Automated deformation assessment of masonry lined tunnels

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with support from Bedi Consulting Ltd.

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Masonry lined tunnels

Figure 1: Typical masonry lined tunnel entrance

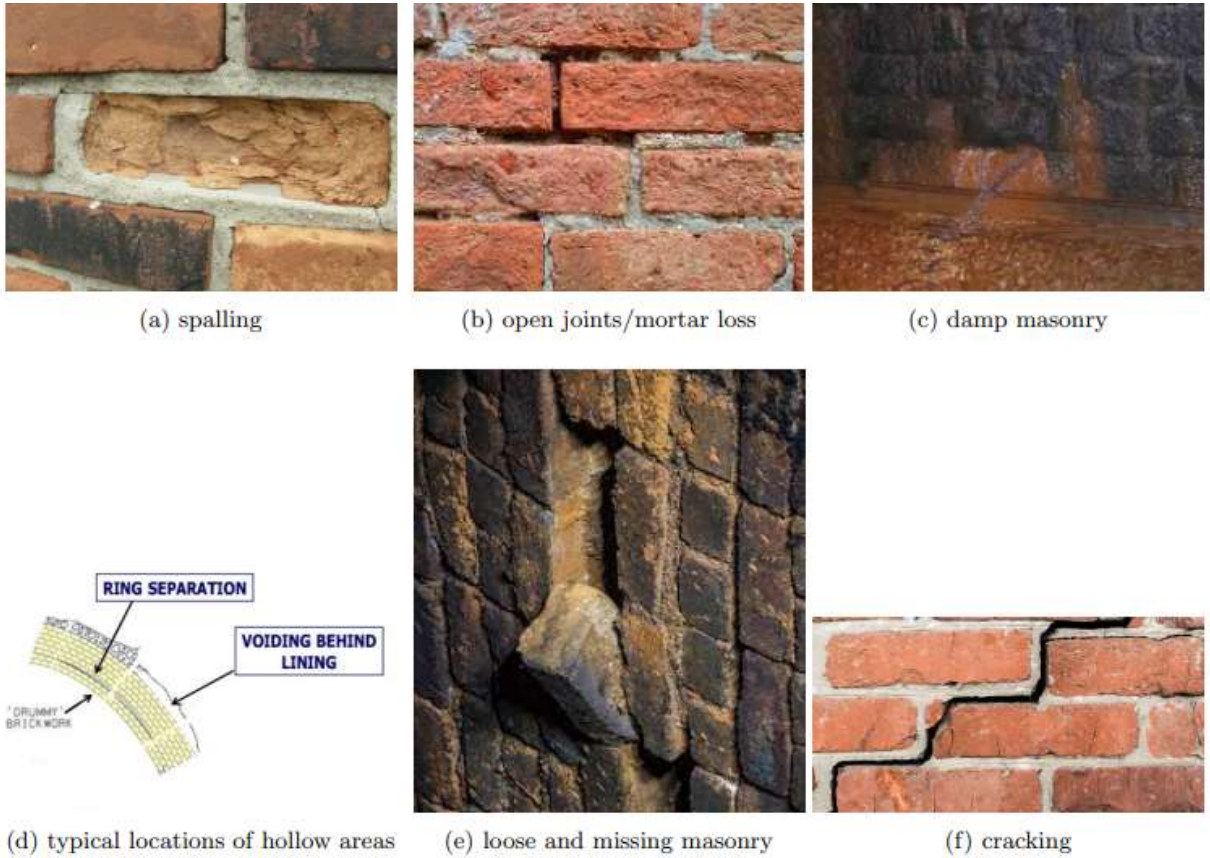


Figure 2: Typical masonry tunnel defects

Visual condition assessment

- Reports are standardised in Tunnel Condition Marking Index (TCMI)
- Defect identification is manual
- Lining damage map is generated
- Structural condition score is calculated

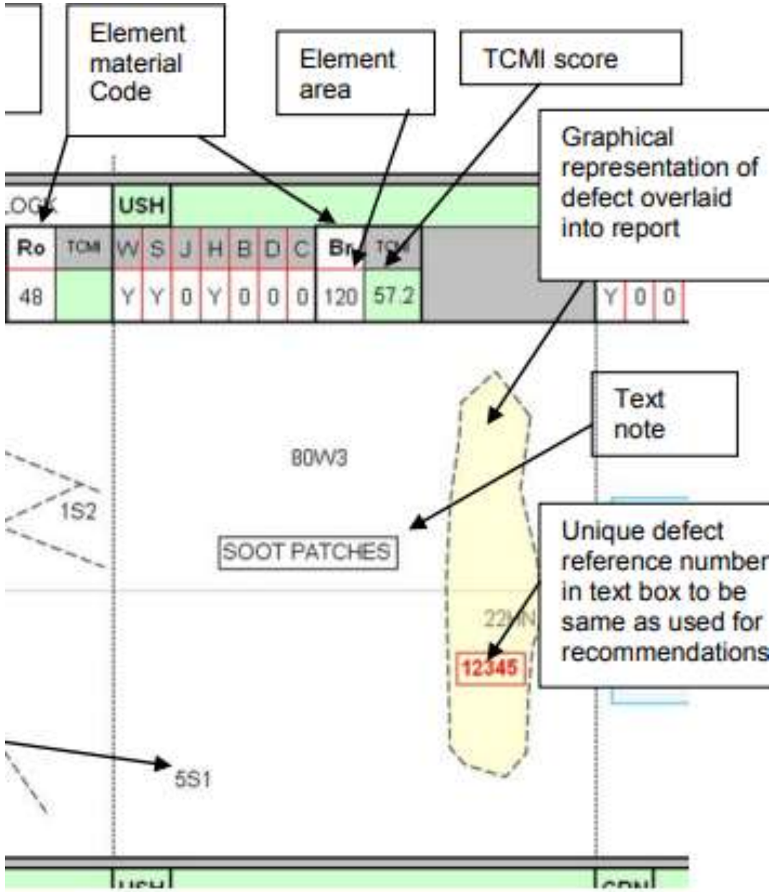
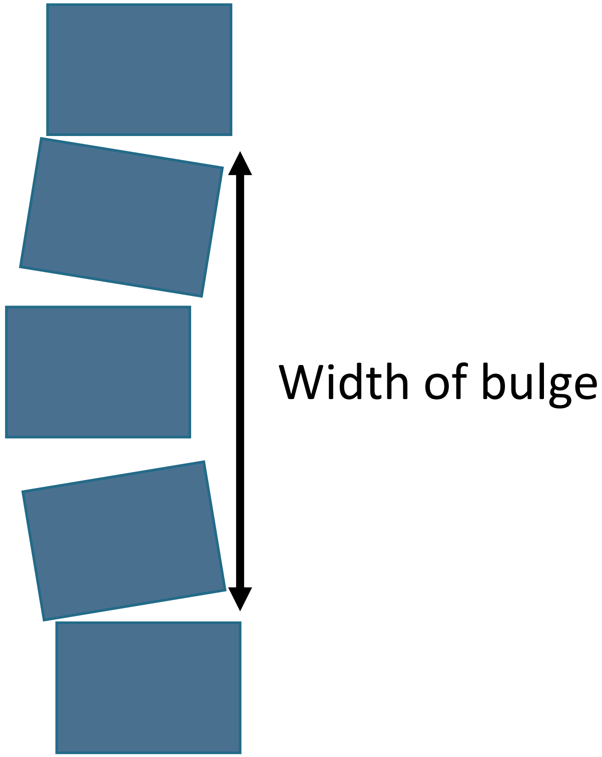


Figure 3: Extract of TCMI report (NR_L3_CIV_006_4c)

Tunnel lining deformation

- Lining bulging can lead to arch instability
- Lidar enables more accurate measurements
- Depth of deformation is still difficult to determine manually



Masonry tunnel spalling severity

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Figure 4: Typical masonry spalling

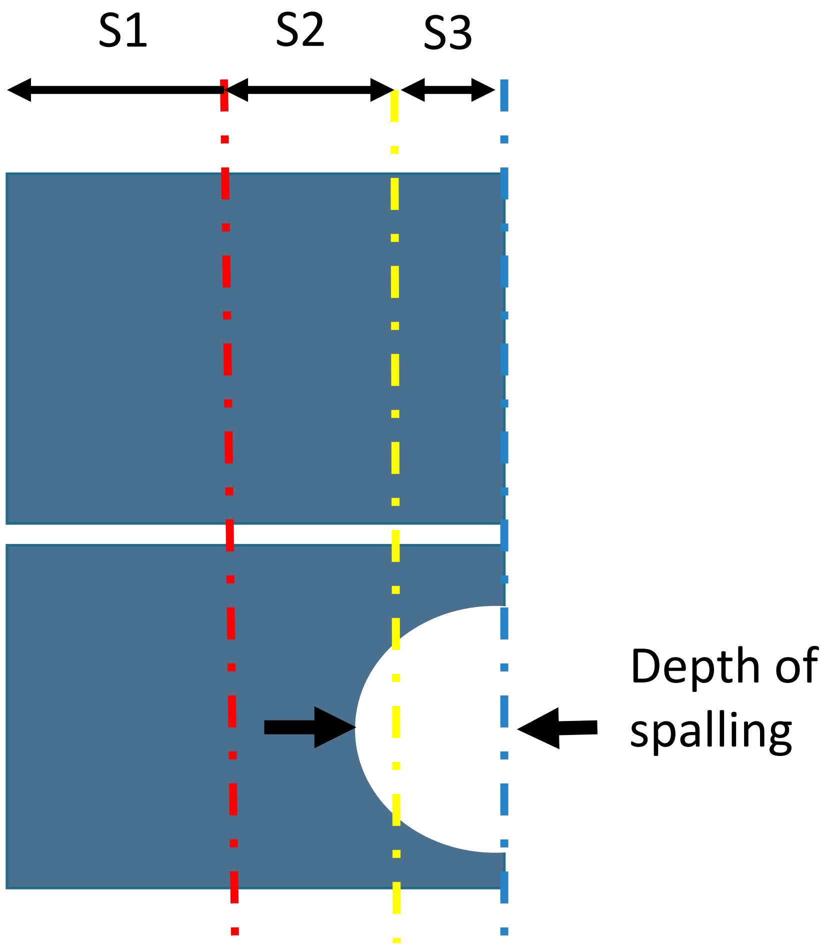

Figure 5: Spalling severities

Masonry tunnel spalling severity

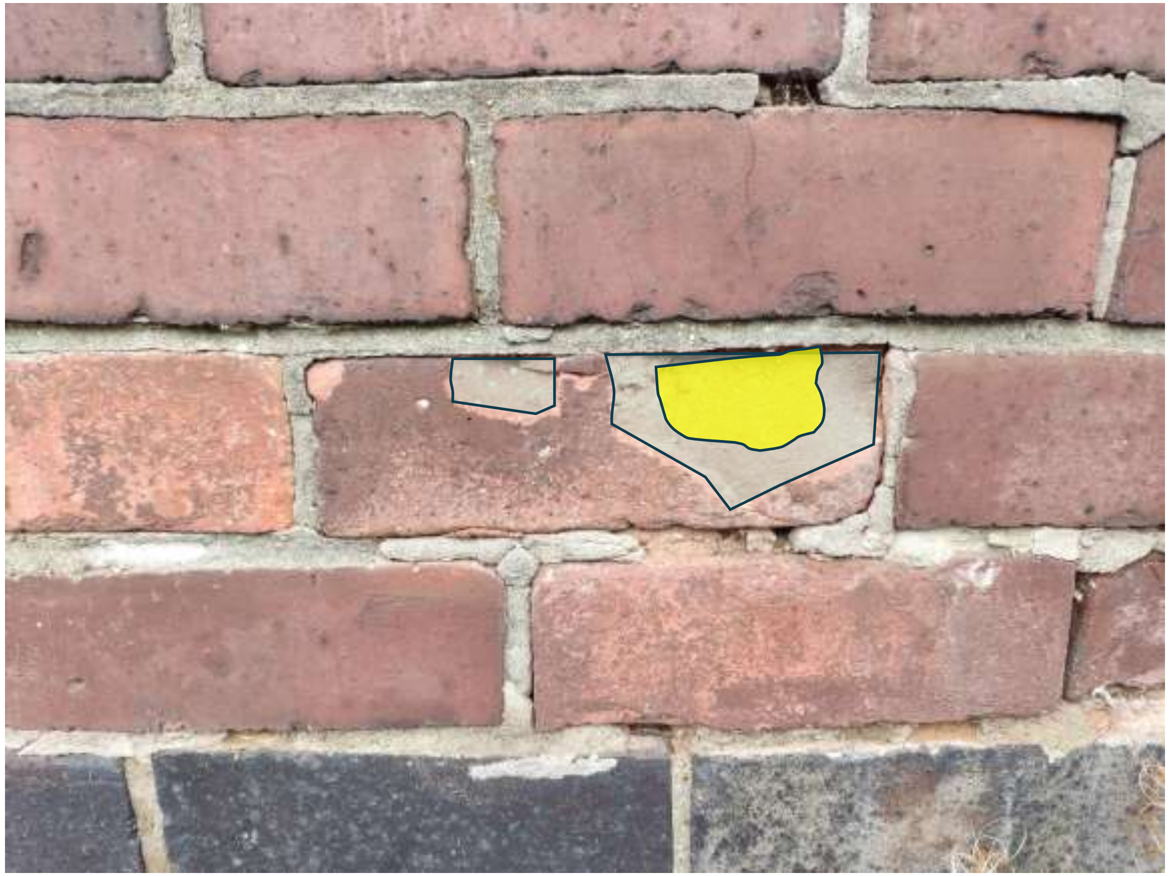

Figure 4: Typical masonry spalling

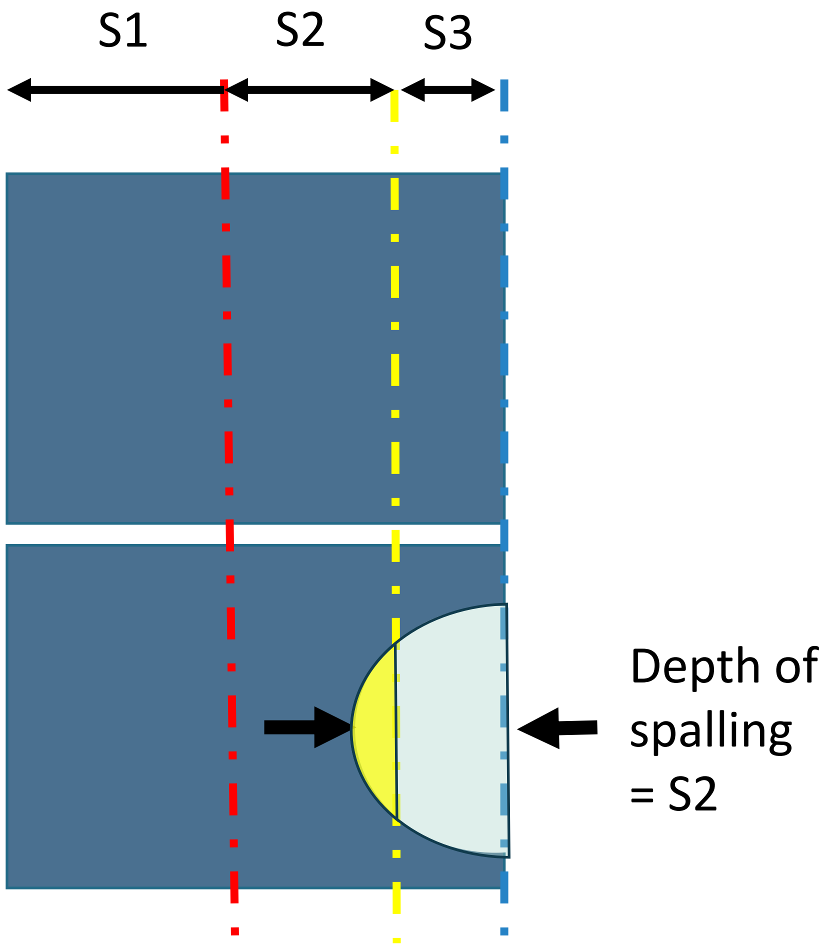

Figure 5: Spalling severities

Assessment challenges

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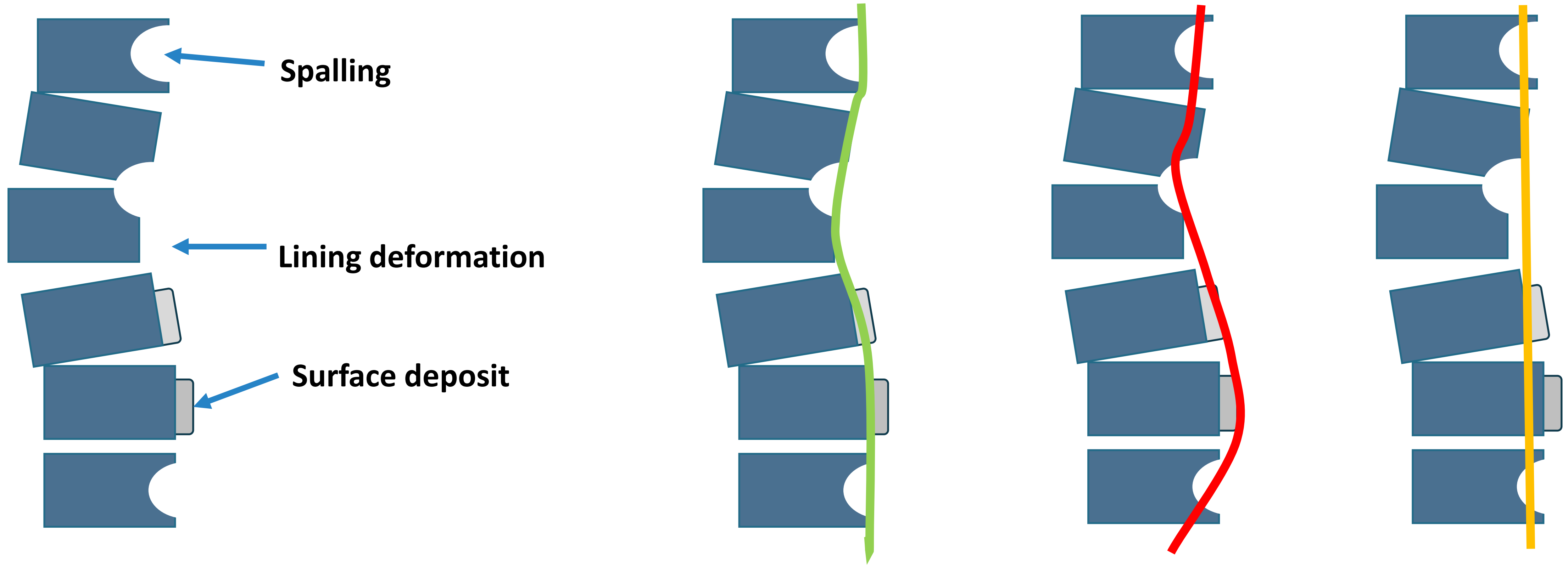

Figure 5: a) Typical masonry damage

b) Lining profile without surface damage

c),d) Lining surface best fit attempts

Condition assessment workflow

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Tunnel site inspection + lidar survey → Manual defect marking → Damage severity measured manually → TCMI completed → Decision on urgent repairs → Long term structure plan edited

Case study tunnels

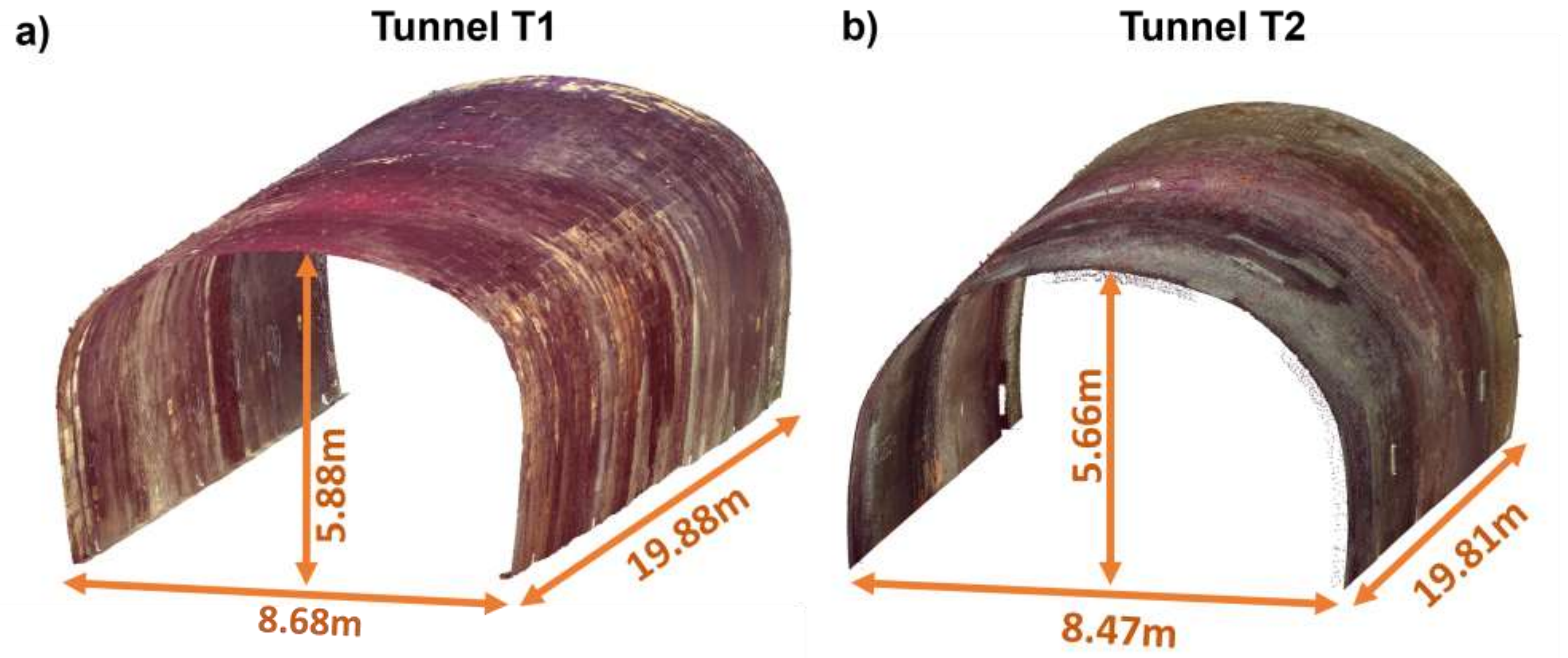

Figure 6: Case study 3D point clouds obtained by lidar

Synthetic masonry

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- Synthetic data can further improve generalisability
- Large variety of masonry geometries possible
- Damaged areas modelled with random Bezier curves
- Spalling depths given random profiles

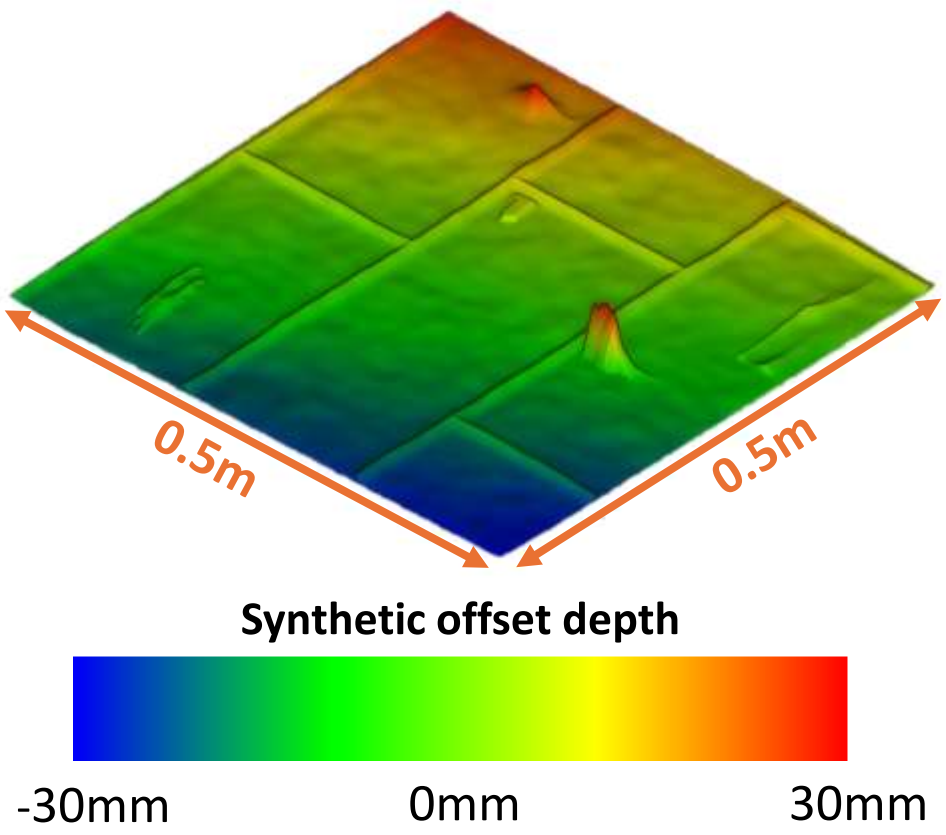

Figure 17: randomly generated wall depth map

Unfold Point cloud → Find joint locations → Find damage locations → Fit undamaged surface → Determine defect depth

Tunnel generator

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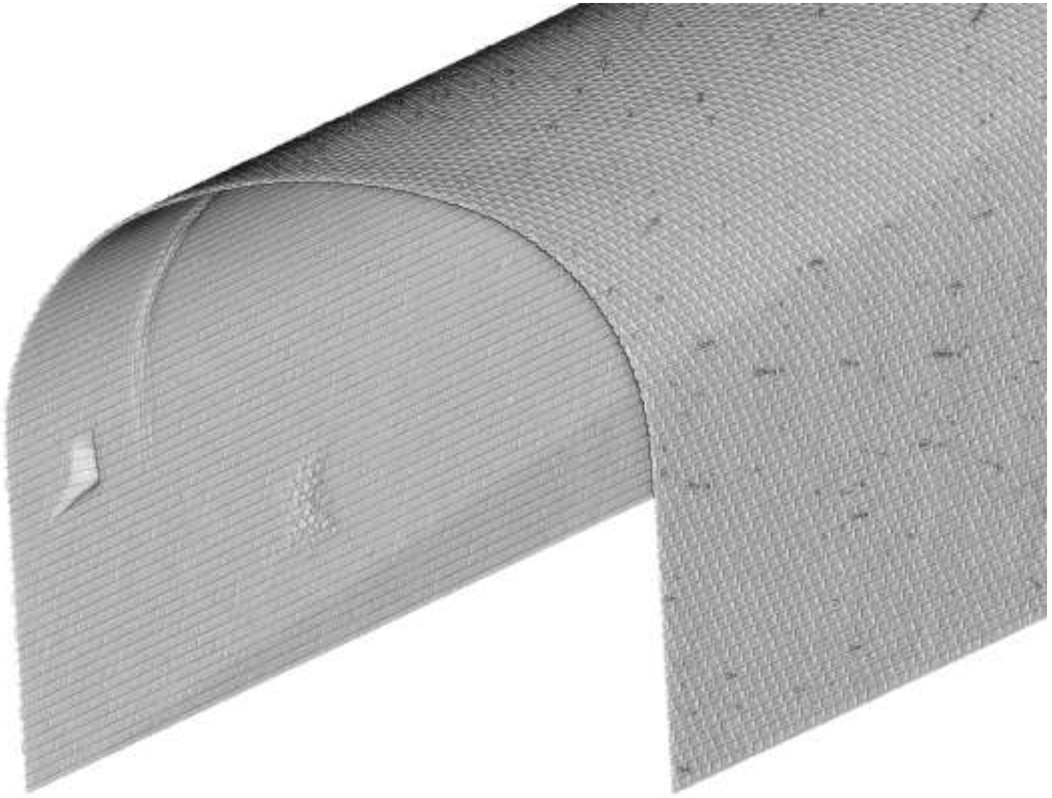
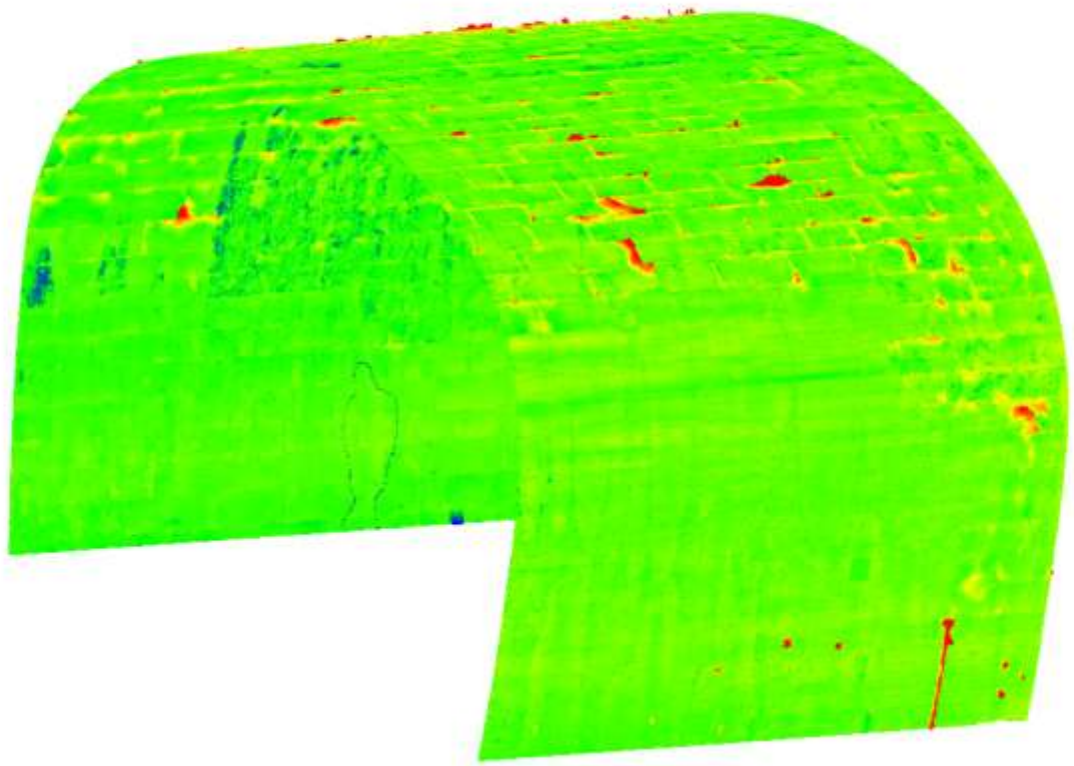
- Synthetic tunnel point clouds were generated to augment the dataset
- Ideal tunnel geometry was defined as a three-centred arch on vertical sidewalls
- Offsets were applied using randomised synthetically generated masonry.



Ground truth creation

- Gaussian processes used to fit different tunnel cross-sections
- Smoothing and filtering applied with trial and error to isolate spalling from lining deformations
- Joints manually masked out



Automated damage assessment

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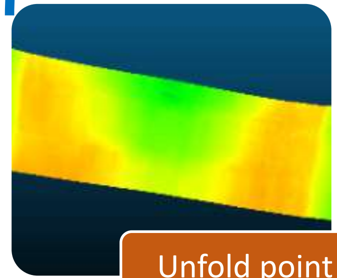
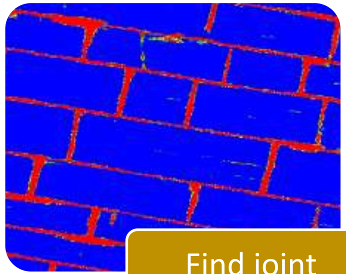
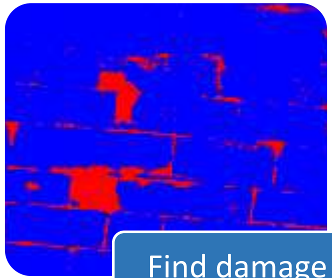
Tunnel site inspection + lidar survey → Automated spalling marking → Automatic damage severity calculation → TCMI completed → Decision on urgent repairs → Long term structure plan edited



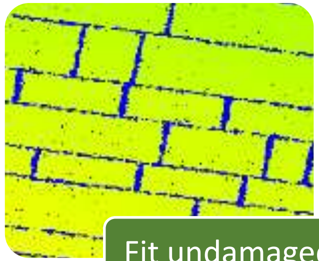
Unfold point cloud



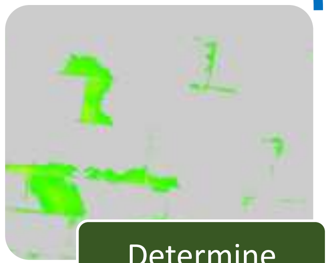
Find joint locations



Find damage locations



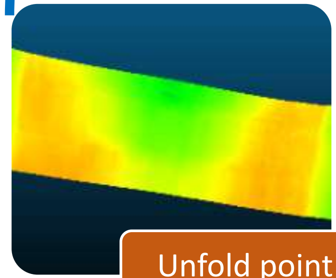
Fit undamaged surface



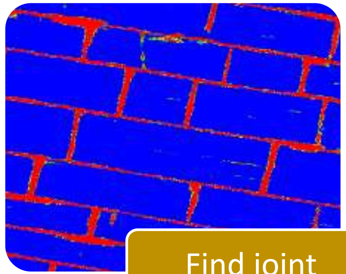
Determine defect severity

Automated damage assessment

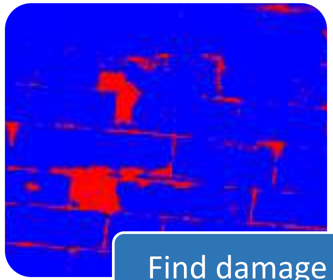
Tunnel site inspection + lidar survey → Automated spalling marking → Automatic damage severity calculation → TCMI completed → Decision on urgent repairs → Long term structure plan edited



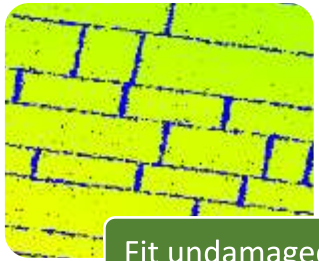
Unfold point cloud



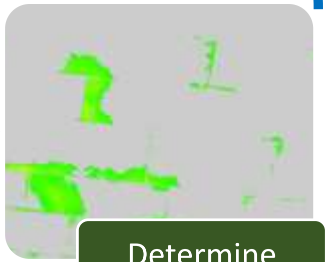
Find joint locations



Find damage locations



Fit undamaged surface



Determine defect severity

Determine deformations

Semantic segmentation

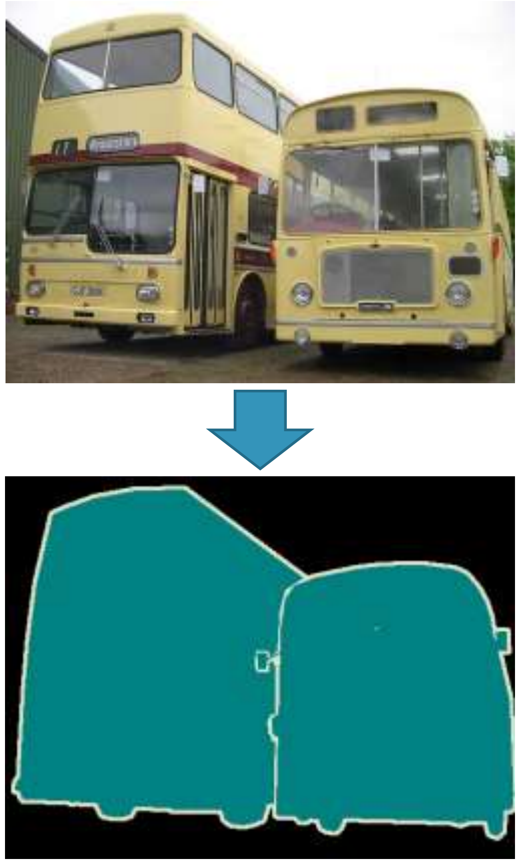


Figure 11: Semantic segmentation example (Pascal VOC2011 from host.robots.ox.ac.uk)

U-Net Encoder-Decoder CNN

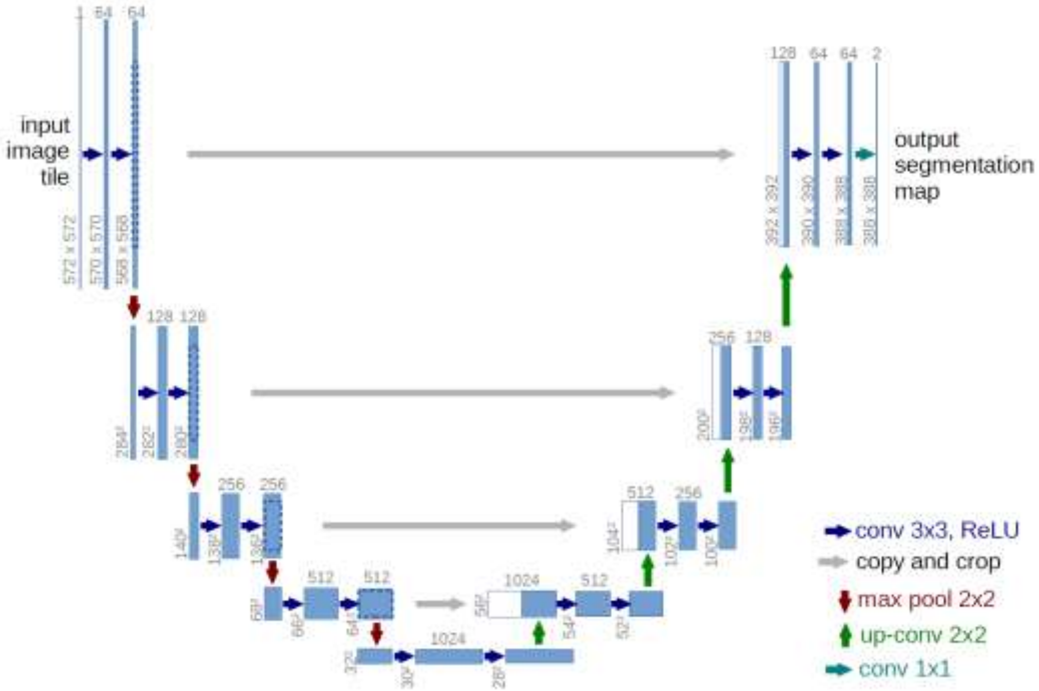


Figure 12: U-Net architecture (Ronneberger et al.)

Tunnel unwrapping

- Cylinder fit to tunnel using PCA
- Tunnel unwrapped around cylinder
- Offset from cylinder set as scalar field

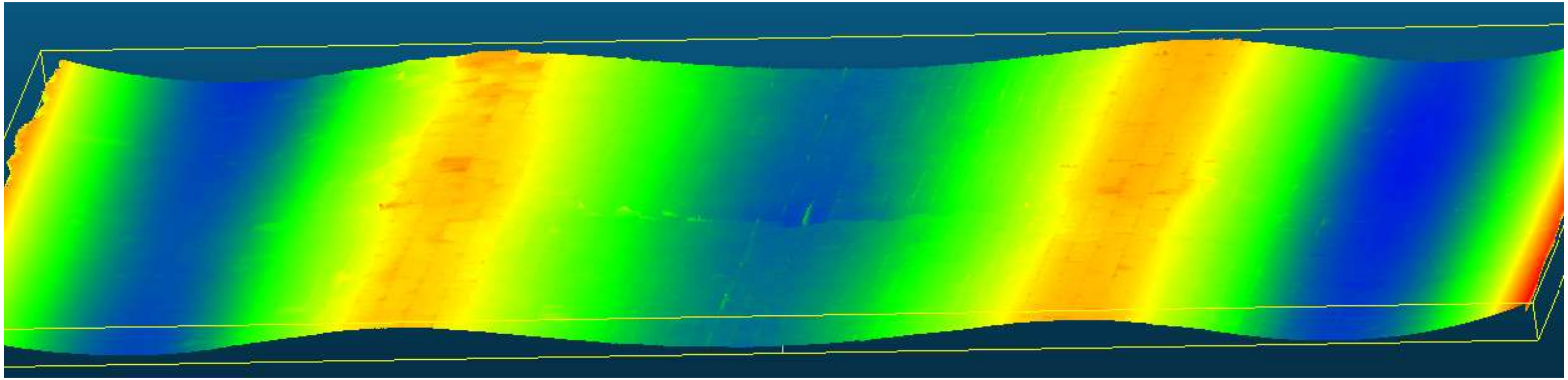


Figure 13: Unwrapped tunnel point cloud

Unfold Point cloud → Find joint locations → Find damage locations → Fit undamaged surface → Determine defect depth

Joint Segmentation

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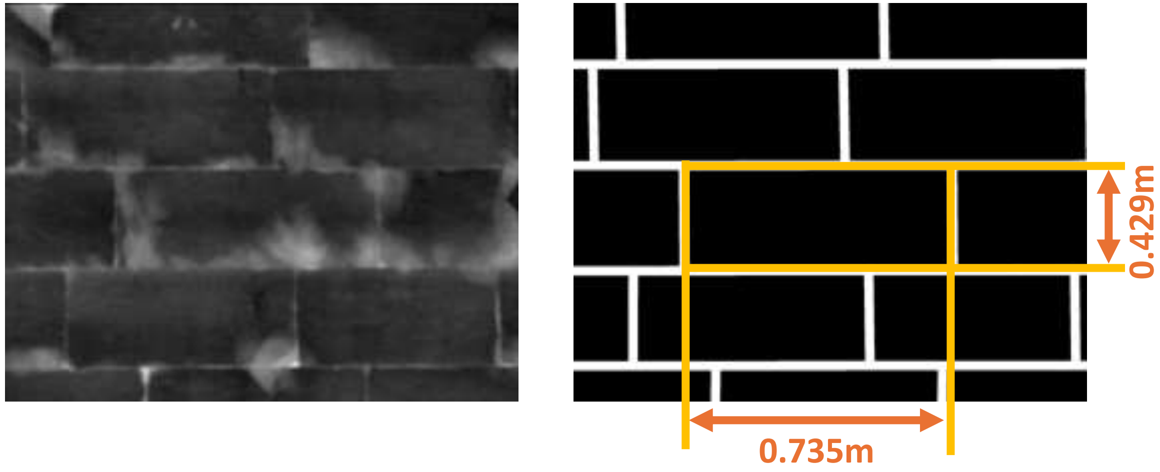
- U-Net style neural networks trained for joint segmentation
- Dice loss function
- 10m section of each tunnel used as training set.
- Tunnel rasters split into 512x512 patches



a) Input Raster *b) Joint mask*

Figure 15: Expanded view of training data

Unfold Point cloud → Find joint locations → Find damage locations → Fit undamaged surface → Determine defect depth

Data augmentations

- Data augmentation synthetically increases size of dataset
- Augmentations given range of magnitudes and probabilities
- Augmentations need to be realistic

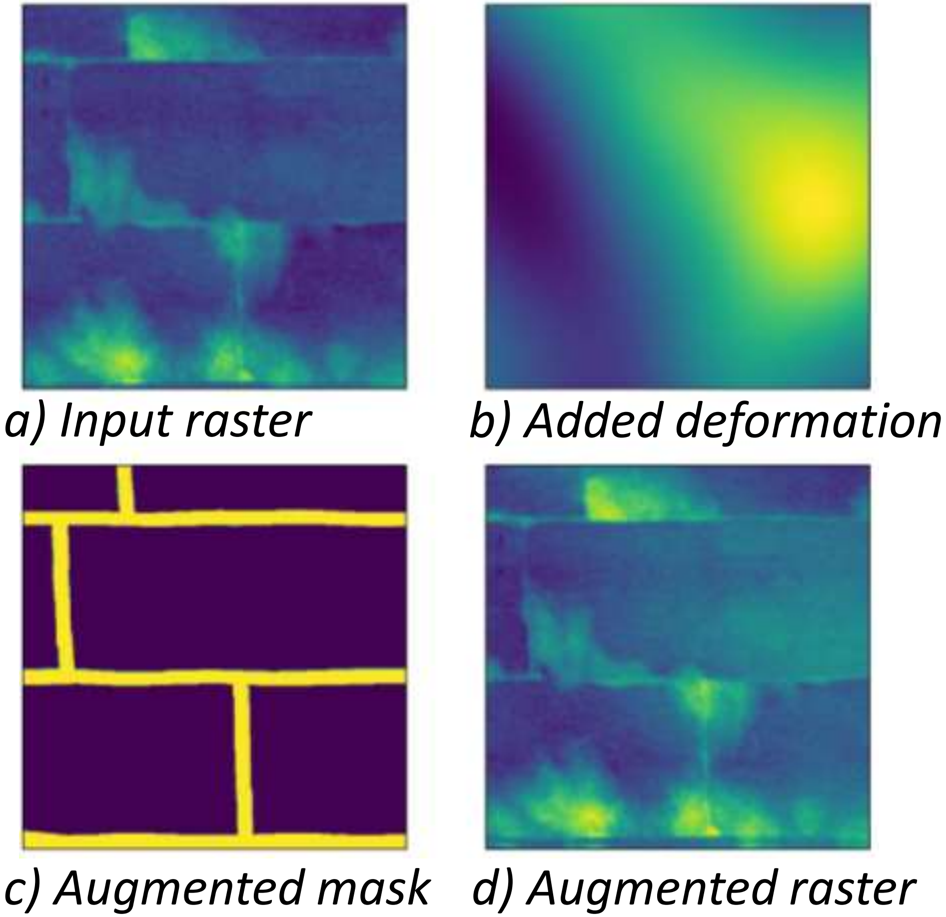


Figure 16: Effect of image augmentation

Performance assessment

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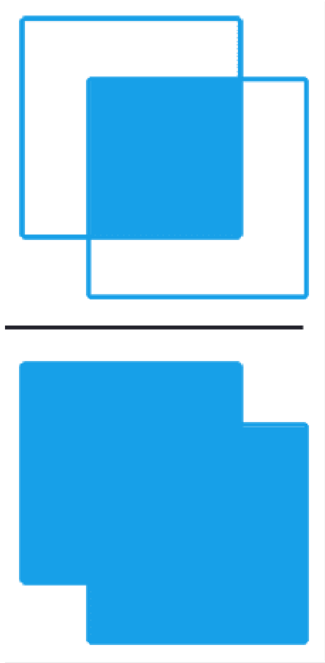
IOU = Intersection Over Union

FP = False Positives

TP = True Positives

FN = False Negatives

$$\text{IOU} = \frac{\text{Intersection}}{\text{Union}} =$$



$$= \frac{TP}{TP + FP + FN}$$

Joint segmentation performance

Tunnel 1 (Stone)

Output	IOU	Blocks identified
Dice Loss	0.569	71%
Warp loss	0.609	77%

Tunnel 2 (Brick)

Output	IOU	Blocks identified
Dice Loss	0.510	51%
Warp loss	0.568	59%

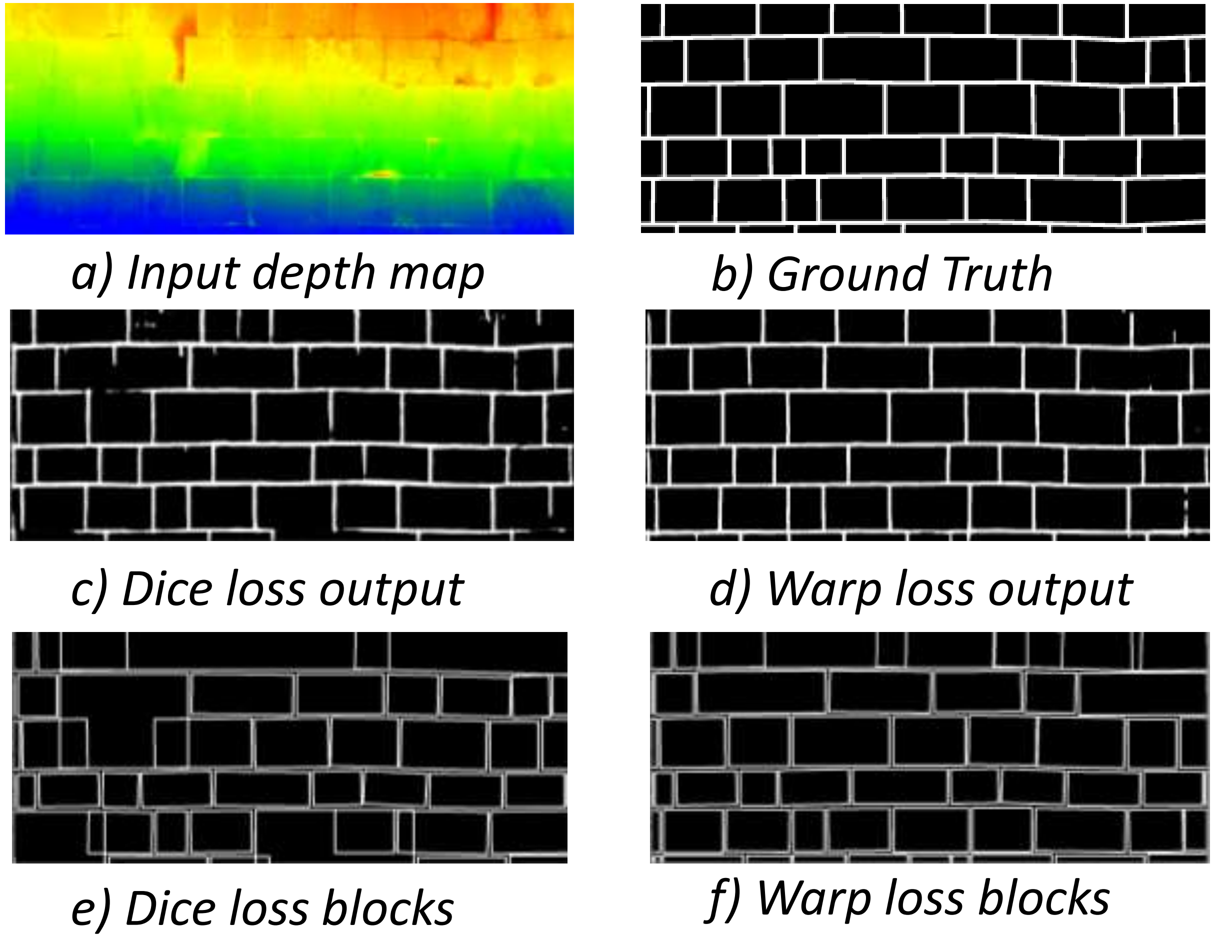


Figure 9: randomly generated wall depth map

Damage detection

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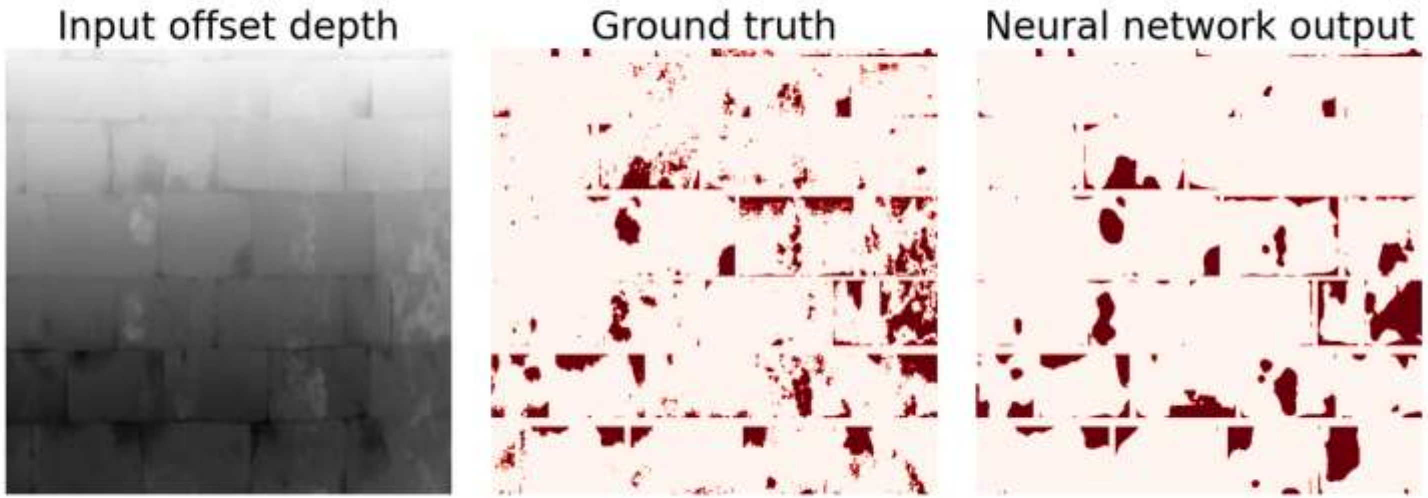
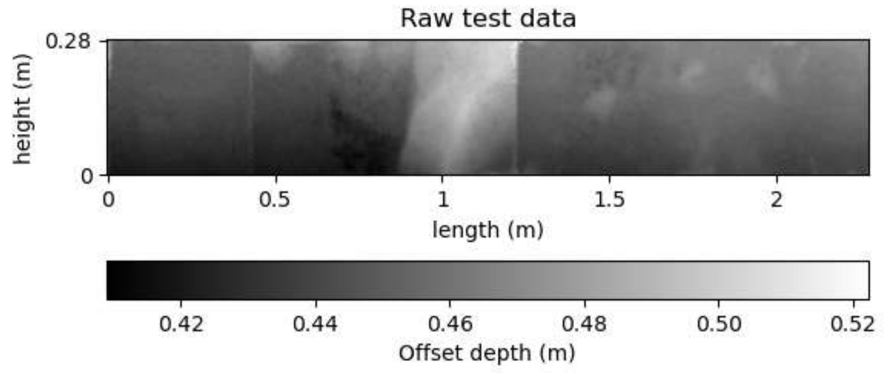
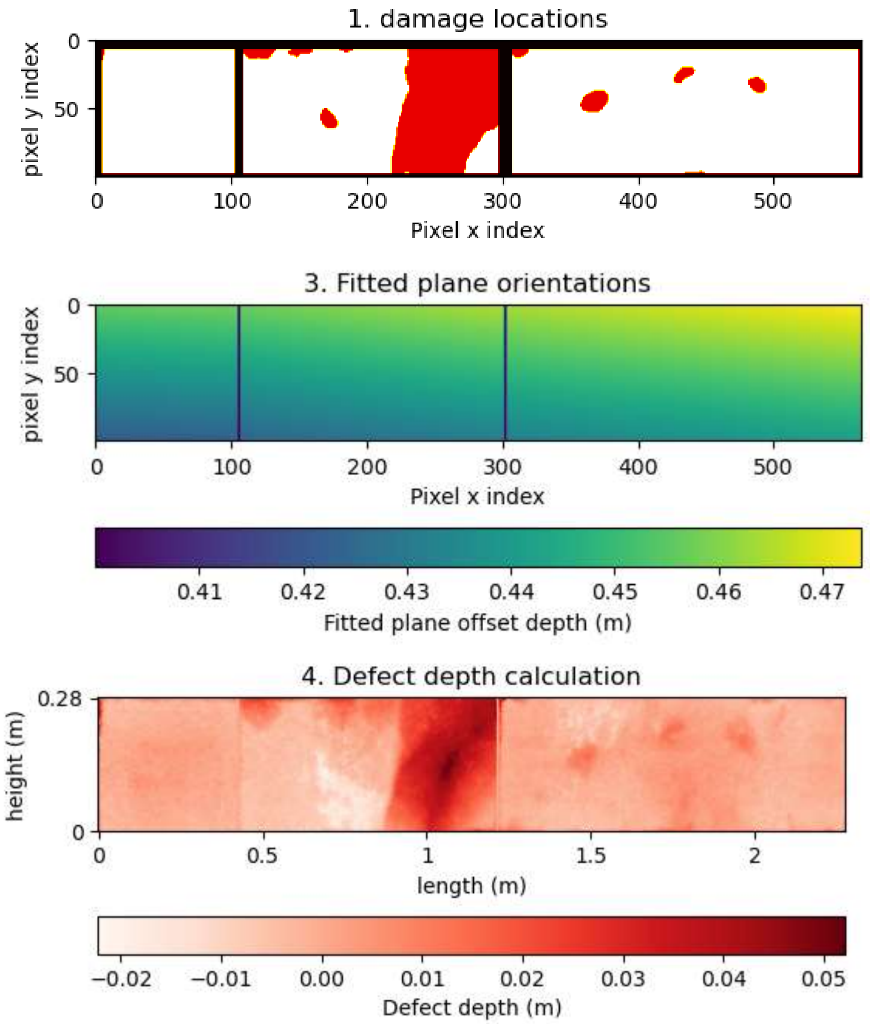
- U-Net style neural networks trained for damage segmentation
- Training masks created by taking offset of cloud from manually defined undamaged surface



Unfold Point cloud → Find joint locations → Find damage locations → Fit undamaged surface → Determine defect depth

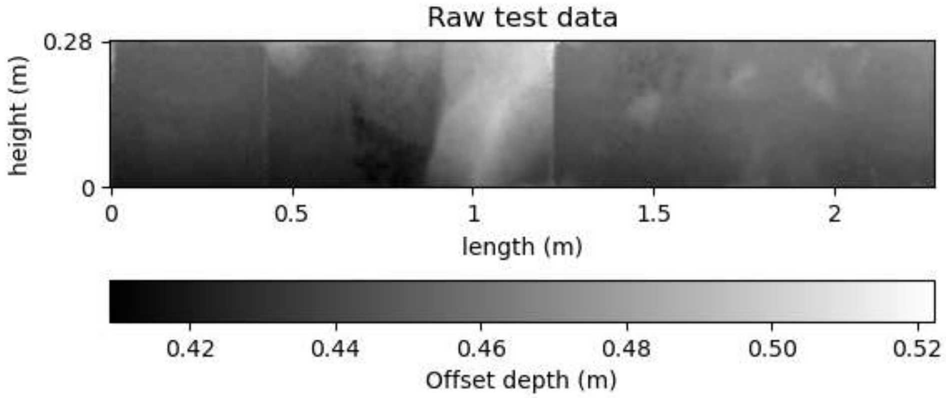
Surface Fitting

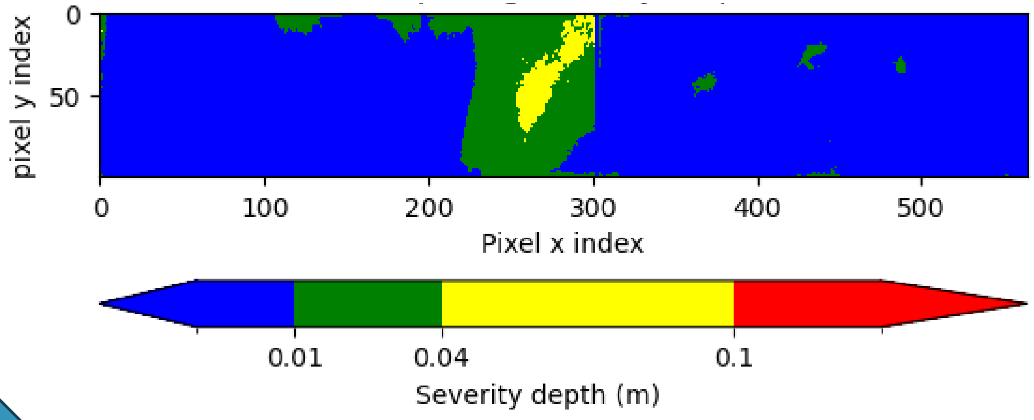


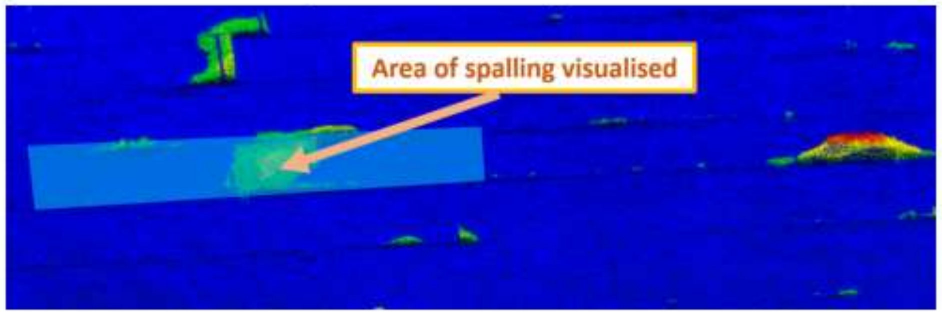


Unfold Point cloud → Find joint locations → Find damage locations → Fit undamaged surface → Determine defect depth

Spalling severity segmentation







Unfold Point cloud → Find joint locations → Find damage locations → Fit undamaged surface → **Determine defect depth**

Spalling severity segmentation

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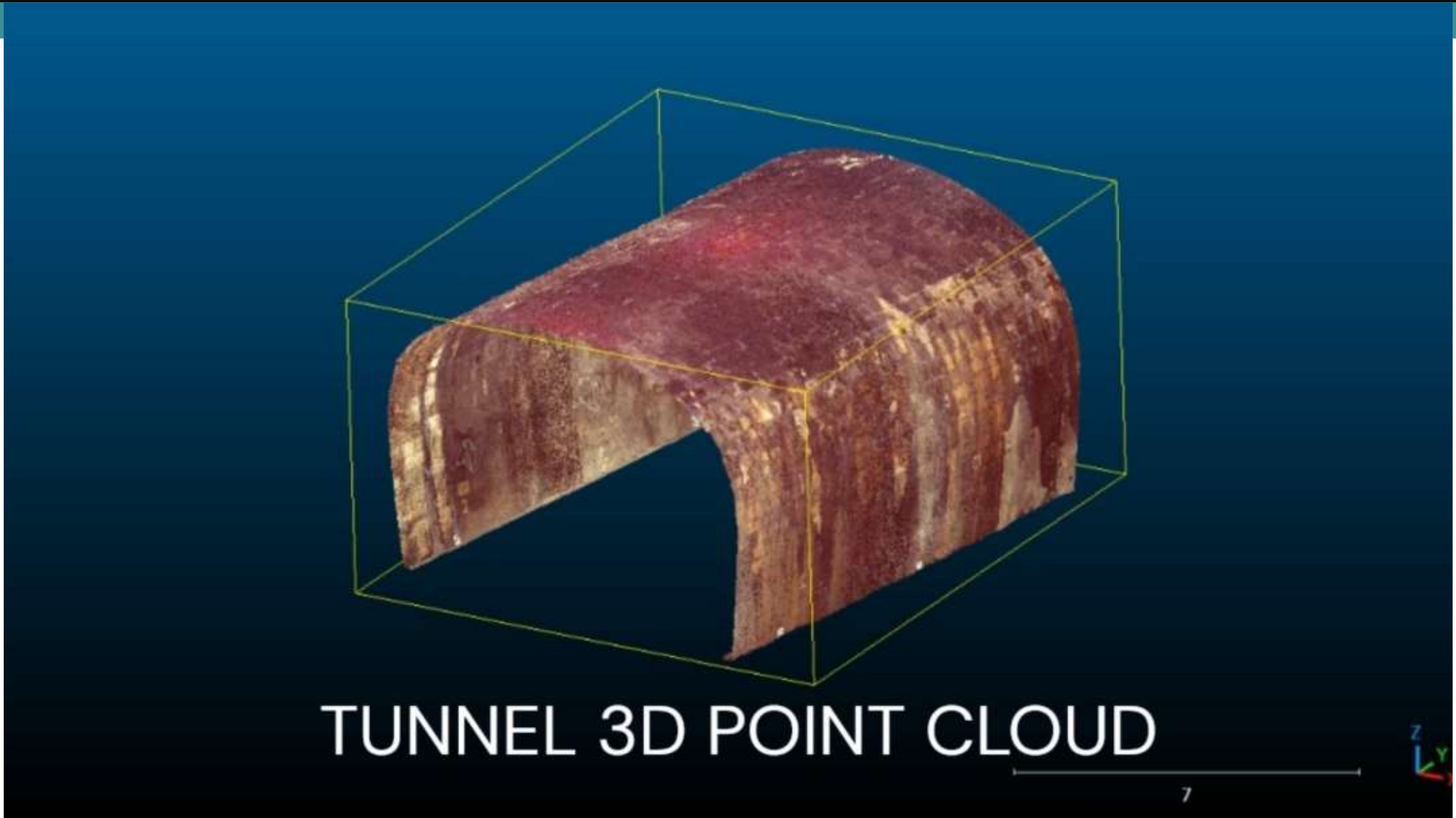

Spalling performance assessment

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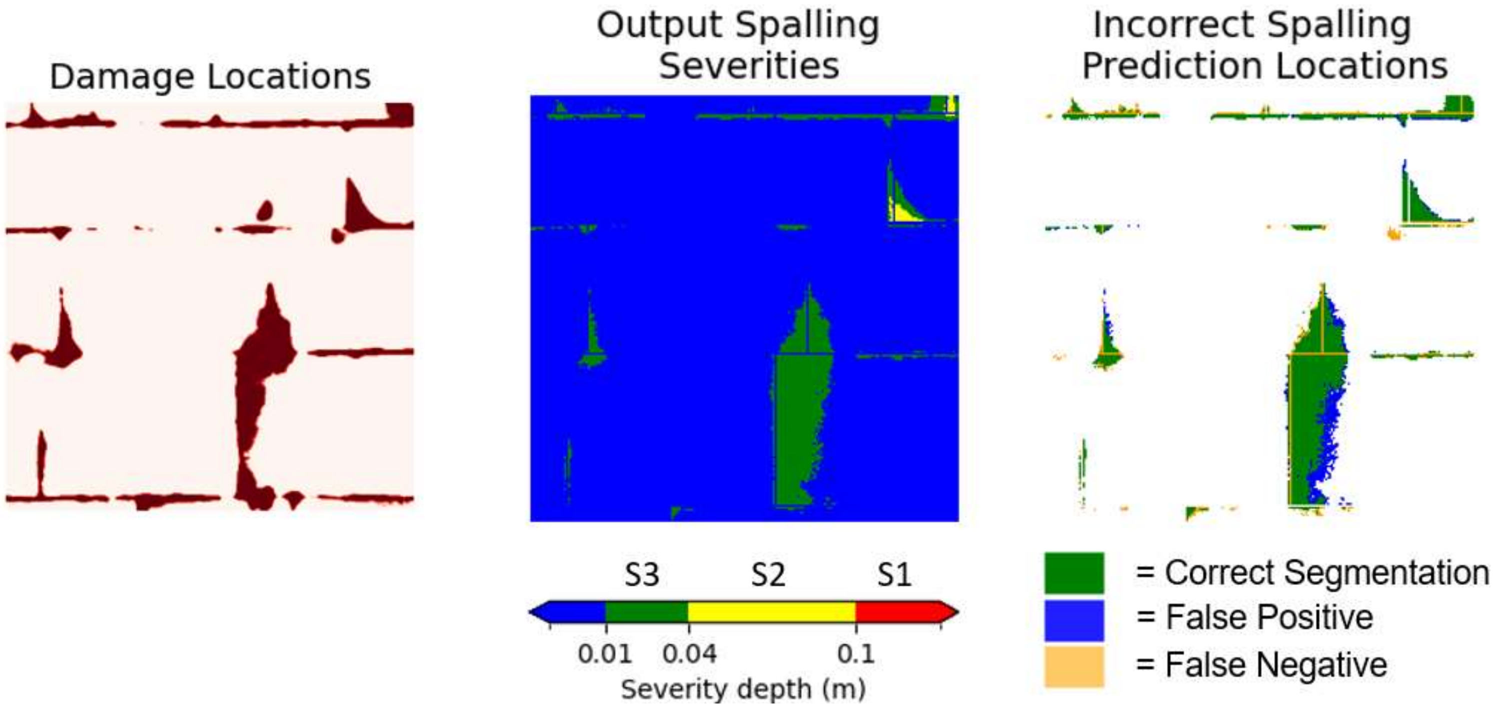
Tunnel 1 (Stone)

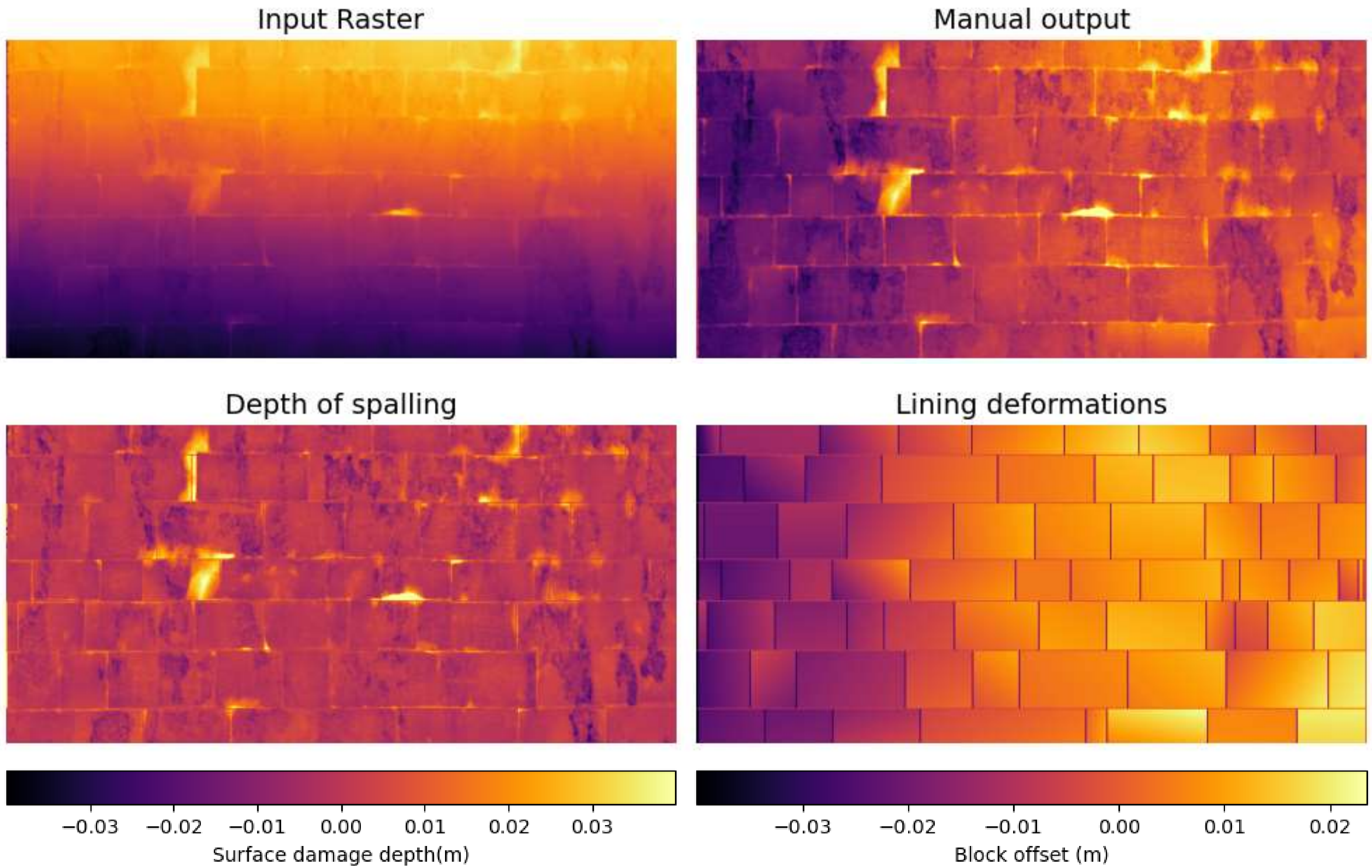
Severity level	Depth of spalling	IOU
S1	>100mm	0.648
S2	>40mm	0.507
S3	>10mm	0.498

Tunnel 2 (Brick)

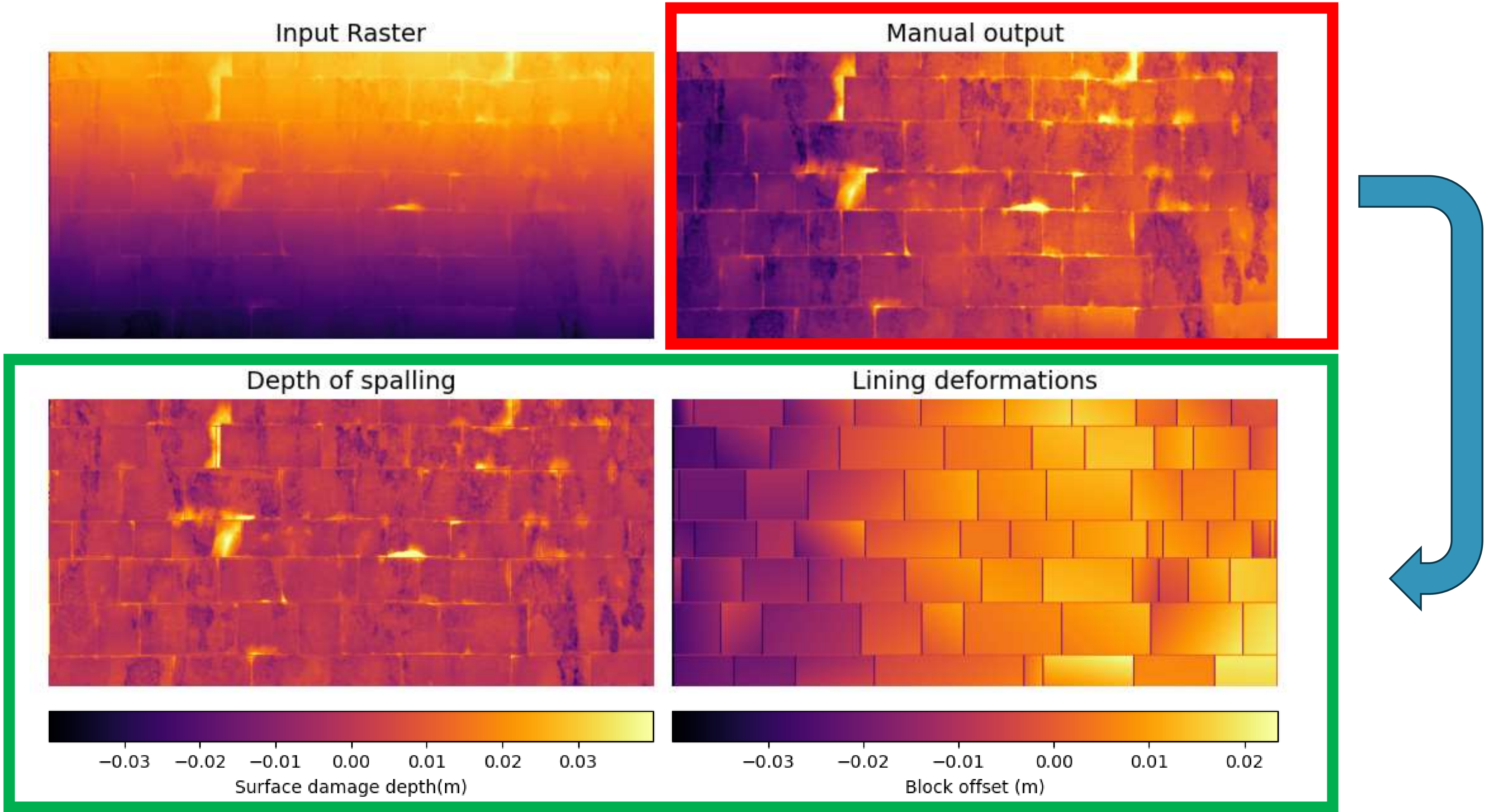
Severity level	Depth of spalling	IOU
S1	>50mm	N/A
S2	>20mm	0.237
S3	>10mm	0.432



Visualisation of offset areas



Visualisation of offset areas



Machine learning potential

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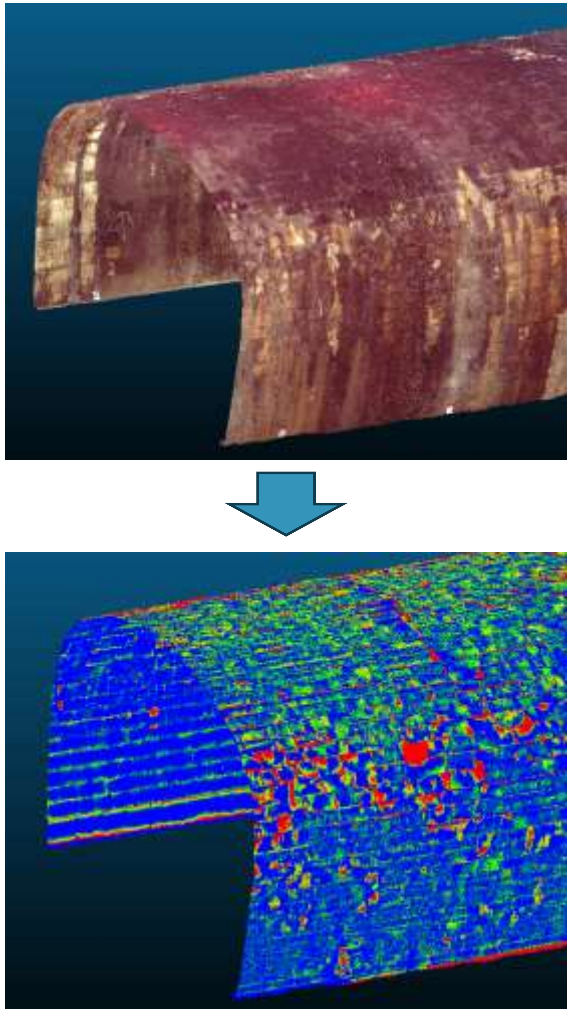
Capability	Status
Can reduce analysis time	✓
Improves assessment reproducibility	✓
Improves inspection health and safety	✓
Replaces a human engineer	✗
Can be used ‘off the shelf’	•••
Requires advanced data collection equipment	•••



Questions?

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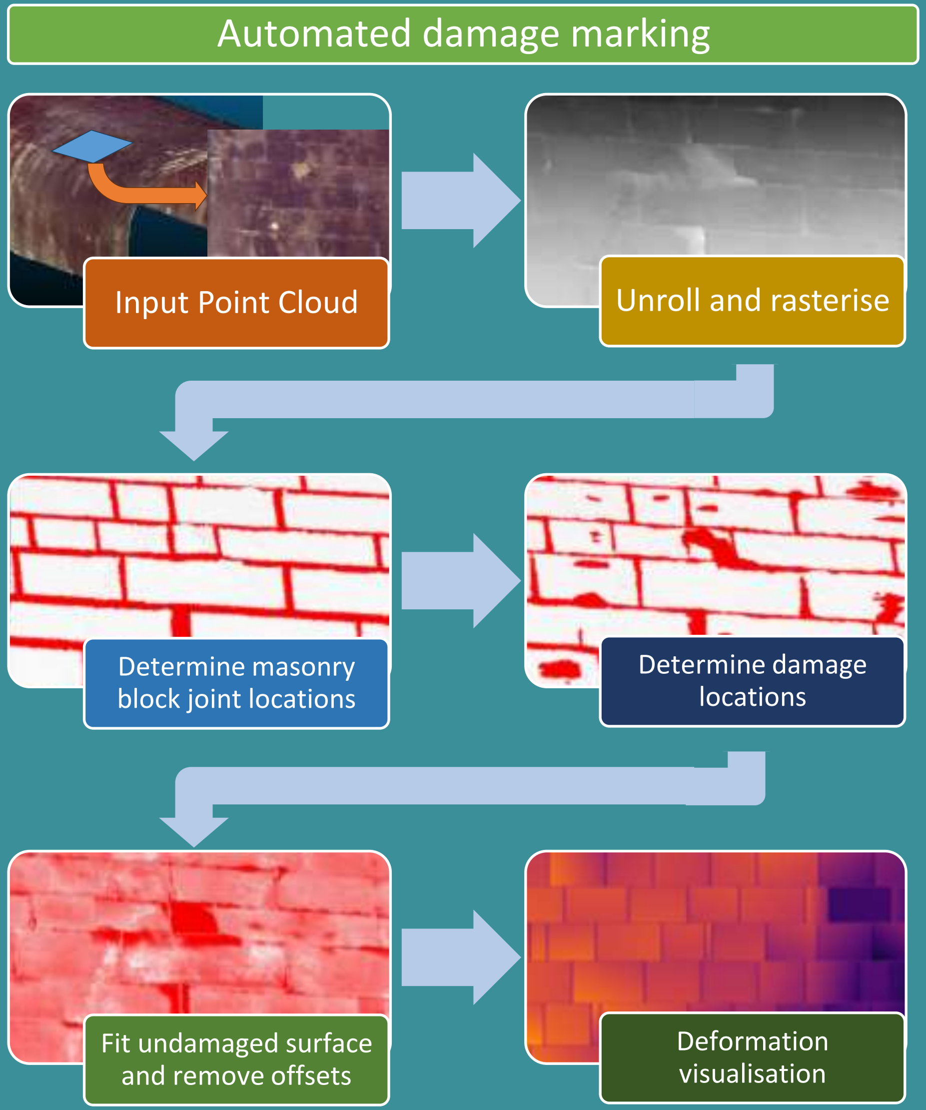
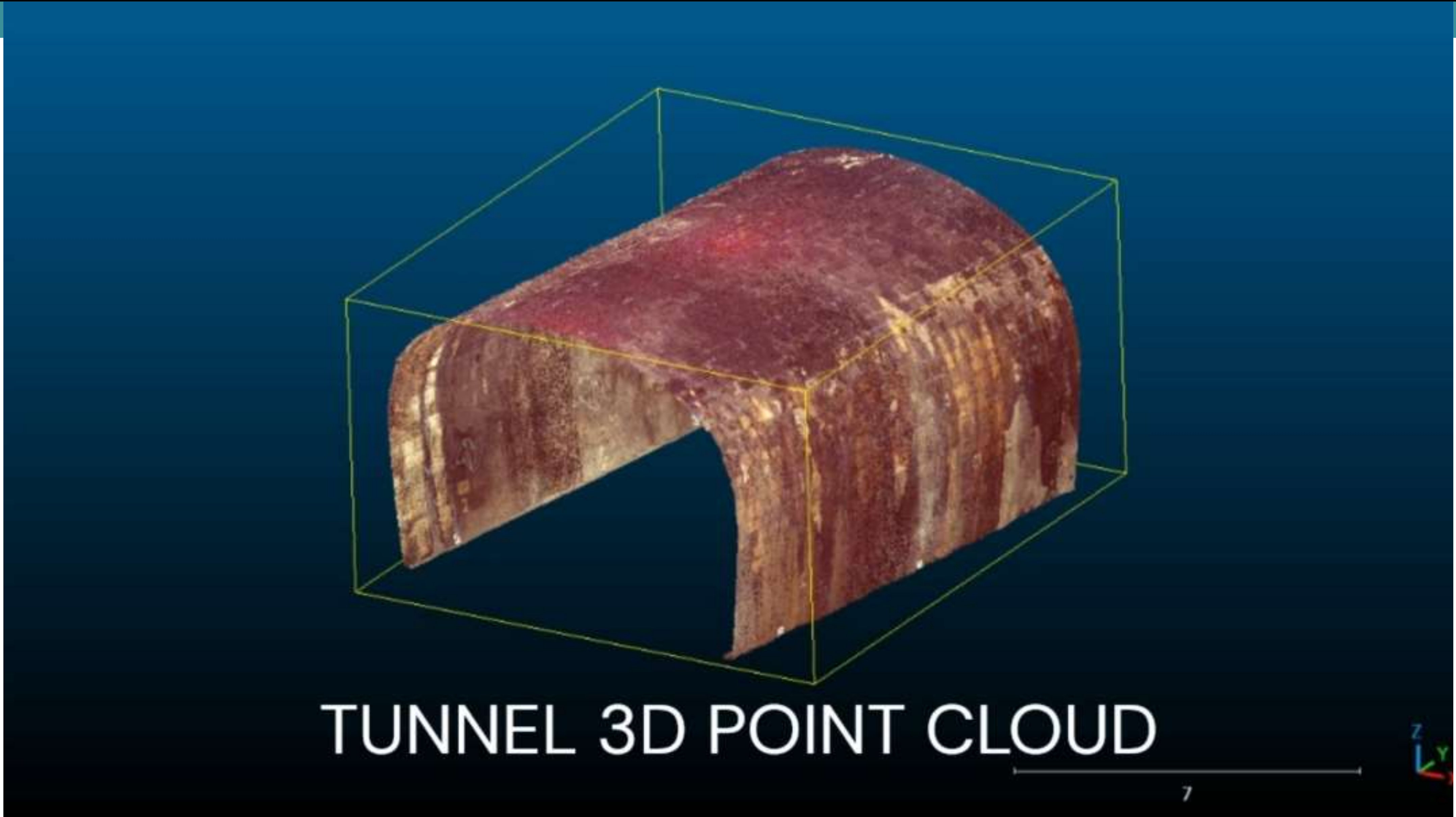
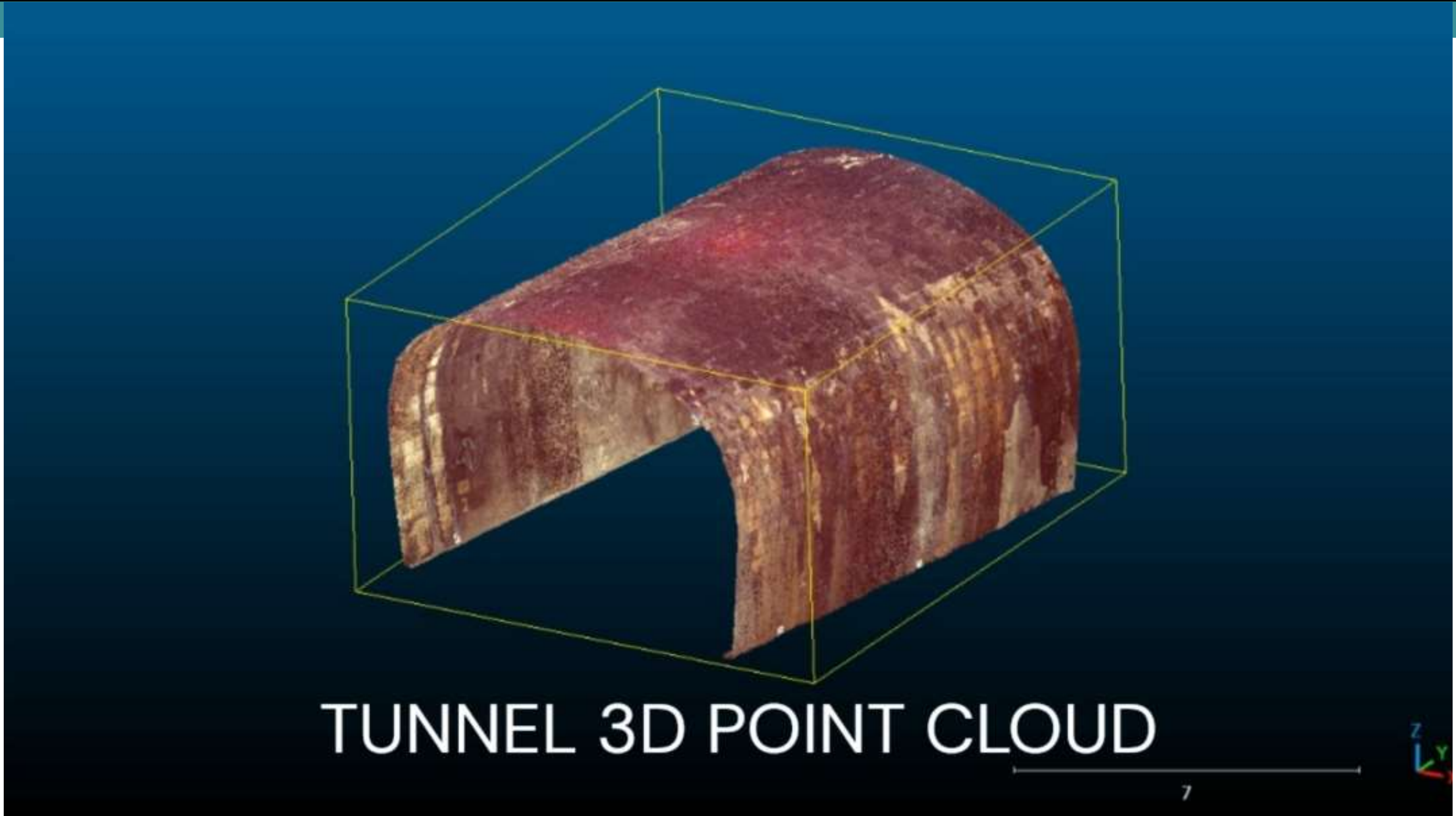
Thank you for Listening



Spalling severity segmentation



Spalling severity segmentation



Upcoming Research

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Automated **masonry spalling severity segmentation** in historic railway tunnels using deep learning and a block face plane fitting approach, (under review)

Smith, J., Paraskevopoulou, C., Cohn, A., Kromer, R., Bedi, A., Invernici, M., 2023.