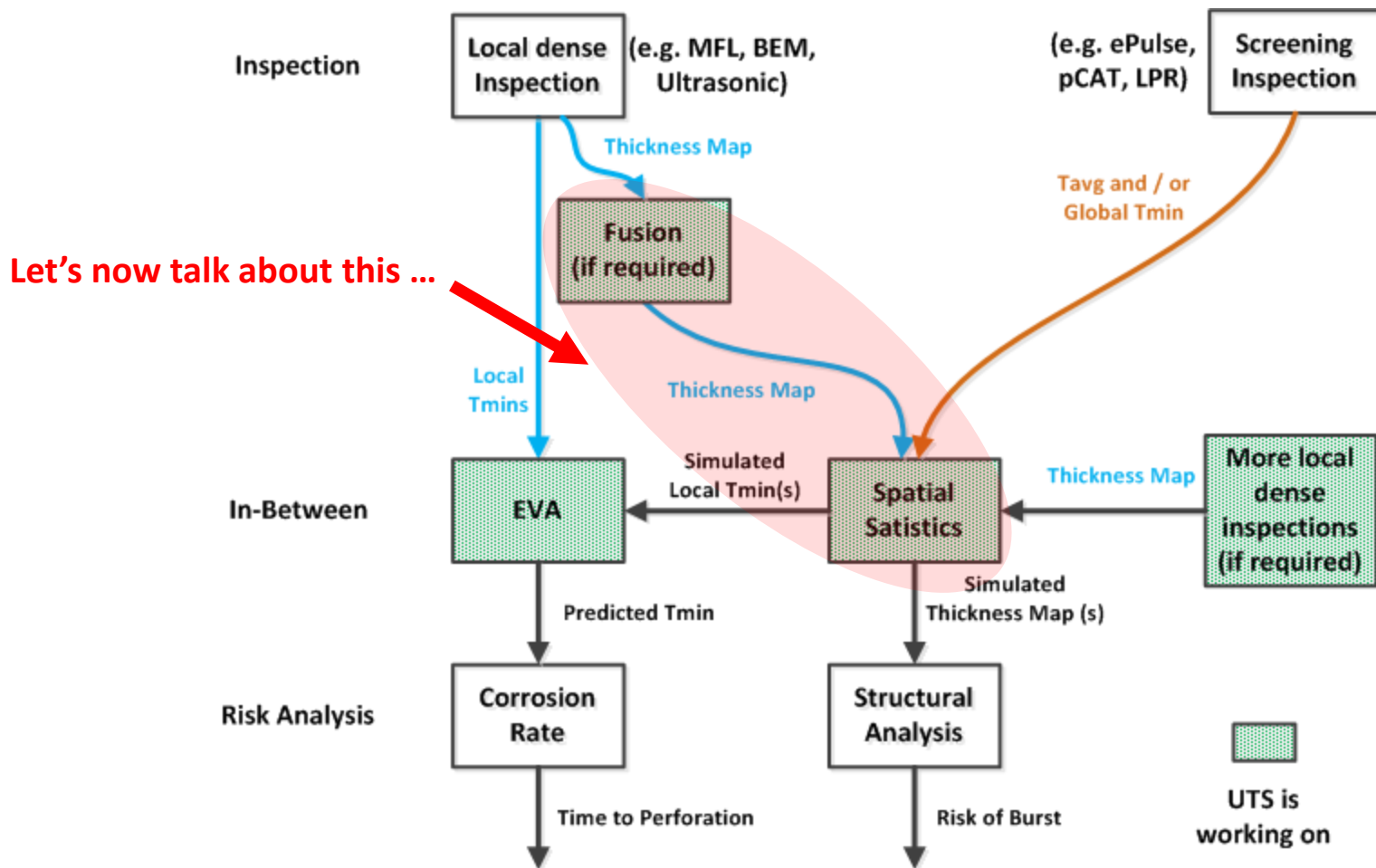
UTS EVA

Validation and Conclusions

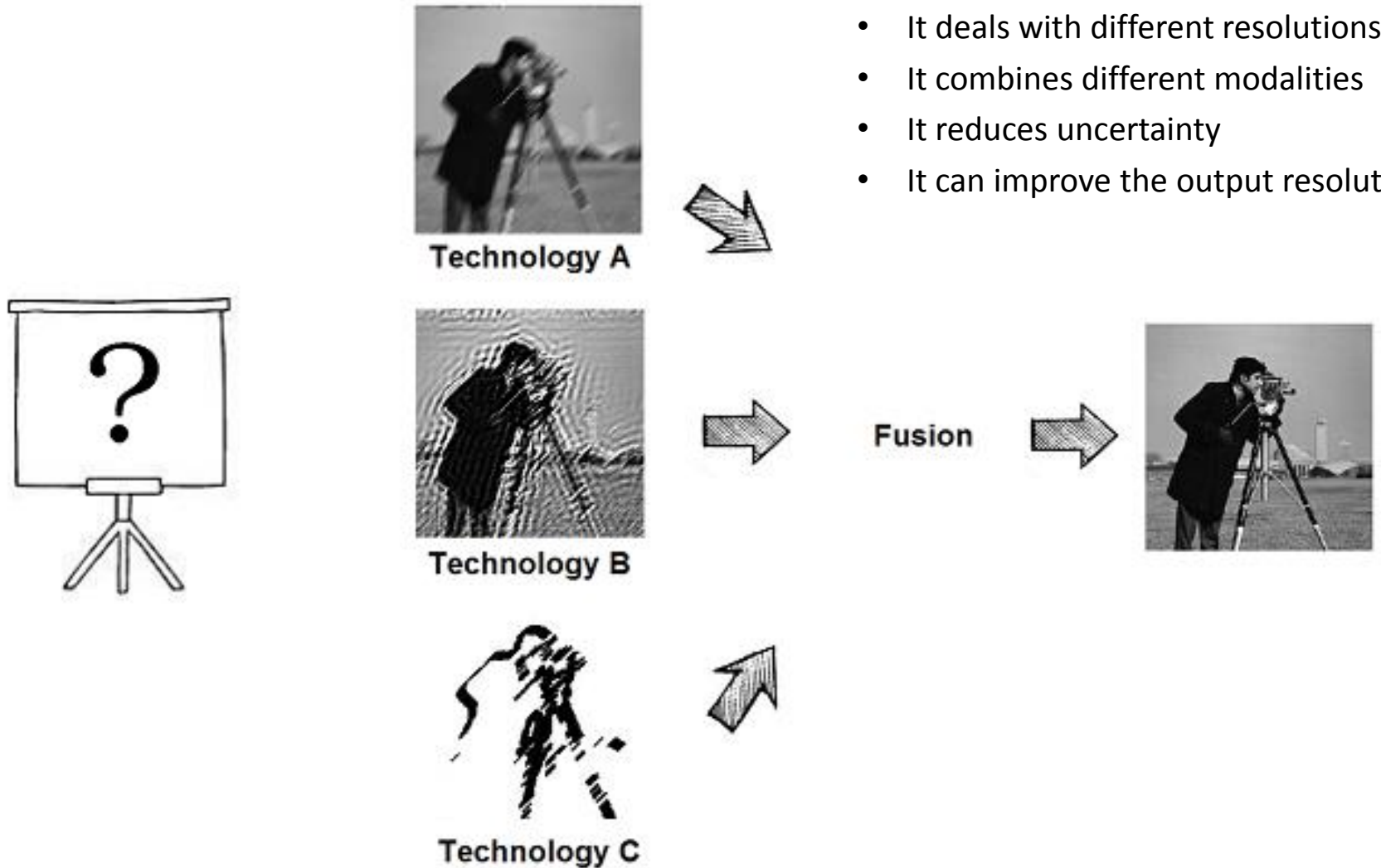


- UTS EVA considers data correlation and can incorporate constraints
- On limited available validation data, UTS EVA analysis improves accuracy

The Big Picture

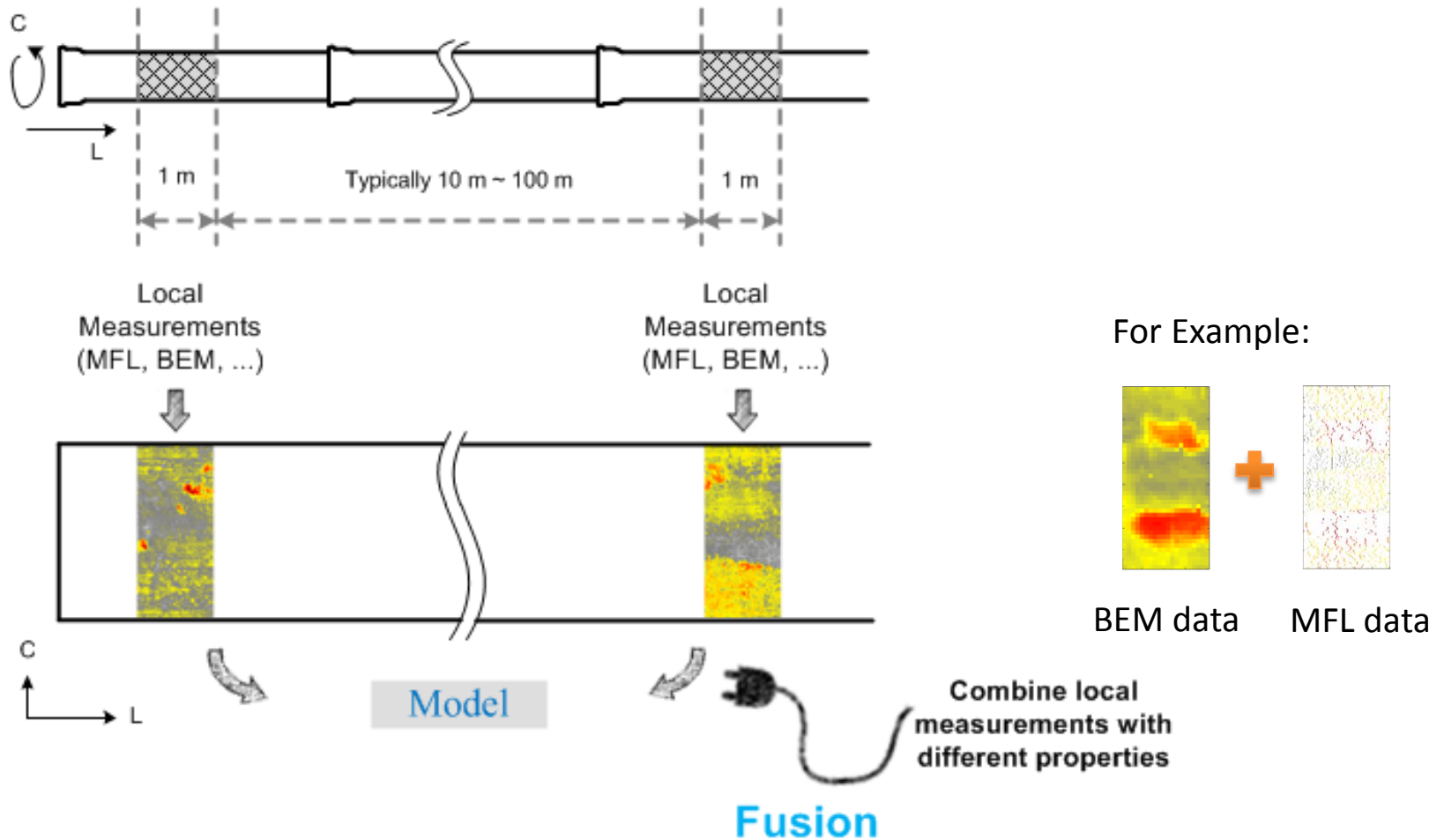


Data Fusion



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

Reminder: In-Between Prediction

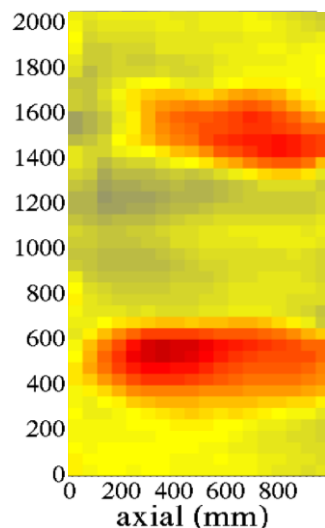


Important Challenges

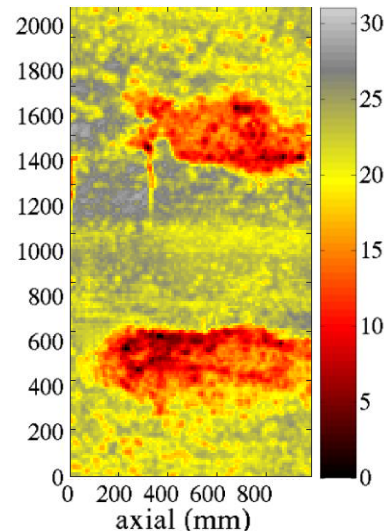
1. Data fusion can be a **computationally expensive** process in that relations between all the data points needs to be calculated and maintained throughout for most accurate results
2. A framework has been proposed in this work to **partially overcome** this challenge for in-between interpretations by use of sub-maps (see last TAC presentation, also list of publications)
3. We are working towards developing more reliable solutions for using big data in **training** and **fusion**

Processing Large-scale Data

1. Large-scale data includes both high-resolution data and the extensive amount of sensor data required to inspect a sizeable area
2. Current in-between methods use a matrix of BEM resolution (42X20) to do the sampling, but how can we deal with MFL resolution (192X198) to even allocate the memory?



(a) 42X20

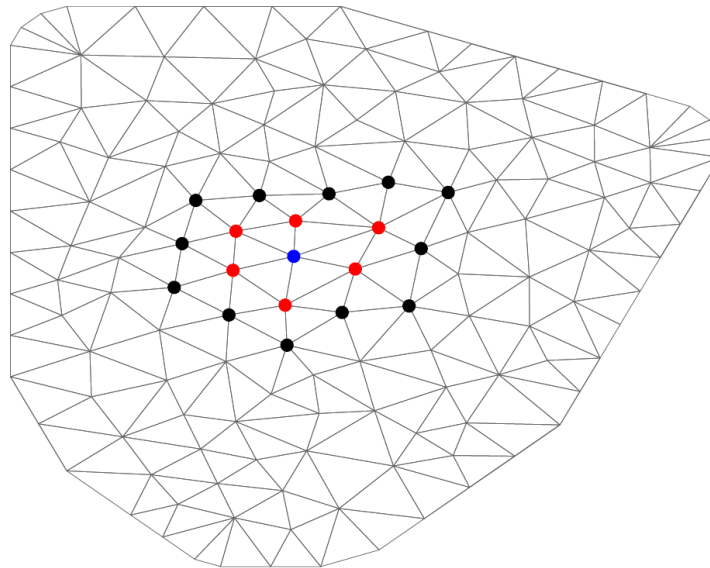


(b) 192X198

Down-sampled ground-truth for Trial 2 Pit 2 at:
BEM resolution (a) and MFL resolution (b)

Processing Large-scale Data

3. A solution is to apply Gaussian Markov Random Fields (GMRF)
 - Compared to Gaussian Processes (GPs) that we use before, GMRF is a discrete model which approximates the continuous field
 - GMRF also gives a probabilistic representation of pipes' remaining wall thickness with consideration of data noise
 - GMRF greatly saves both computation complexity and storage by assuming a local neighbourhood structure (see example below) and the linear interpolation between the nodes of the mesh



Final Thoughts

1. Proposed Framework is flexible to allow for a variety of scenarios drawn from current CA techniques 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. A study on the relationship between average measurements and minimum values has been carried out
4. Framework being put into practice on real test-bed data
5. 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 (80%)
Robust validation of framework with real data; Training (SWC/industry partners) and reporting	In progress (40%)