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**TRB** TRANSPORTATION RESEARCH BOARD

# TRB Webinar: Implementation of UAS into Transportation Infrastructure Inspection

*April 30, 2025*

*1:00PM – 2:30 PM*



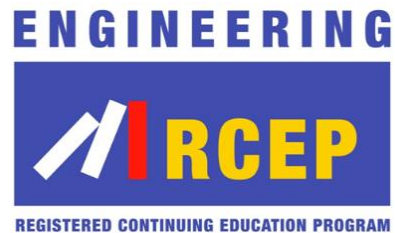
# PDH Certification Information

1.5 Professional Development Hours (PDH) – see follow-up email

You must attend the entire webinar.

Questions? Contact Andie Pitchford at [TRBwebinar@nas.edu](mailto:TRBwebinar@nas.edu)

*The Transportation Research Board has met the standards and requirements of the Registered Continuing Education Program. Credit earned on completion of this program will be reported to RCEP at RCEP.net. A certificate of completion will be issued to each participant. As such, it does not include content that may be deemed or construed to be an approval or endorsement by the RCEP.*



# Purpose Statement

This webinar will share leading applications of UAS to help provide safe and efficient infrastructure assessment capabilities. Presenters will share three case studies: one on bridge inspection, another on airport pavement inspection, and a third on construction modeling.

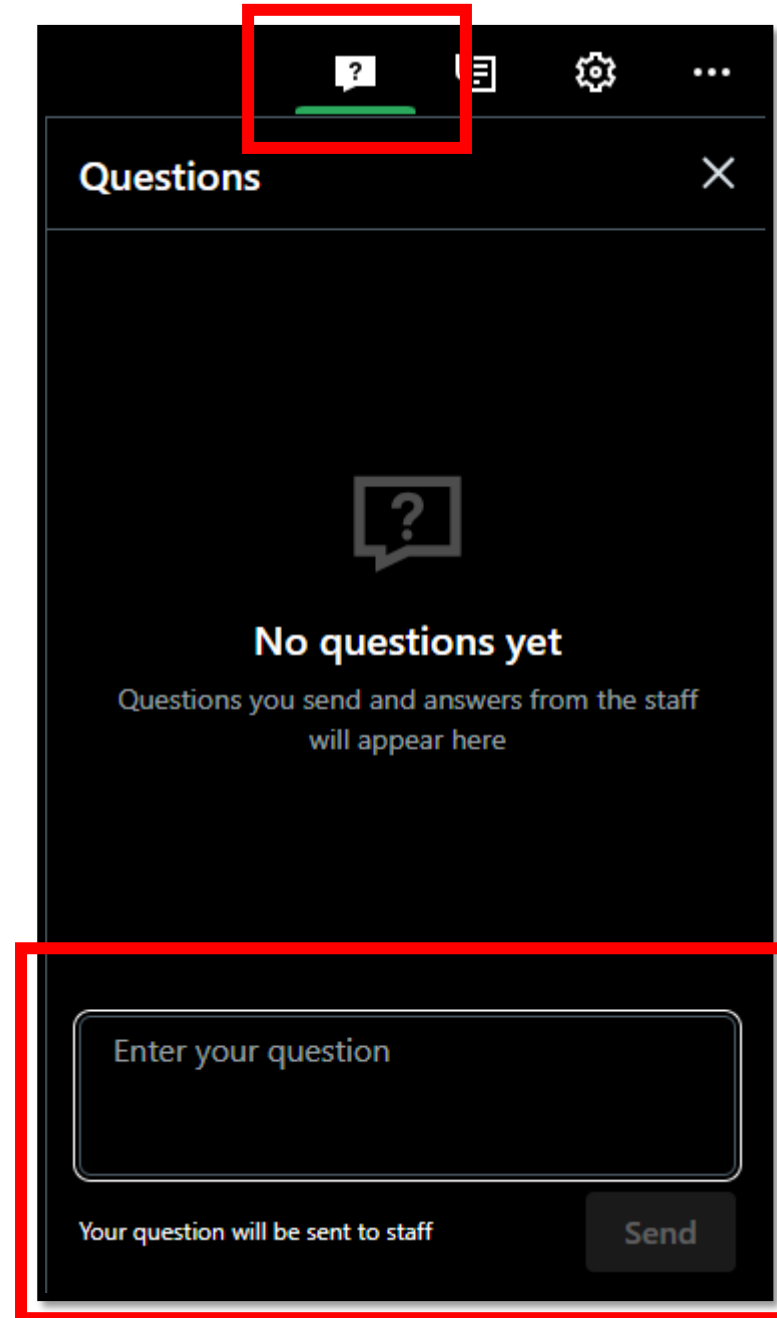
# Learning Objectives

At the end of this webinar, you will be able to:

- (1) Leverage UAS technology to assist infrastructure inspection
- (2) Identify how UAS technology deployment can help reduce time and costs and increase safety for inspections
- (3) Understand which sensors and platforms are being used for infrastructure inspection

# Questions and Answers

- Please type your questions into your webinar control panel
- We will read your questions out loud, and answer as many as time allows



# Today's presenters



**Dr. Colin Brooks**  
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**Dr. Halil Ceylan**  
[hceylan@iastate.edu](mailto:hceylan@iastate.edu)



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Medicine*



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**NATIONAL  
ACADEMIES**



IOWA STATE UNIVERSITY



# **Eyes in the Sky: Unlocking Airfield Pavement Inspection with sUAS**

**Halil Ceylan, Ph.D., Dist.M.ASCE**

**Dept. of Civil, Construction and Environmental Engineering (CCEE)**

**ISU Site Director, FAA PEGASAS Center of Excellence on General Aviation**

**Program for Sustainable Pavement Engineering and Research (PROSPER)**

**Institute for Transportation (InTrans)**

**Iowa State University (ISU)**

**TRB Webinar**

**April 30, 2025**

# Acknowledgements

- Project sponsors on sUAS research
  - FAA and PEGASAS
- Our collaborators, including but not limited to,
  - Michigan Tech Research Institute
  - Applied Pavement Technology, Inc.
- FAA Technical Point of Contacts

## PROSPER

### Program for Sustainable Pavement Engineering and Research

PROSPER | ABOUT PROSPER

#### About PROSPER



- More than 15 professional staff, post-doctoral students, and visiting scholars
- Over 70 Ph.D./M.S./M.E. graduate student researchers
- Over 70 undergraduate student researchers



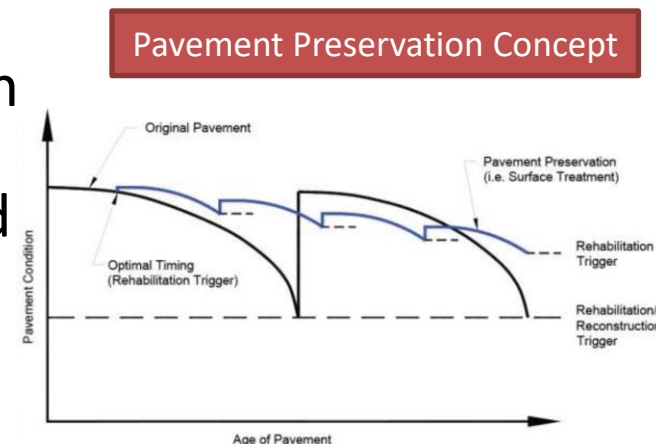
<https://prosper.intrans.iastate.edu/>

## Director Introduction: Halil Ceylan, Ph.D., Dist.M.ASCE

- Title(s)
  - Pitt-Des Moines, Inc. Endowed Professor, Civil, Construction and Environmental Engineering (CCEE)
  - Director, Program for Sustainable Pavement Engineering and Research (PROSPER)
  - ISU Site Director, Partnership to Enhance General Aviation Safety, Accessibility and Sustainability (PEGASAS), FAA Center of Excellence on General Aviation
- Education
  - Ph.D. Civil Engineering, University of Illinois at Urbana-Champaign, 2002
  - M.S. Civil Engineering, University of Illinois at Urbana-Champaign, 1995
  - B.S. Civil Engineering, Dokuz Eylul University, Izmir, Turkey, 1989

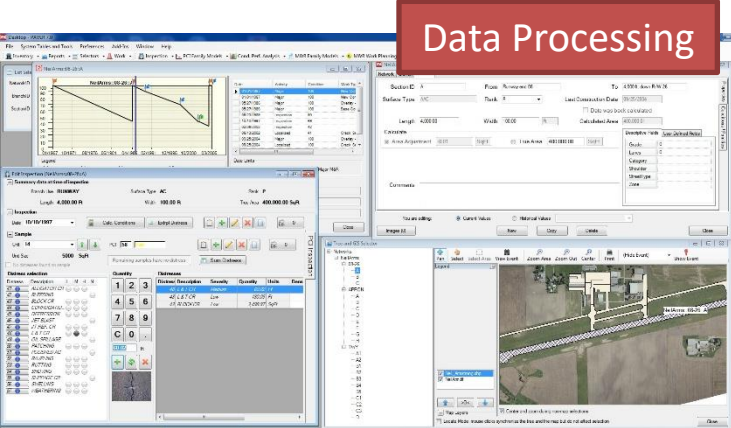
- **Background**
- Data Collection and Analysis
- Notable Results
- ML in Pavement Inspection
- Summary
- Questions and Answers

- Airfield pavement inspections are crucial for maintaining safe and serviceable pavements
- 3.32 billion USD was allocated for airfield pavement improvement in 2019
- Early pavement damage detection is essential for timely pavement maintenance
- Airport pavements are visually inspected



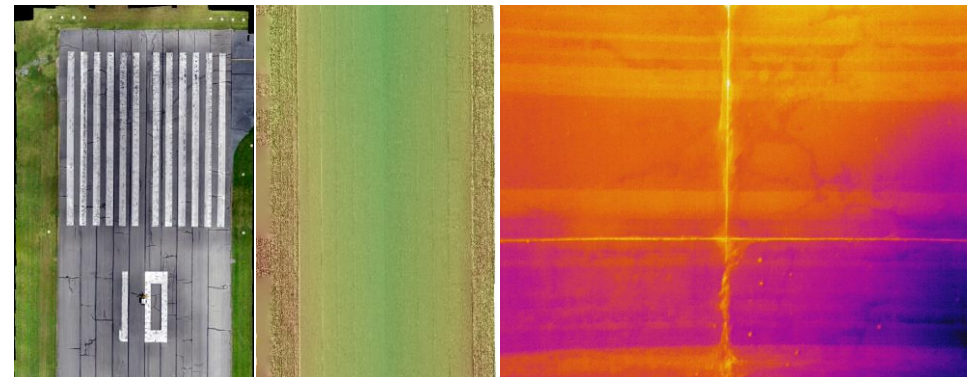
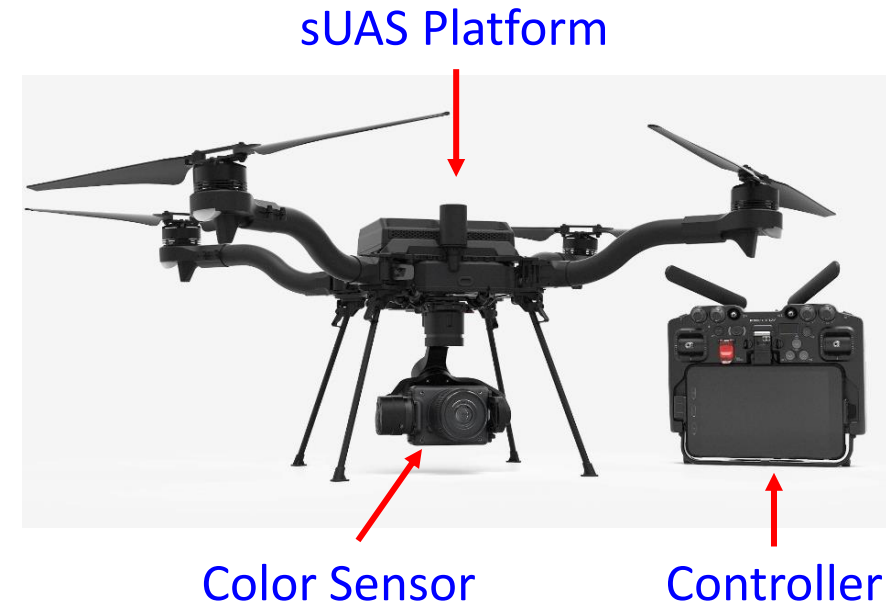
# Background (Cont'd)

- PCI value calculated – value ranges from 0 (failed) to 100 (perfectly new)
- Small Unmanned (Uncrewed) Aircraft Systems (sUAS) became potential pavement inspection tools
- ISU-led team conducting research on the feasibility of sUAS for pavement inspection



## Background (Cont'd)

- sUAS aka drone is an unmanned aircraft weighing <55 lbs, including everything on board / attached
- Consists of
  - Unmanned Aircraft
  - Ground Control Station
  - Command & Control Link



Sample Data (Color, Elevation, Thermal)

## Background (Cont'd)

- Drone operations are particularly effective for missions that are dangerous or dull
  - Humans are not put at risk
  - Continuous operations are possible
- Operations with drone often cost less than using manned aircraft



- Background
- **Data Collection and Analysis**
- Notable Results
- ML in Pavement Inspection
- Summary
- Questions and Answers

# Data Collection and Analysis

- Our Notable sUAS Related Inventories

**Blue List**



Freefly Astro

**NDAA**



Aurelio x6



Mavic 2 Enterprise Advanced



Sony LR1



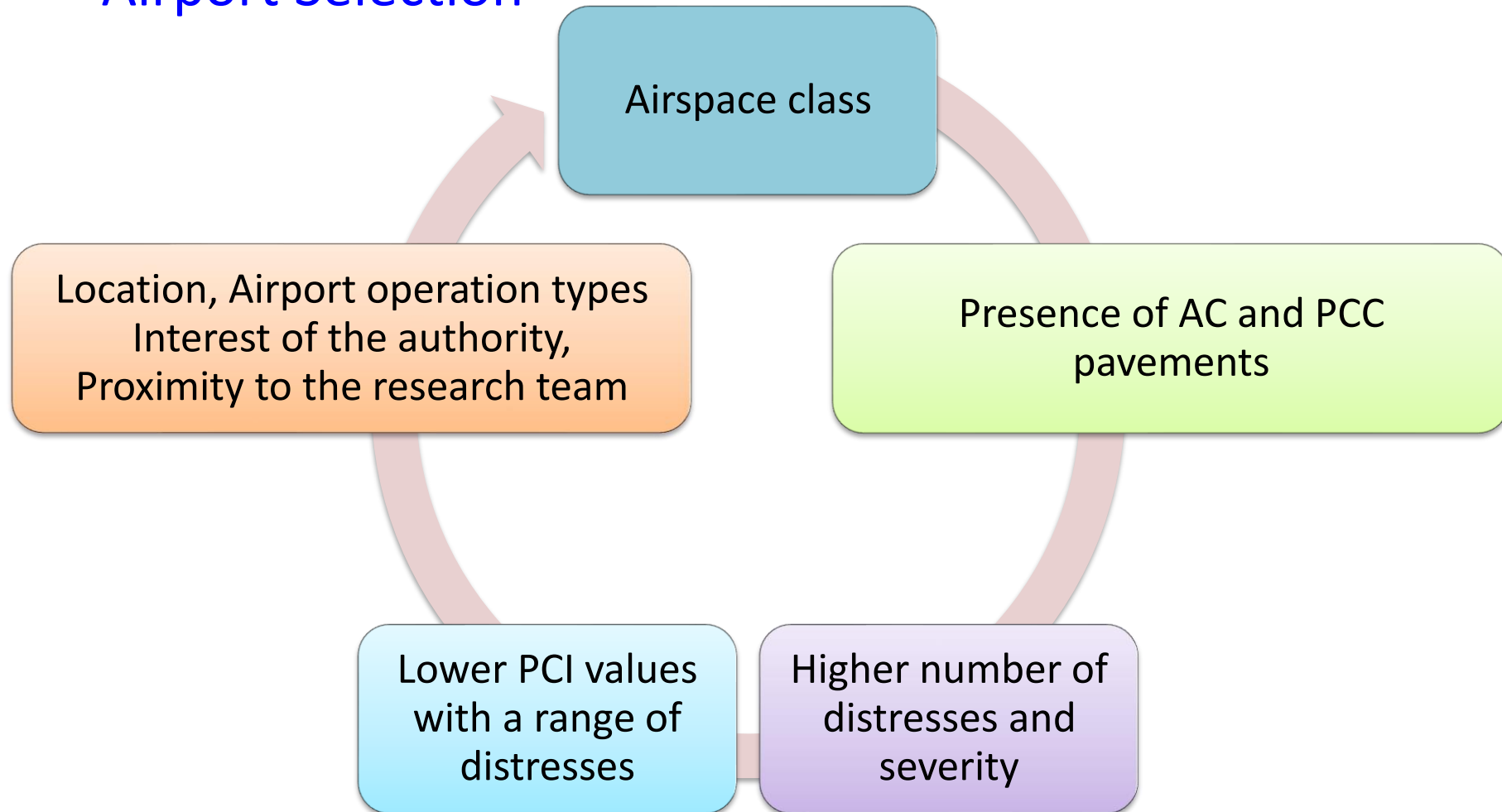
Nikon D850



Aeropoint

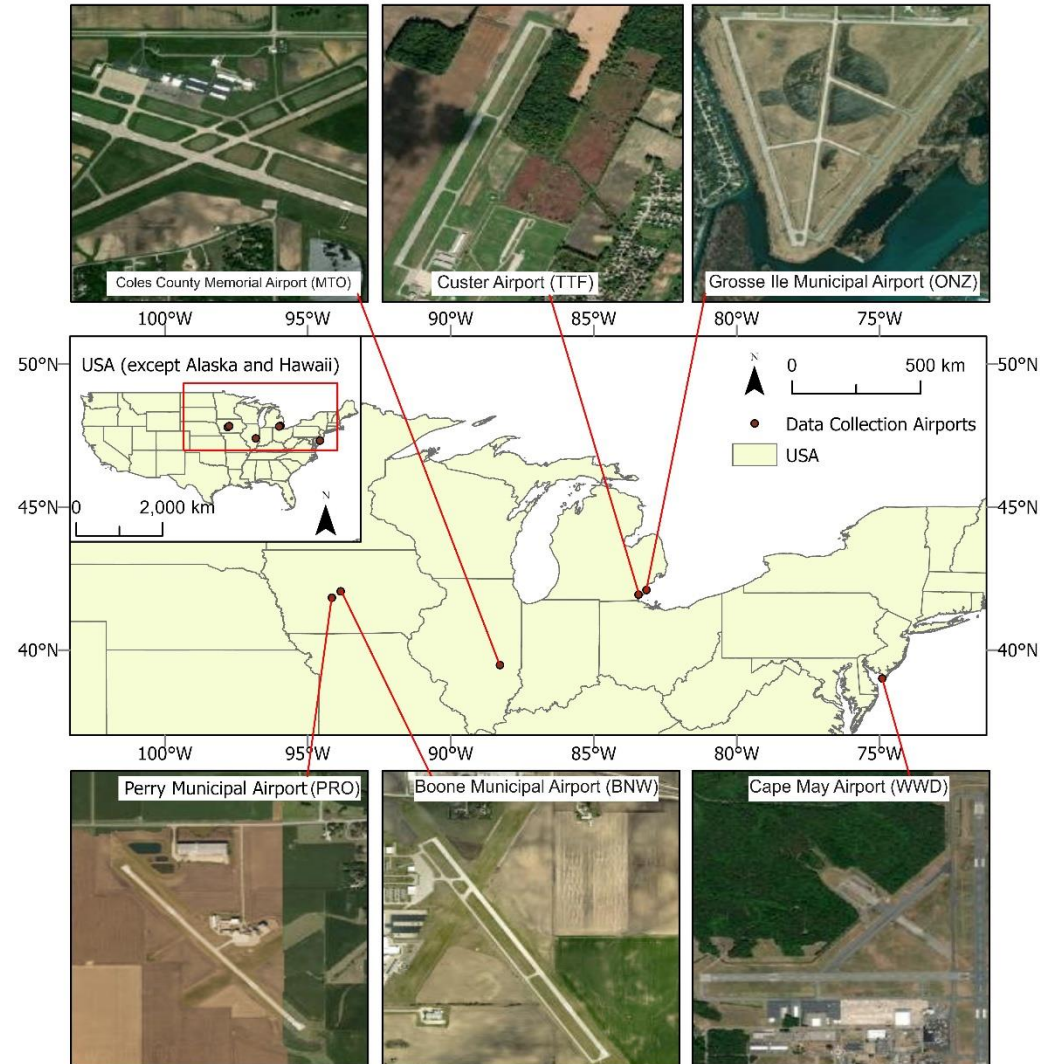
## Data Collection and Analysis (Cont'd)

- Airport Selection



# Data Collection and Analysis (Cont'd)

- Field Demonstration



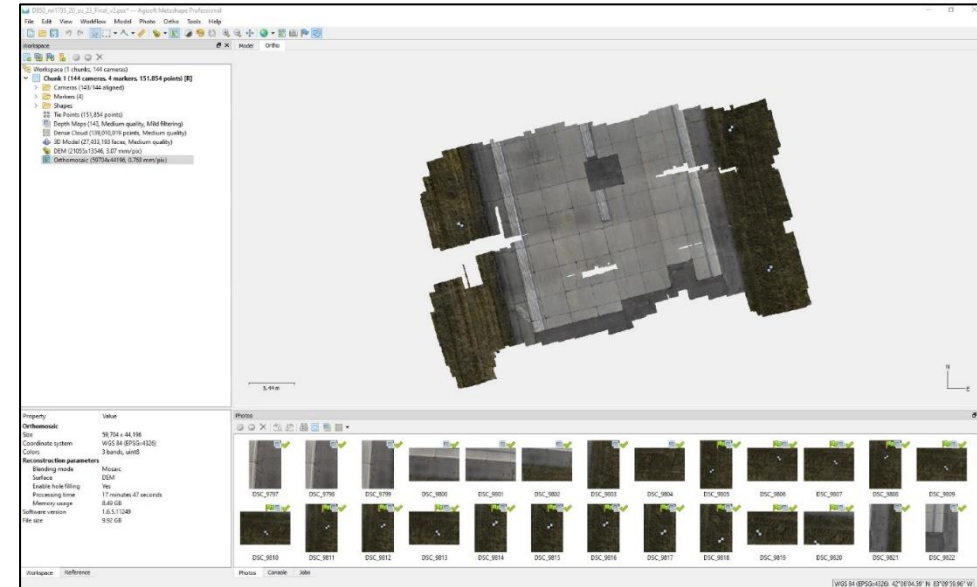
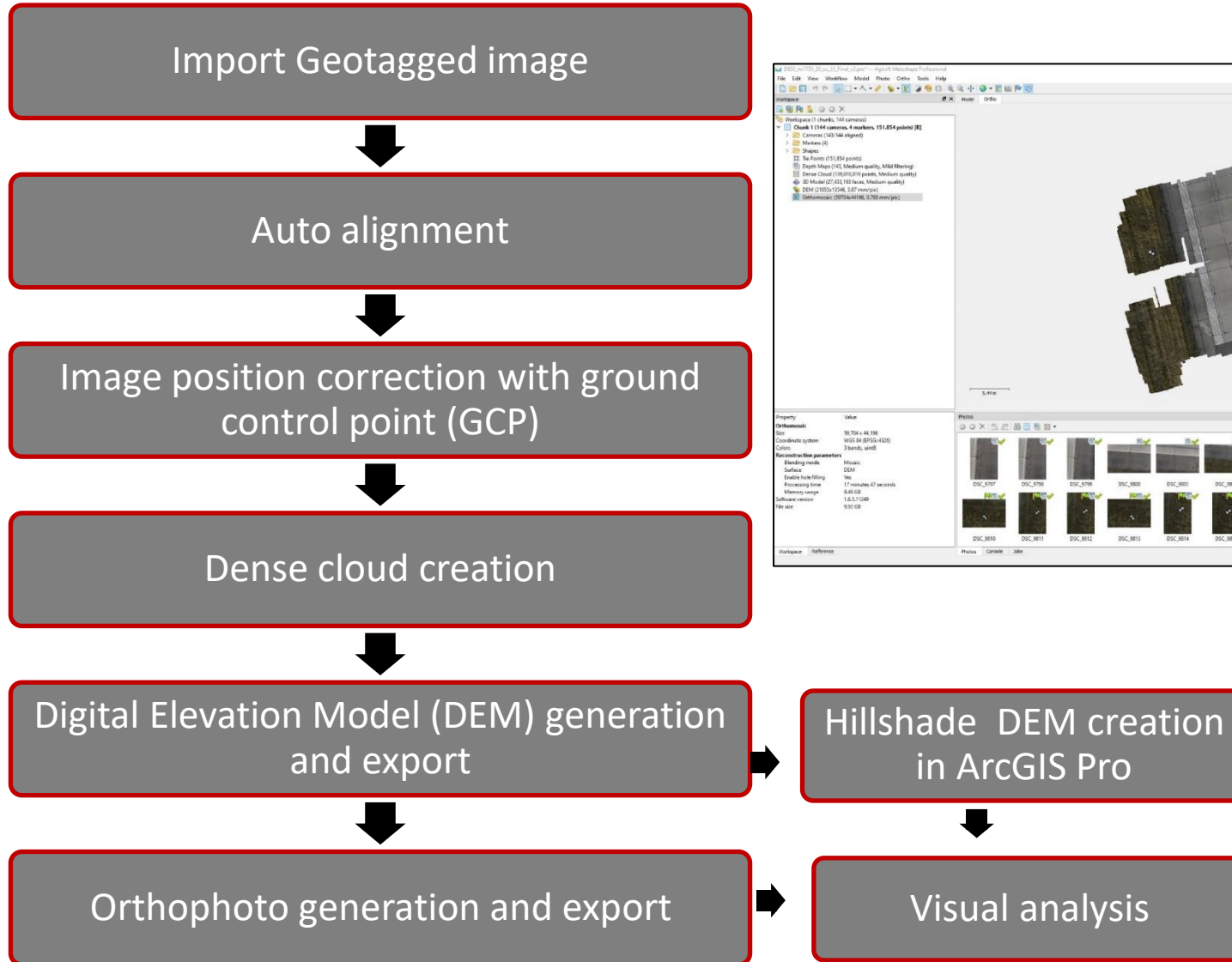
# Data Collection and Analysis (Cont'd)

- Airfield Pavement Inspection: Field Safety First

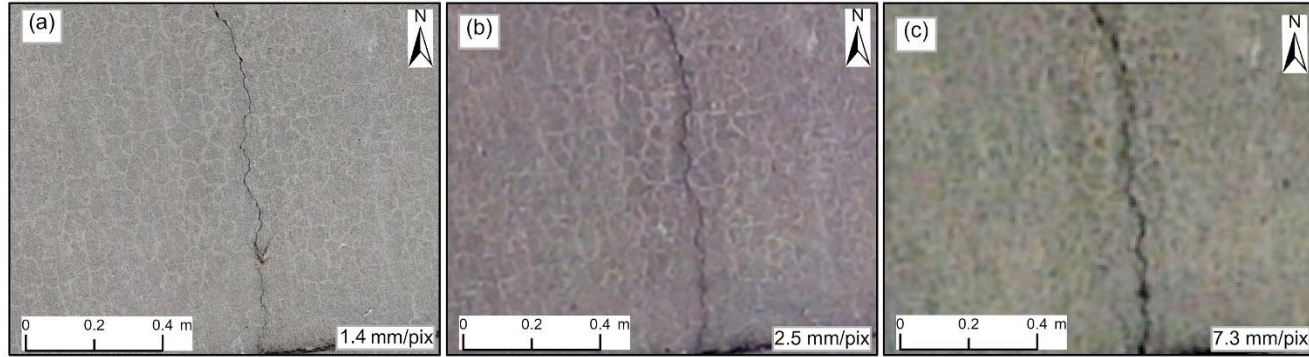


# Data Collection and Analysis (Cont'd)

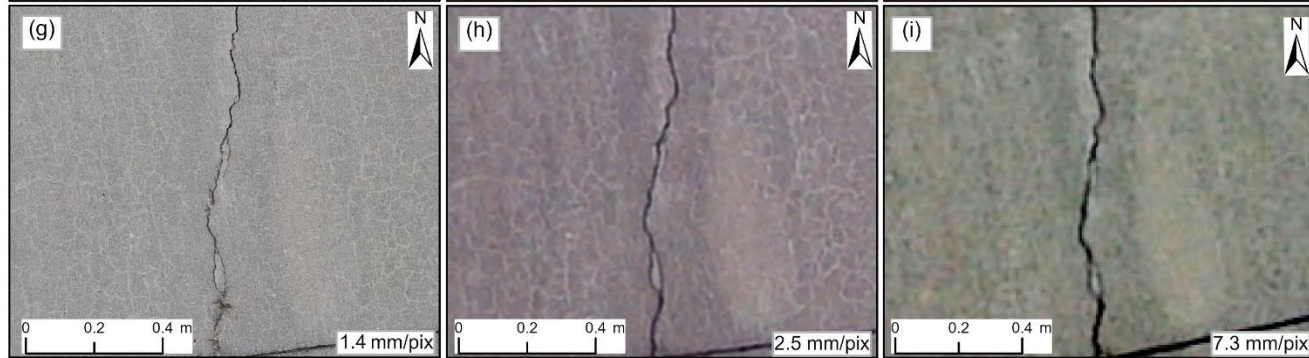
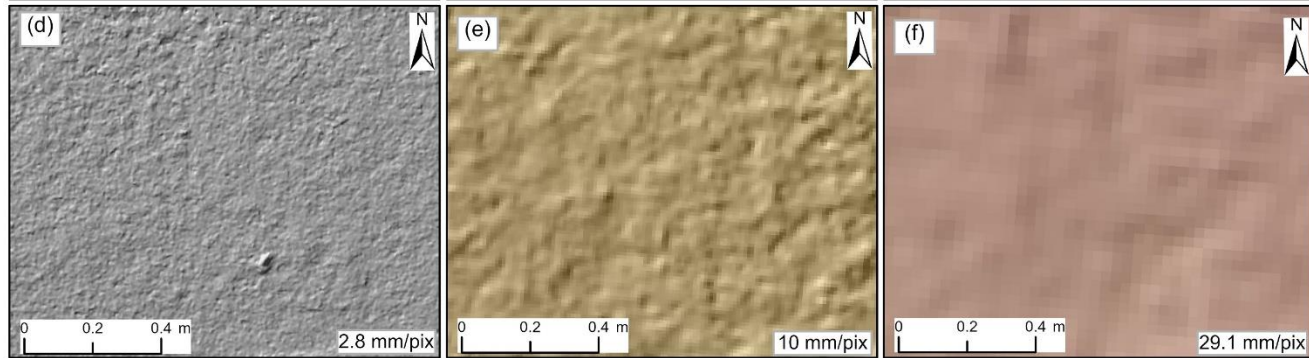
## Data Processing



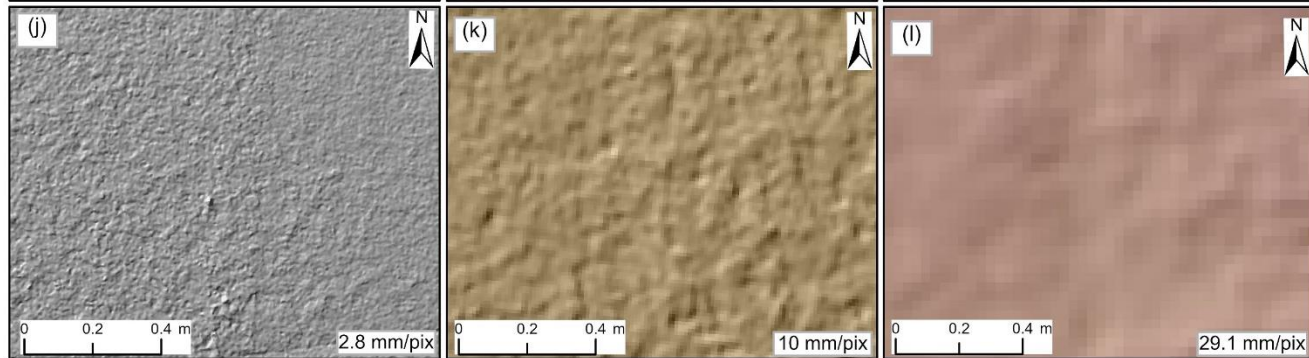
- Airfield Pavement Inspection
  - 5 field data collection and 1 validation site
  - 6 platforms and 9 sensors
  - Data resolutions
    - 0.75 mm/pix to 21 mm/pix RGB orthophoto
    - 2.98 mm/pix to 84 mm/pix DEM
    - 8 mm/pix and 31 mm/pix stereo thermal

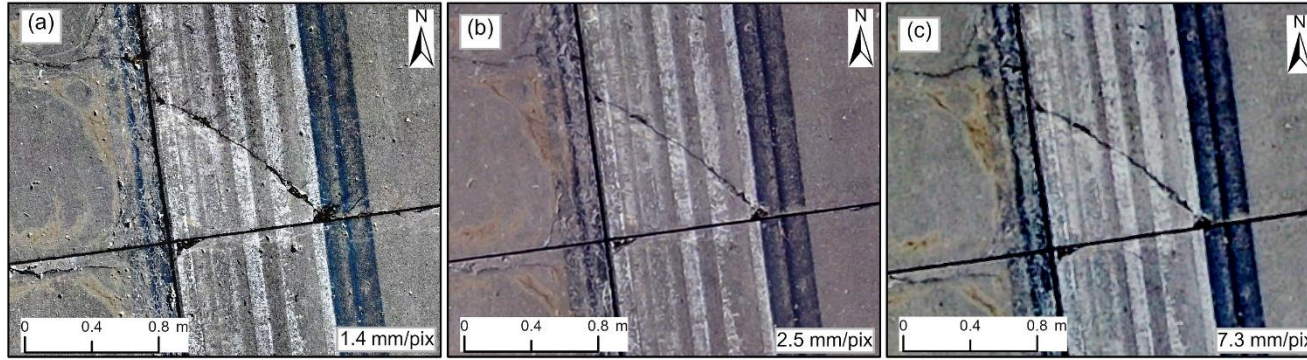


LTD Cracks (L) (a-f)  
on PCC Pavement

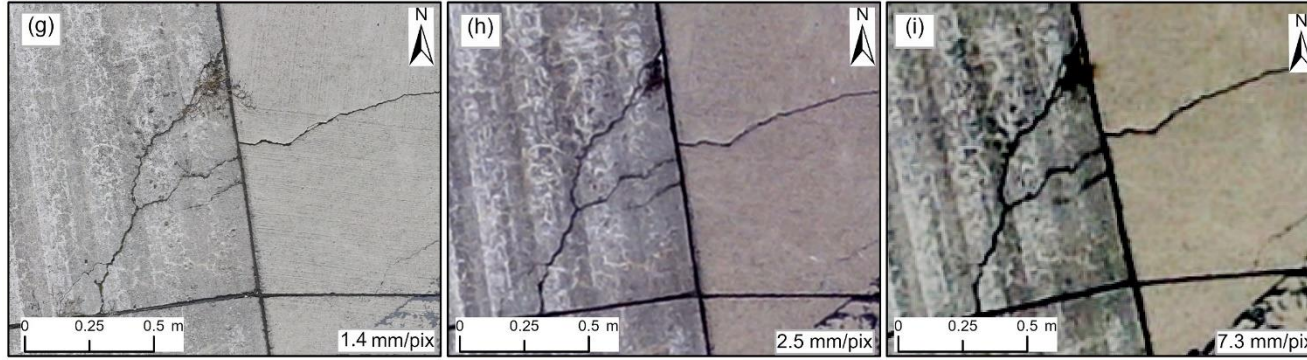


LTD Cracks (M) (g-l)  
on PCC Pavement

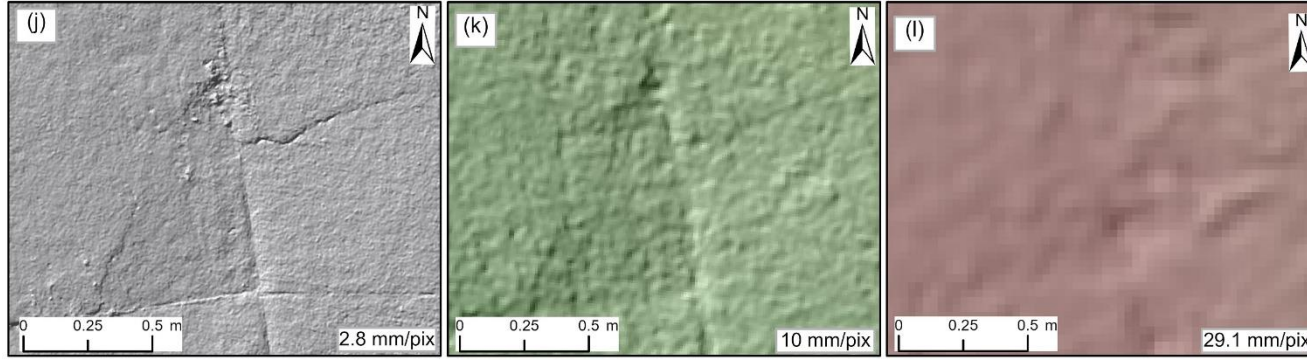


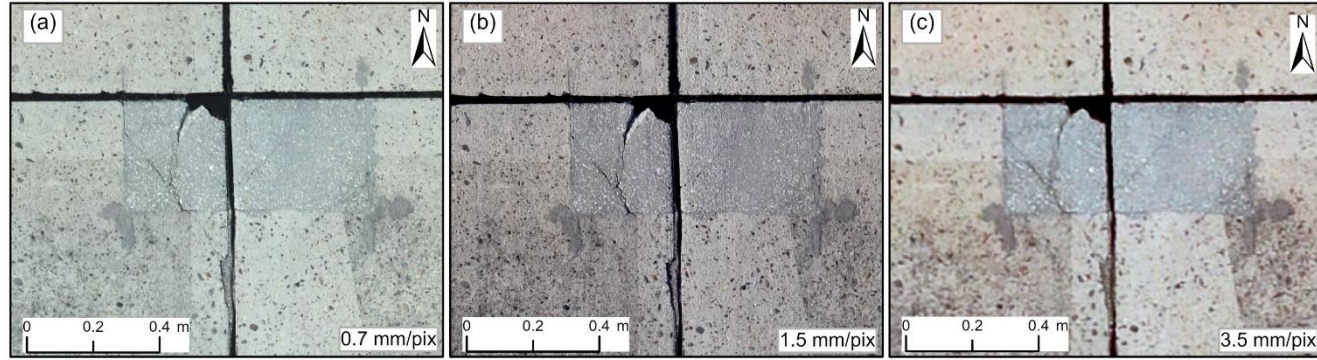


Corner Breaks (L) (a-f)  
on PCC Pavement

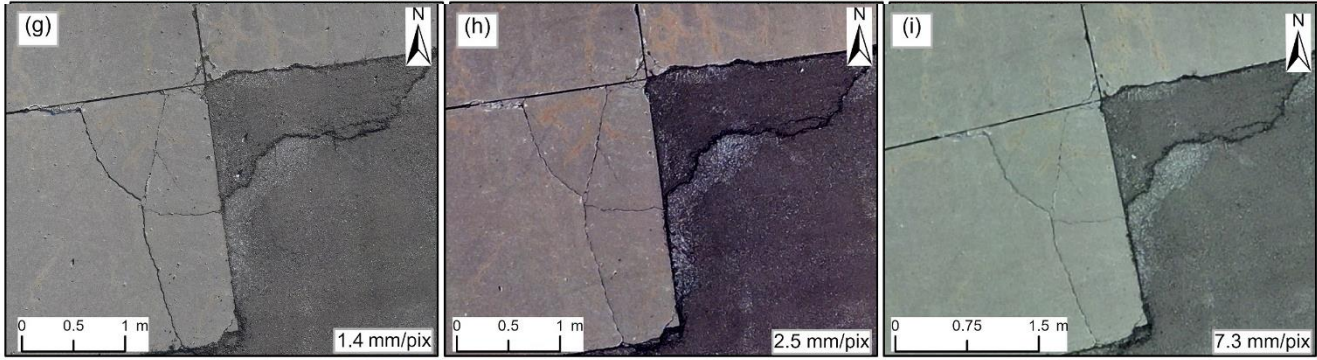
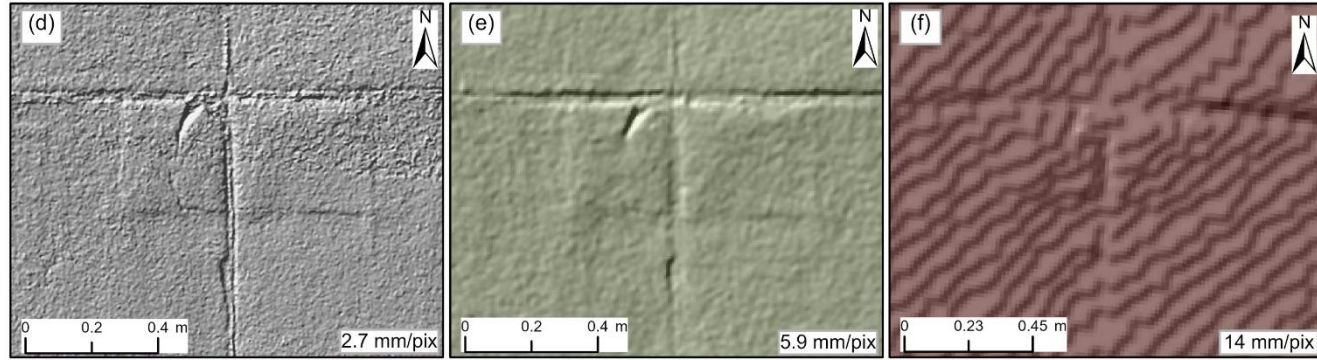


Corner Breaks (M) (g-l)  
on PCC Pavement

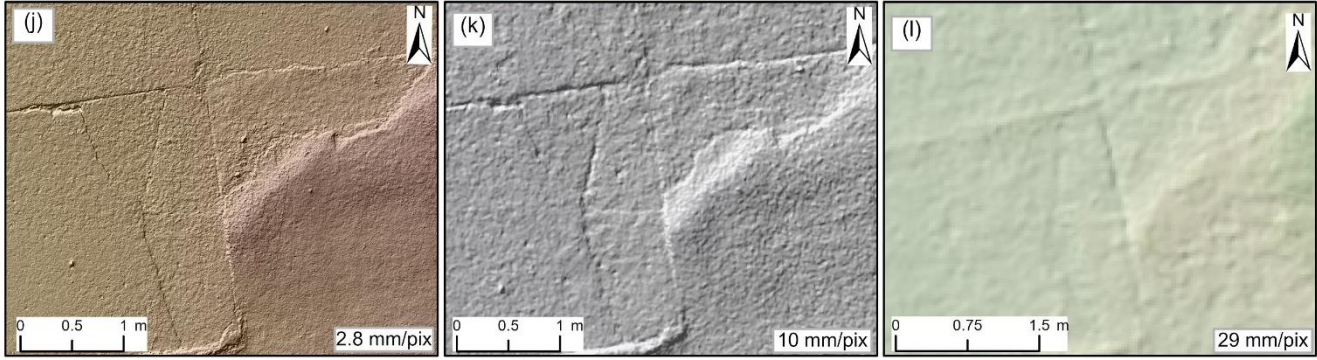


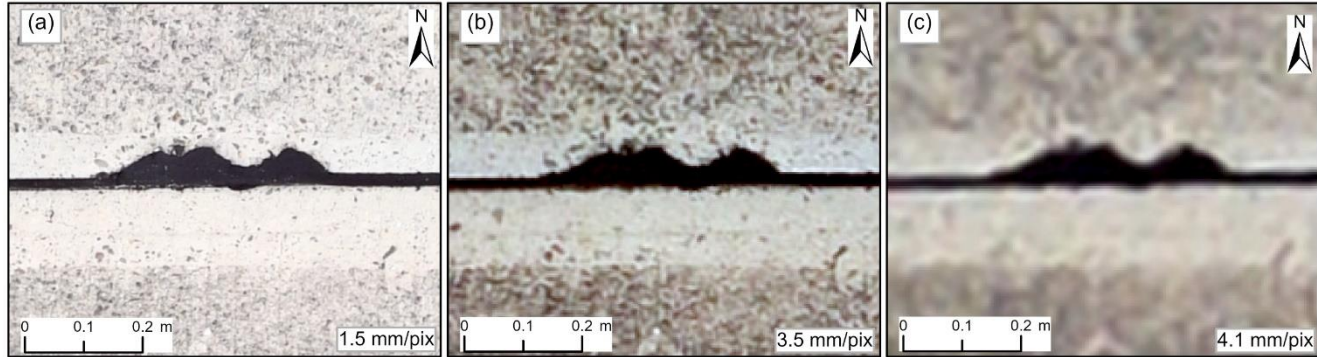


Small Patch (L, M) (a-f)  
on PCC Pavement

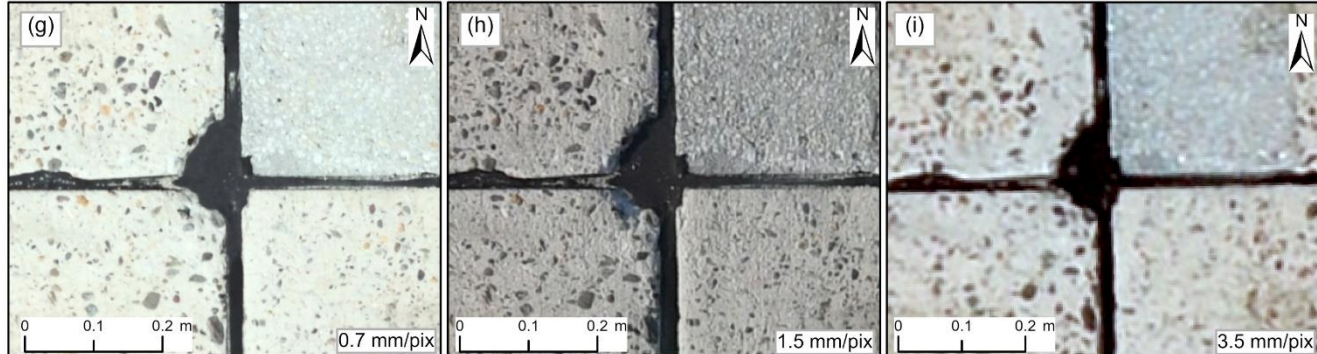
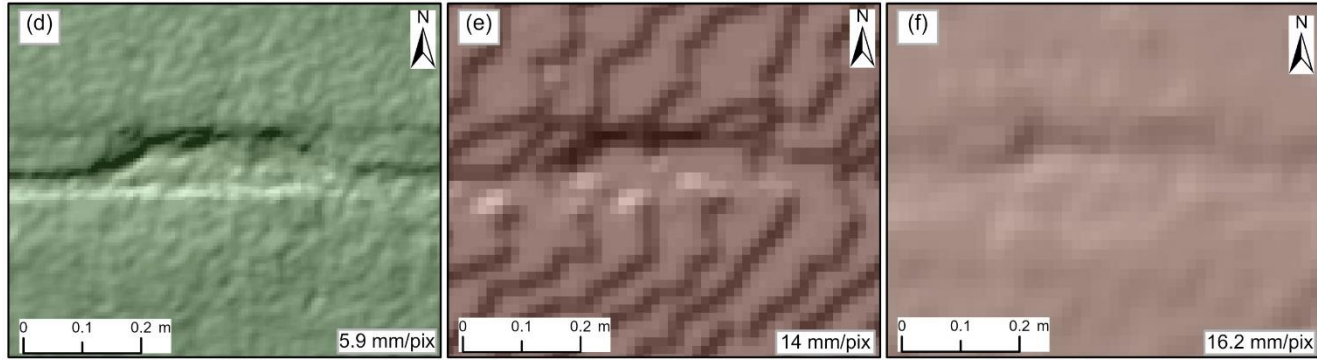


Large Patch (H) and  
Shattered Slabs (M) (g-l)  
on PCC Pavement

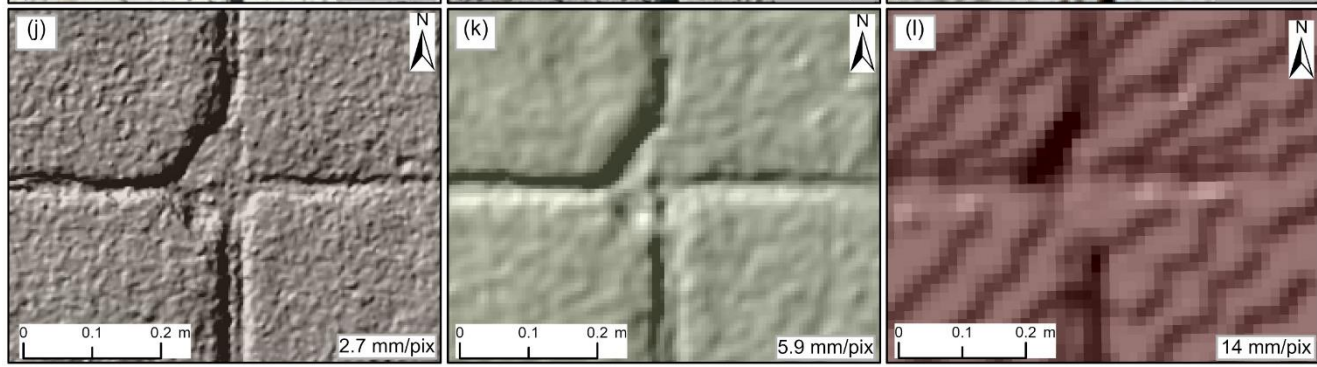


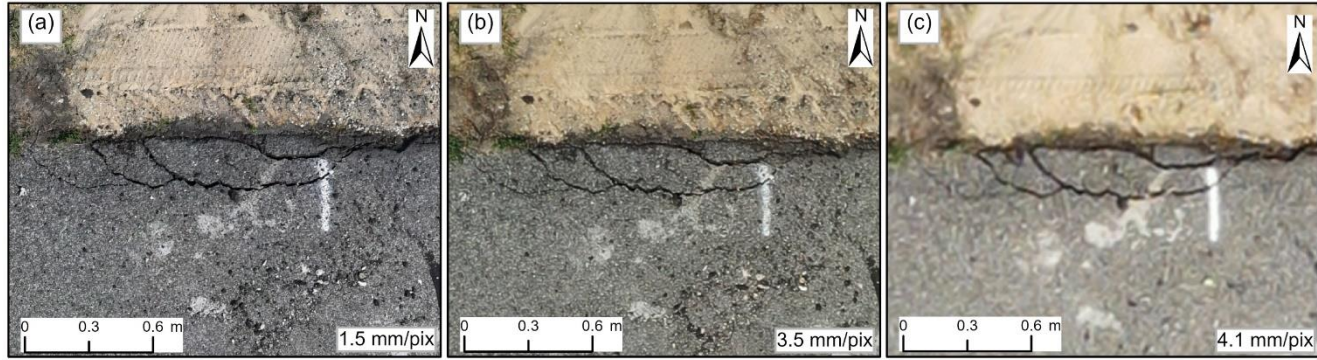


Joint Spalling (L) (a-f)  
on PCC Pavement

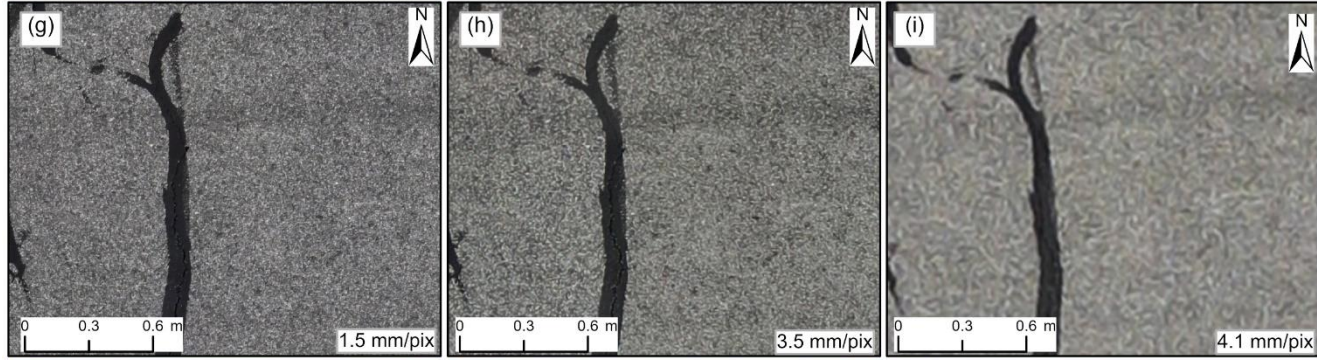
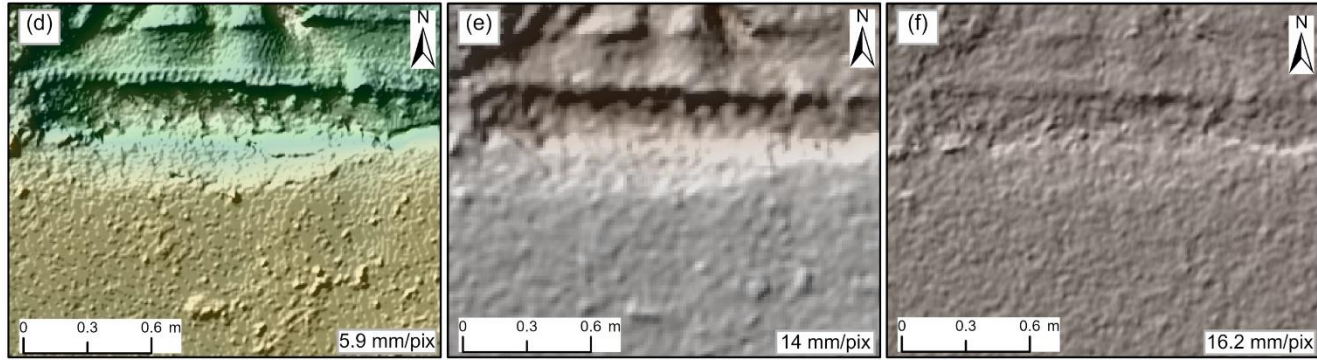


Corner Spalling (M) (g-l)  
on PCC Pavement

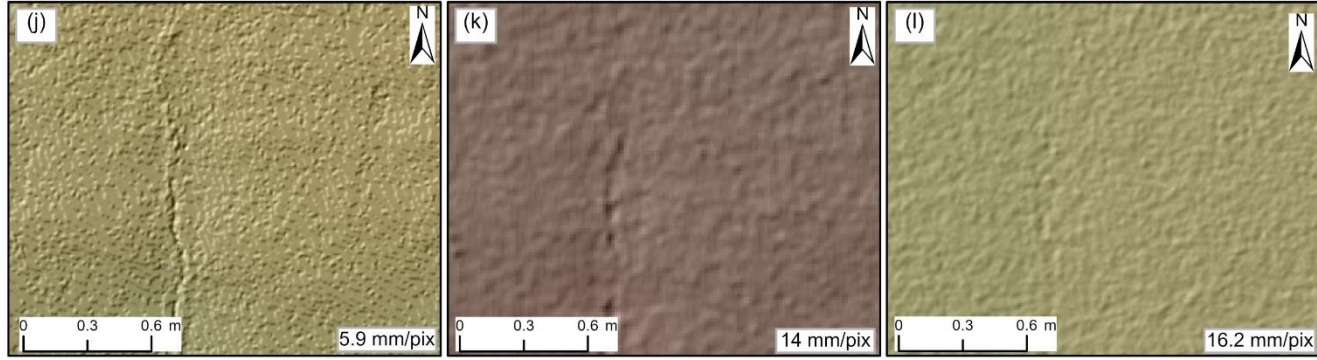




Alligator Cracks (L) (a-f)  
on AC Pavement

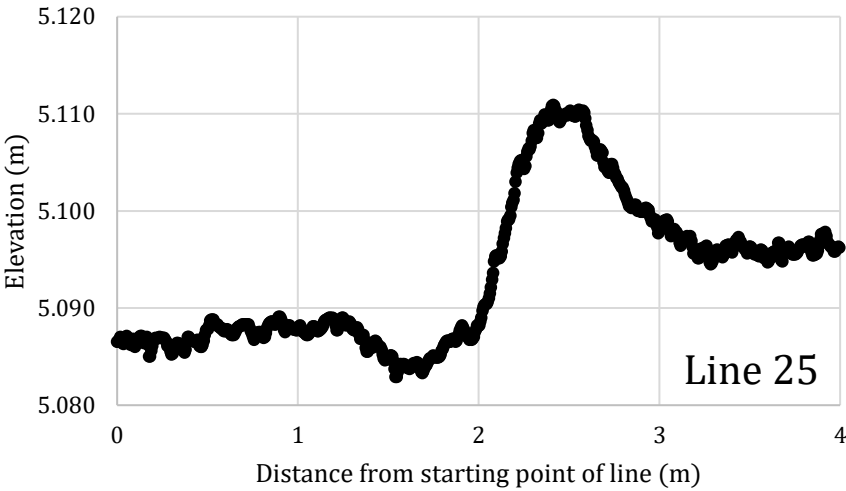
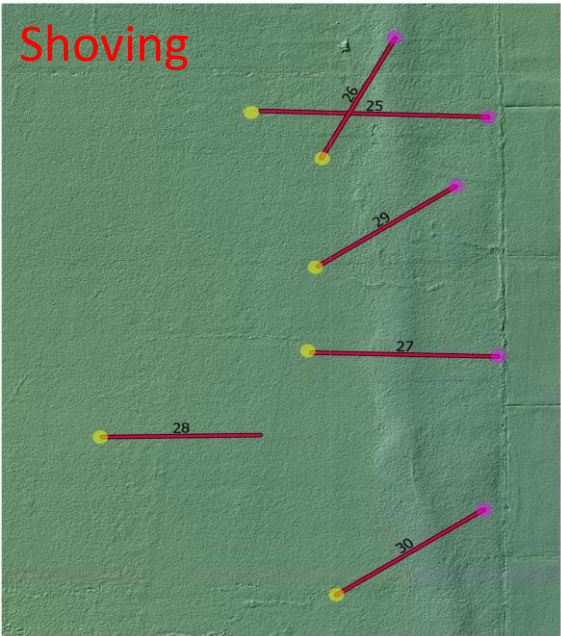
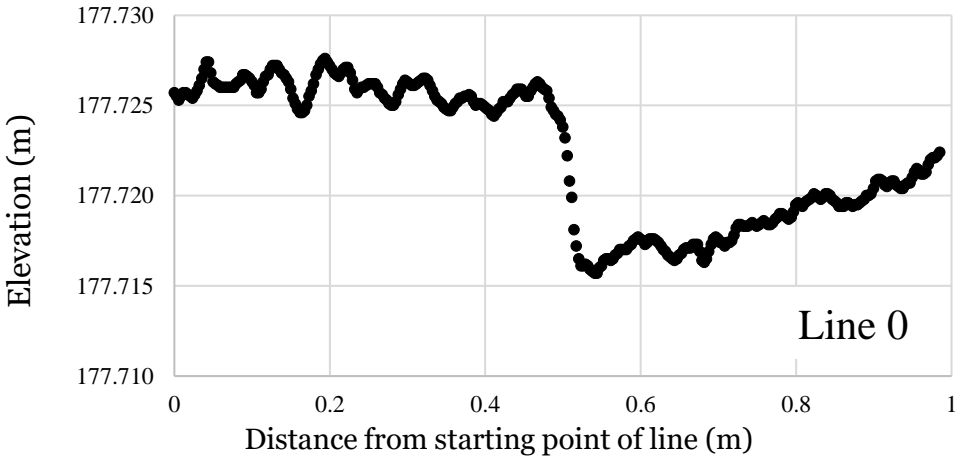


L&T Cracks (L) (g-l)  
on AC Pavement



- Background
- Data Collection and Analysis
- **Notable Results**
- ML in Pavement Inspection
- Summary
- Questions and Answers

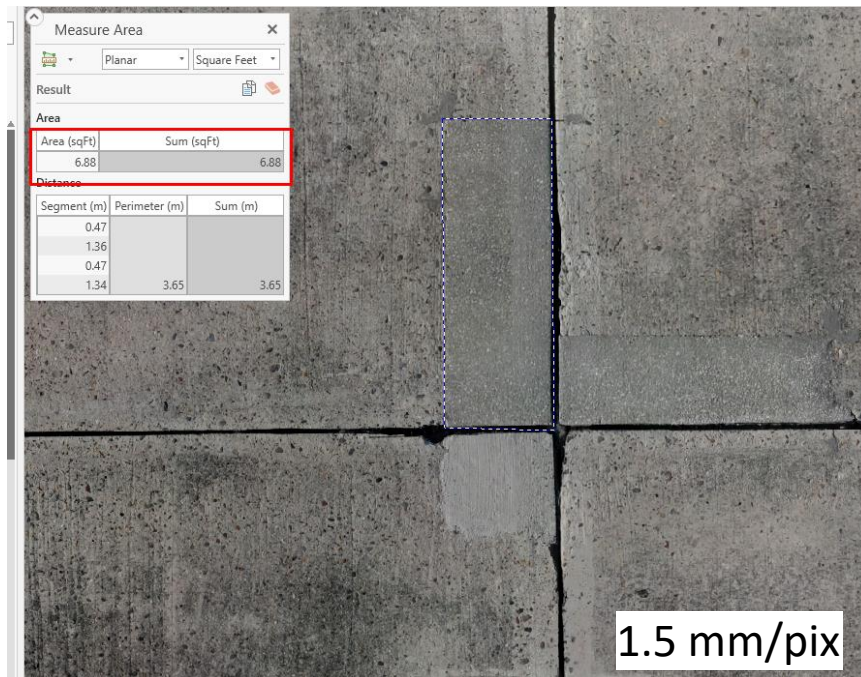
# Notable Results



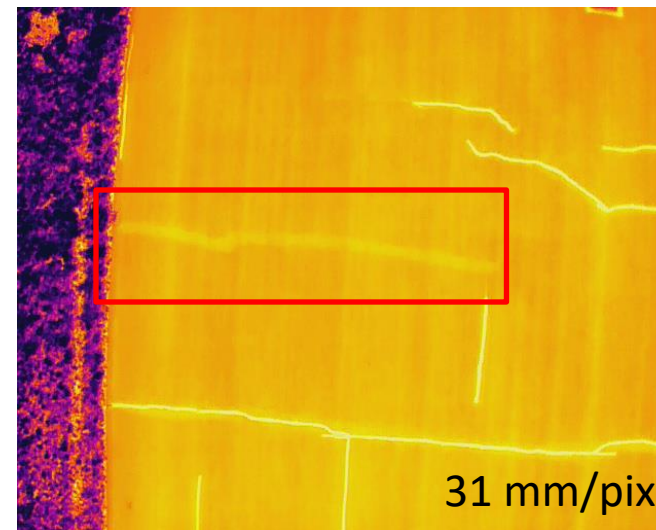
## Notable Results (Cont'd)

### Patching and L&T cracks identification

Patching is divided into two types: small (less than 5.5 square feet) and **large (over 5.5 square feet)**.



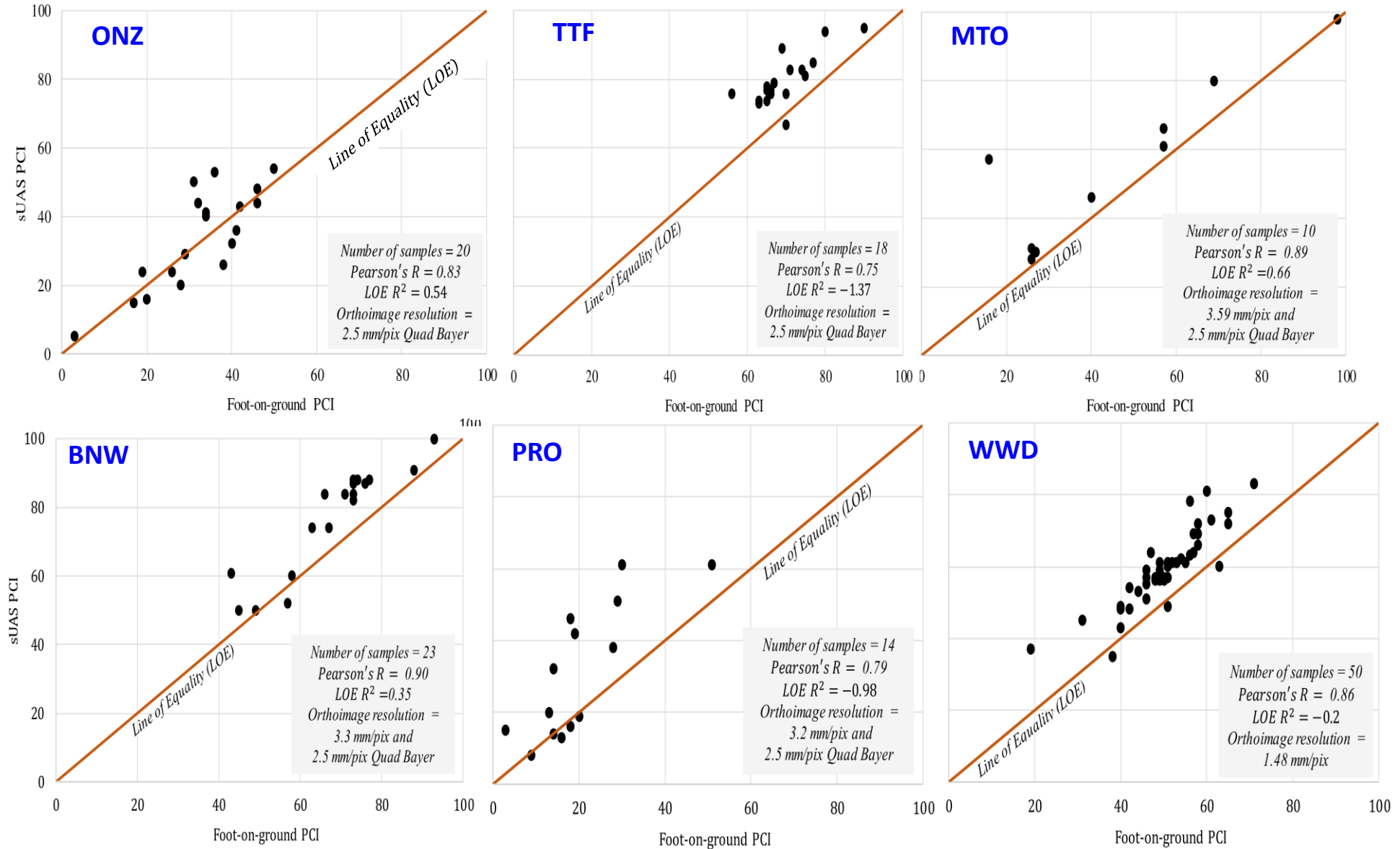
Large patching (L) noted as **small patching (L)**



L&T cracks underneath the recent asphalt overlay show heat signature in thermal data

- Airfield Pavement Inspection: Summary
  - RGB detect 13/14 available PCC pavement distresses and 6/9 AC pavement distresses
  - DEMs useful for faulting and shoving
  - Resolutions Recommendations
    - RGB: 1.5 mm/pix recommended
    - DEM: 6 mm/pix is highly recommended
    - Thermal: <30 mm/pix is adequate

# Notable Results (Cont'd)

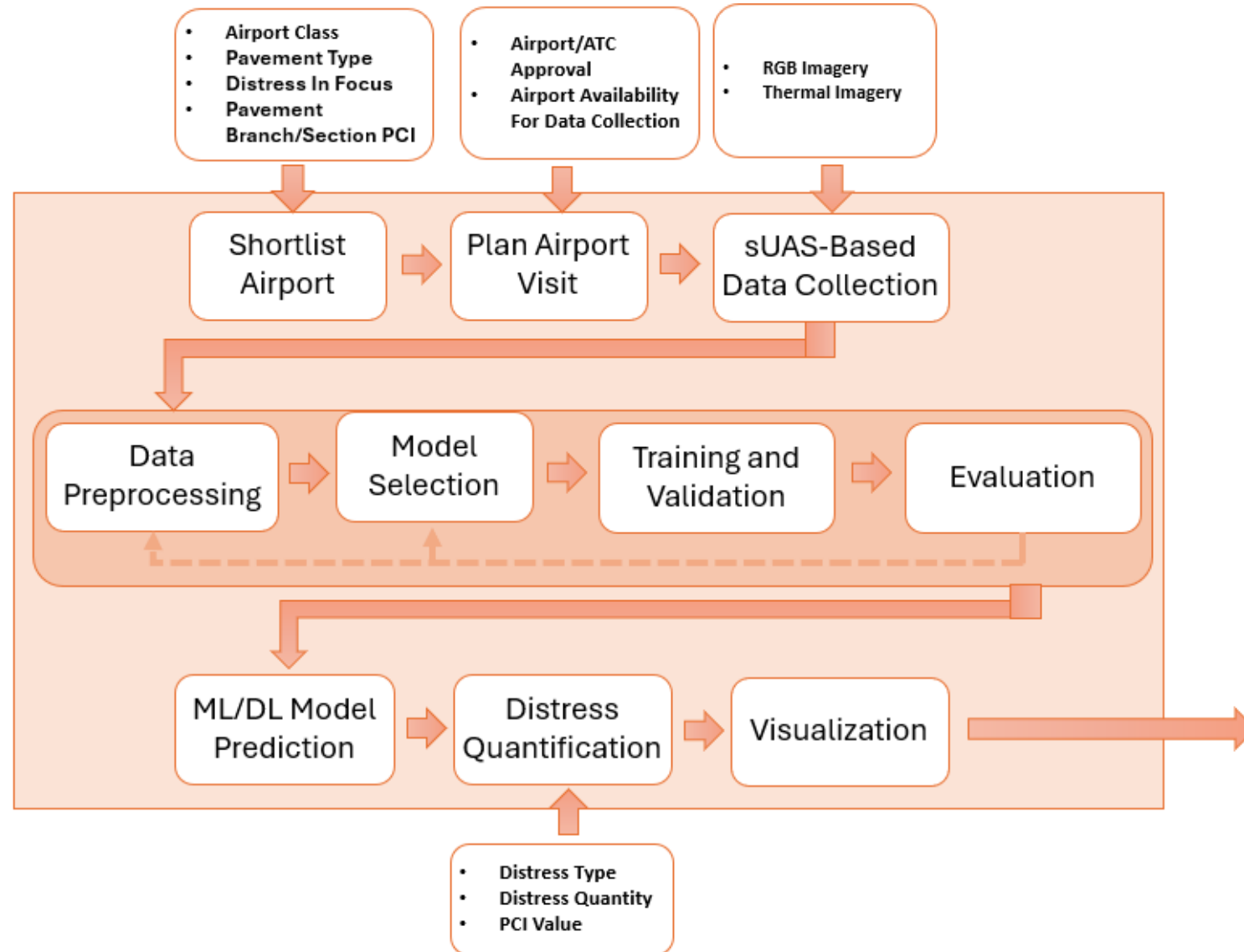


- Background
- Data Collection and Analysis
- Notable Results
- **ML in Pavement Inspection**
- Summary
- Questions and Answers

- Ongoing FAA-funded project
  - Evaluate ML models for distress detection in sUAS Data
  - Benefits:
    - Cost-effective
    - Survey large pavement in a shorter time
    - Scalability and adaptability
    - Potential to complement traditional inspection
    - Real-time analysis potential

# ML in Pavement Inspection (Cont'd)

- Workflow



# ML in Pavement Inspection (Cont'd)

- Different DL Models

Architecture	Probable Models	Functionality
VGG	VGG-16/VGG-19	Image Classification
ResNet	ResNet-152v2	Image Classification
Inception	Inception-v4/ Inception-ResNet-v2	Image Classification
R-CNN	Faster R-CNN/Mask R-CNN	Object Detection
YOLO	YOLOv8/v9/v10/v11/v12 (N/S/M/B/L/X)	Object Detection, Image Classification, Instance Segmentation
U-Net	U-Net/U-Net++	Semantic Segmentation
Transformer-Based	ViT/RT-DETR/Segformer	Object Detection, Image Classification, Semantic Segmentation
GANs	Vanilla GAN, DCGAN	Image Generation & Augmentation

- Sample of DL-Based Crack Detection



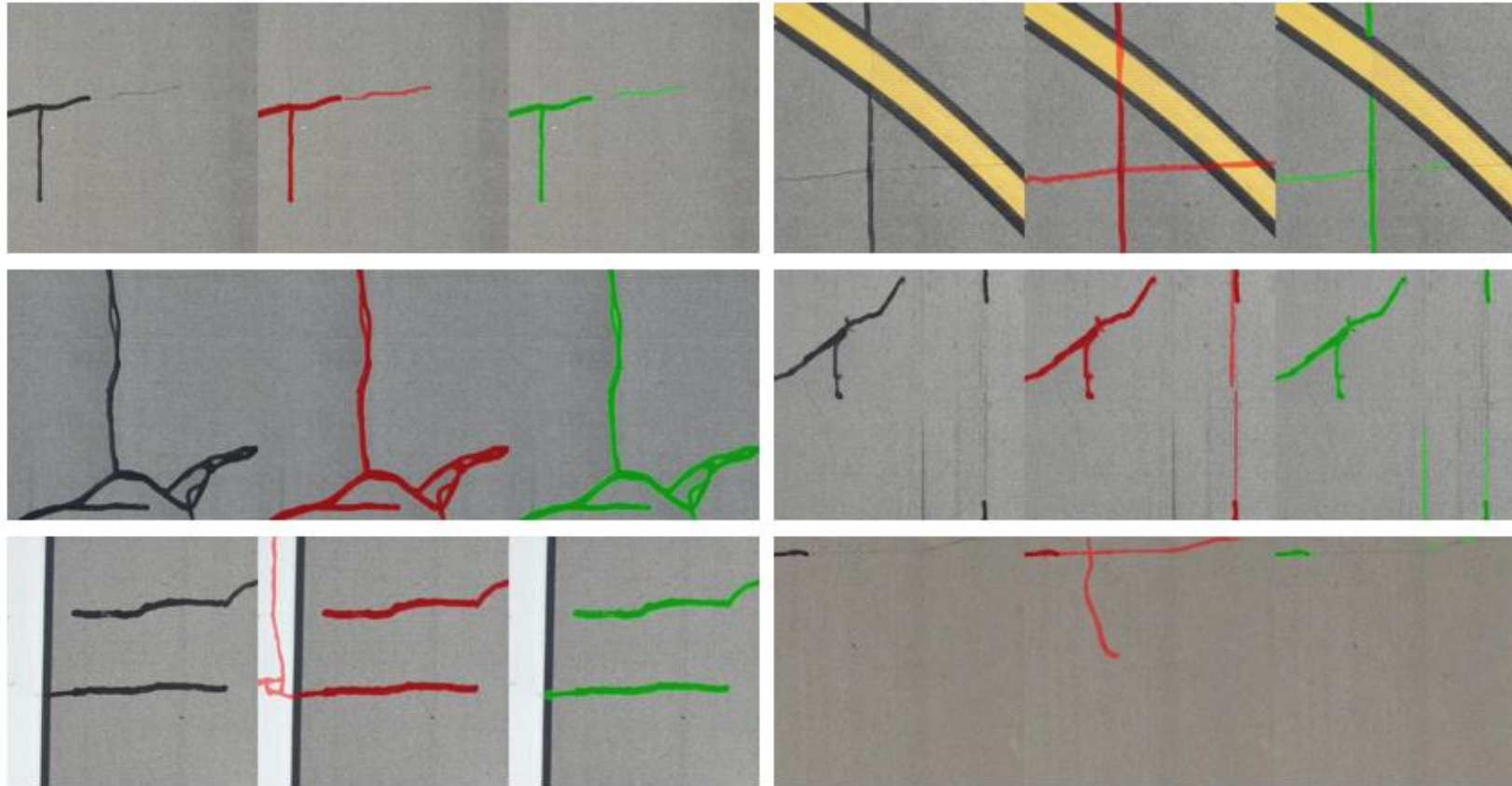
Annotated Label

Predicted Results

Cracks detected by the YOLOv11s model

# ML in Pavement Inspection (Cont'd)

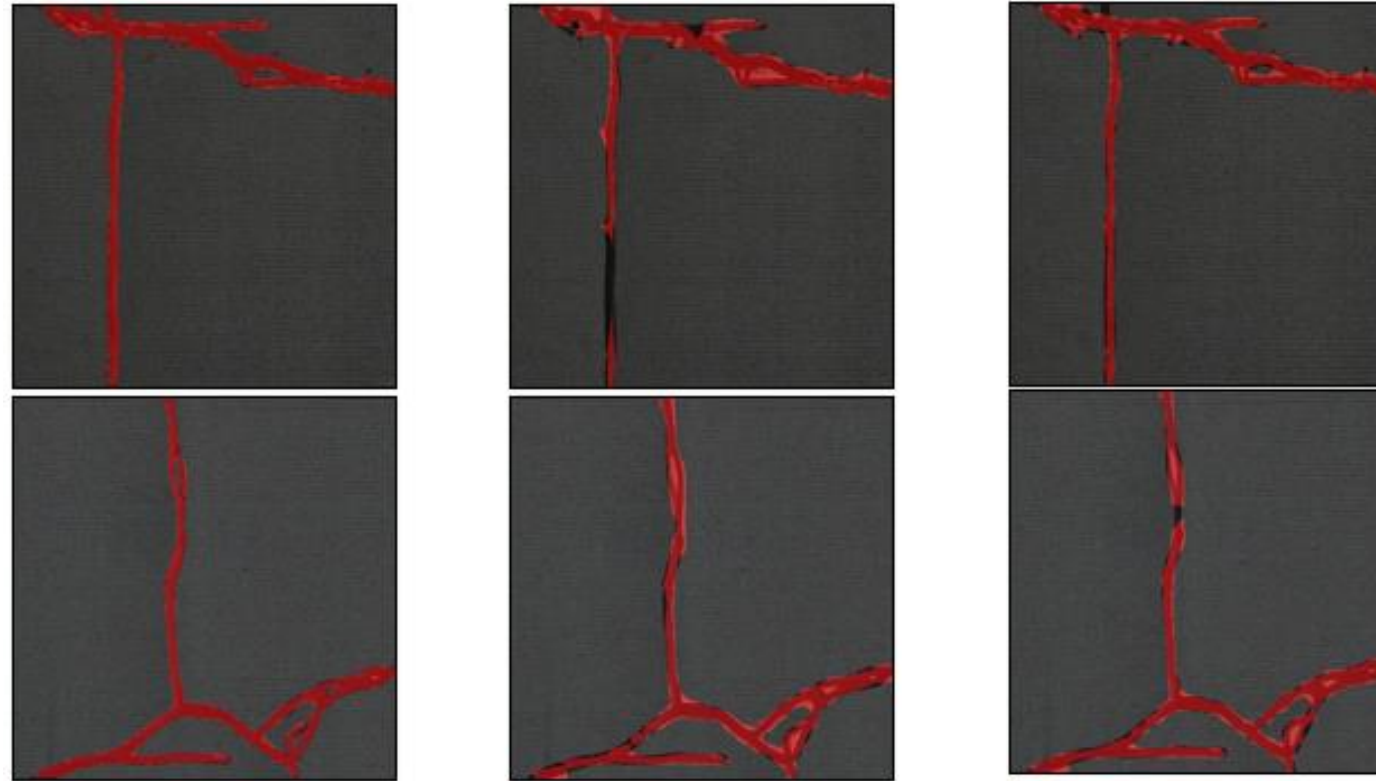
- Sample of DL-Based Crack Detection



Sealed Cracks detected by the UNET model

Red: Annotated Mask; Green: Predicted Mask

- Sample of DL-Based Crack Detection



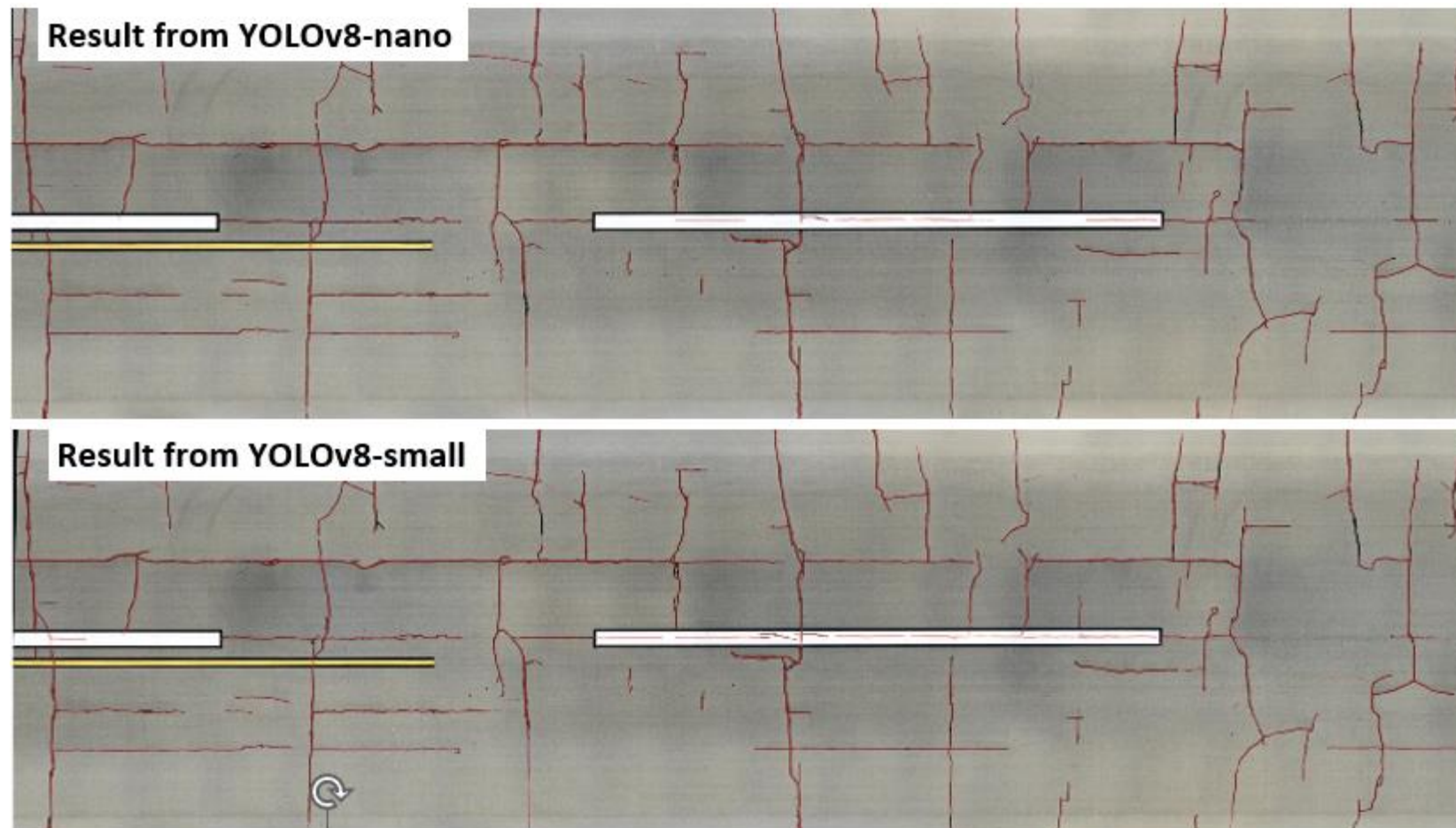
Semantic Mask

Segformer (B0)

Segformer (B1)

Sealed cracks detected by the Segformer models

- Large Scale Crack Detection
  - Pavement section dimensions: 91 m x 25.5 m



- Background
- Data Collection and Analysis
- Notable Results
- ML in Pavement Inspection
- **Summary**
- Questions and Answers

- sUAS could successfully be used for airfield pavement distress detection
- Majority of the distresses are detected in RGB and DEM data
- Thermal data can add additional value
- Correlation between manual PCI and sUAS-based PCI is high
- ML models are fast and accurate for crack detection

- The following learning objectives are met
  - Leverage sUAS to assist in infrastructure inspection
  - Understand which sensors and platforms are being used for infrastructure inspection (*partially*)

# Contact Information

**Halil Ceylan, Ph.D., Dist.M.ASCE**

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in [Civil, Construction and Environmental Engineering](#)

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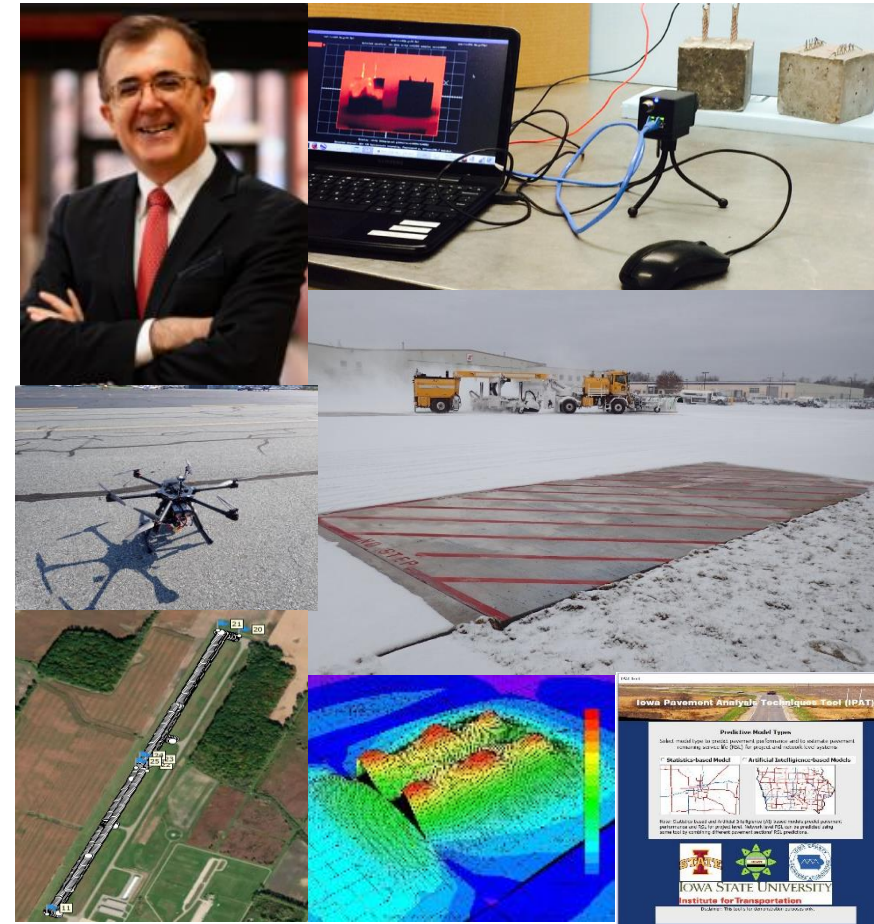
[Institute for Transportation](#)  
[410 Town Engineering Bldg.](#)

[Iowa State University](#)  
[813 Bissell Road](#)

[Ames, IA 50011-1066](#)

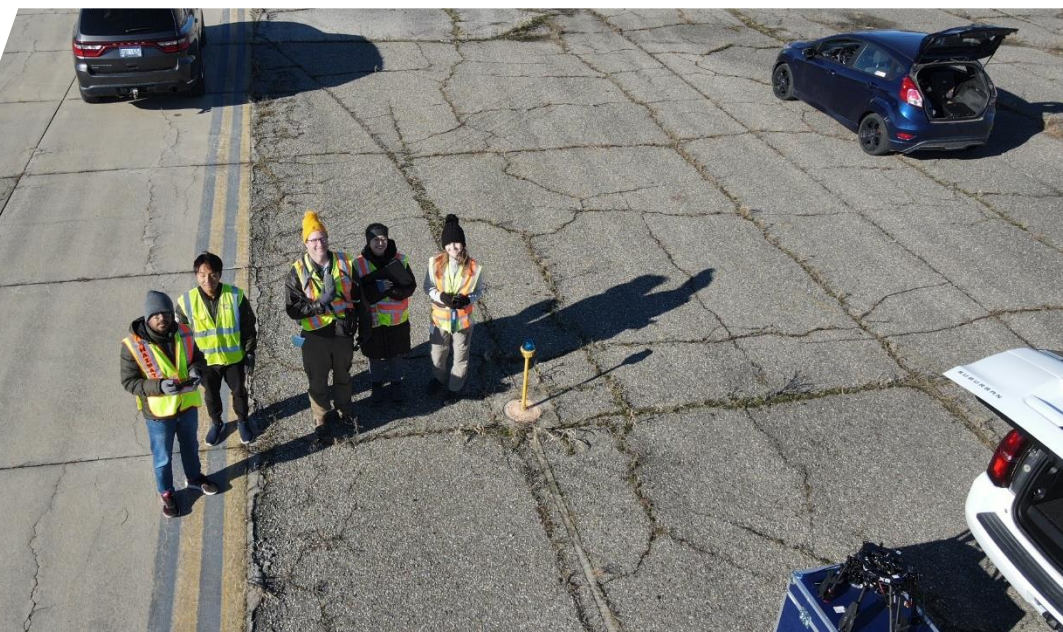
Phone: +1 (515) 294-8051

E-mail: [hceylan@iastate.edu](mailto:hceylan@iastate.edu)





# Questions

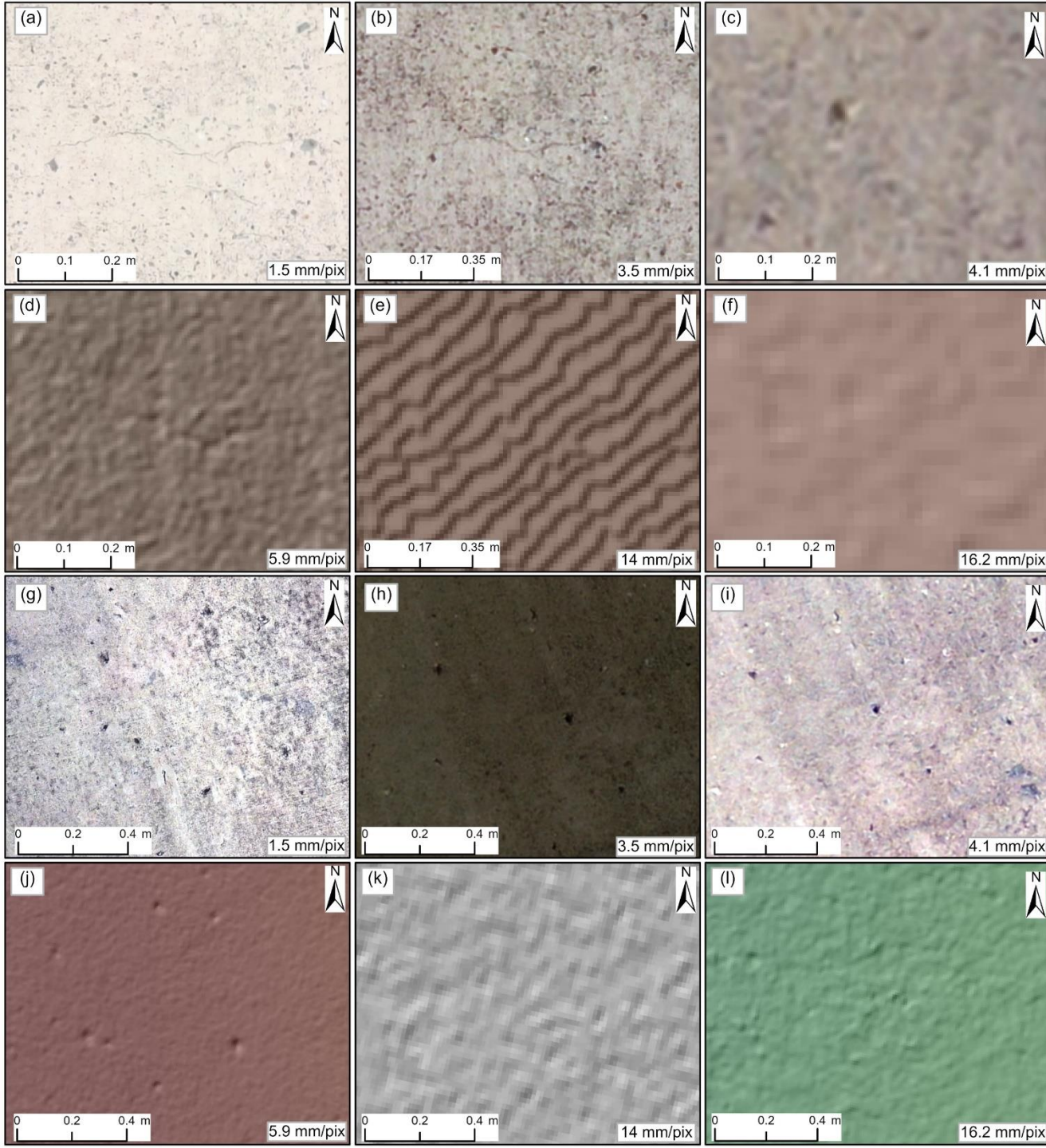


# Extra Slides

# Director Introduction: Halil Ceylan, Ph.D., Dist.M.ASCE (Cont'd)

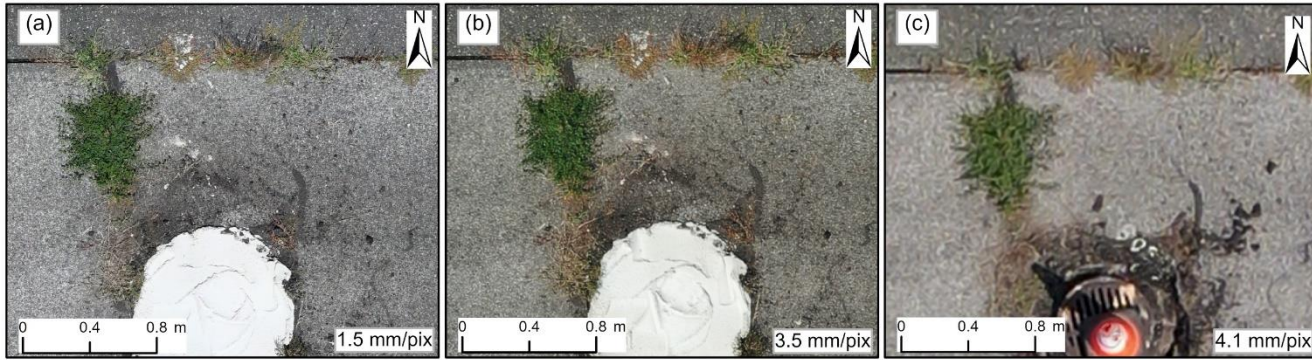
- Recent Awards
  - 2025 American Society of Civil Engineers (ASCE) Francis C. Turner Award
  - 2024 Transportation Research Board (TRB) Roy W. Crum Award
  - 2023 American Society of Civil Engineers (ASCE) Robert Horonjeff Award
  - Dist.M.ASCE, American Society of Civil Engineers (ASCE)
  - Fellow, American Society of Civil Engineers (ASCE)
  - 2022 University of Illinois Alumni Achievement Award
  - 2021 American Society of Civil Engineers (ASCE) James Laurie Prize
  - 2021 University of Illinois at Urbana-Champaign (UIUC) Civil and Environmental Engineering Alumni Association (CEEAA) Distinguished Alumnus Award
  - 2019 FAA PEGASAS Jimenez Faculty/Researcher Award
  - 2018 Award for Mid-Career Achievement in Research
  - 2018 Margaret Ellen White Graduate Faculty Award
  - And 15 other awards
- Teaching
  - CE583/CE483 Pavement Analysis and Design; CE382 Design of Concretes; CE 360 - Geotechnical Engineering



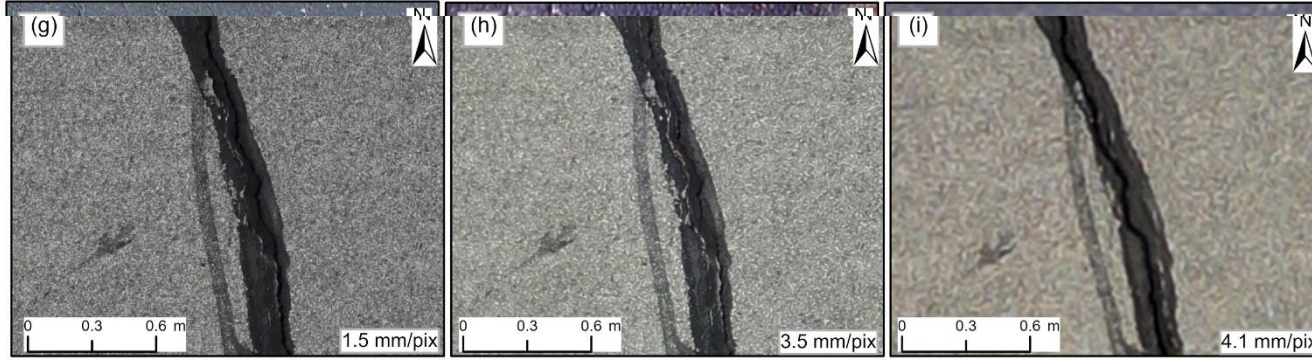
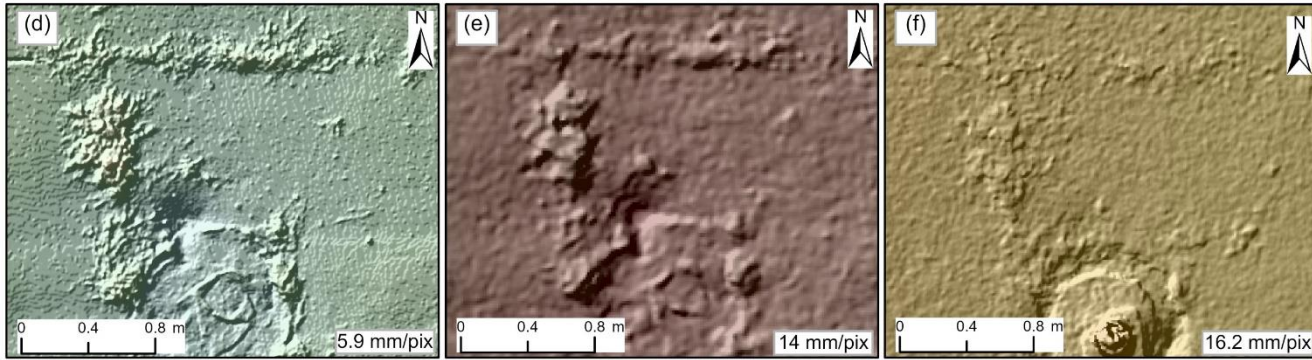


Shrinkage Cracks (a-f)  
on PCC Pavement

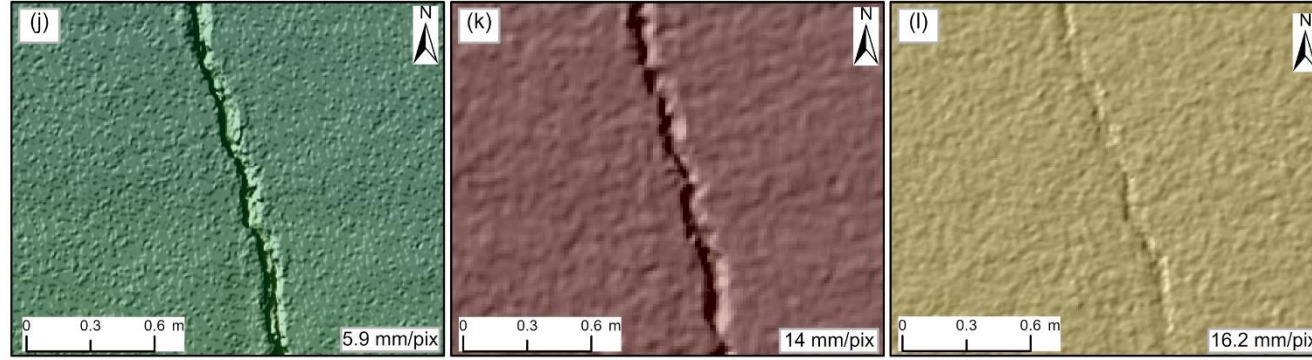
Pops-up (g-l)  
on PCC Pavement



Patching (H)  
Depression (M) (a-f)  
on AC Pavement



L&T Cracks (H) (g-l)  
on AC Pavement



# Notable Results

## PCC Pavement Distress Detection Capabilities

ASTM Distress (PAVER™ Distress #)	Severity	Detection		Minimum Res (mm/pix)	
		RGB	DEM	RGB	DEM
<b>Blowup (61)</b>					
<b>Corner break (62)</b>	L	Yes	No	2.5	ND
	M, H	Yes	No	21	ND
<b>LTD cracks (63)</b>	L	Yes	No	7.26	ND
	M	Yes	No	21	ND
	H*	Yes	NA	21	NA
<b>Durability cracking (64)</b>	L	Yes	No	7.26	ND
	M	Yes	Yes	21	10
	H	Yes	Yes	21	29.1
<b>Joint seal damage (65)</b>	L	No	No	ND	ND
	M	Yes	No	2.5	ND
	H	Yes	Yes	7.26	5.96
<b>Small patching (66)</b>	L	Yes	No	3.3	ND
	M/H*	Yes	Yes	4.5	5.96
<b>Large patching (67)</b>	L	Yes	No	21	ND
	M/H	Yes	No/Yes	21	29
<b>Popouts (68)</b>	NA	Yes	Yes	3.3	5.96

L = Low, M = Medium, H = High, RGB = Red Green Blue, DEM = Digital Elevation Model

mm/pix = millimeter/pixel, NA = Not Applicable, ND = Not Detected

\* = Based on detection of lower severity

Color cells = Distress not available

# Notable Results (Cont'd)

## PCC Pavement Distress Detection Capabilities

ASTM Distress (PAVER™ Distress #)	Severity	Detection		Minimum Res (mm/pix)	
		RGB	DEM	RGB	DEM
Pumping (69)	NA				
Scaling (70)	L				
	M/H*	Yes	Yes	21	10
Settlement or faulting (71)	L	No	No	ND	ND
	M/H*	No	Yes	ND	2.98
Shattered slab (72)	L	No	No	ND	ND
	M, H	Yes	Yes	21	10
Shrinkage cracks (73)**	NA	Yes	No	2.5	ND
Joints spalling (74)	L	Yes	No	2.5	ND
	M	Yes	Yes	2.5	5.96
	H	Yes	Yes	2.5	5.96
Corner spalling (75)	L	Yes**	No	ND	ND
	M	Yes	No	3.3	ND
	H	Yes	Yes	3.3	10
Alkali Silica Reaction (ASR) (76)	L	Yes**	No	7.26	ND
	M	Yes**	Yes	7.26	5.96***
	H	Yes	Yes	7.26	5.96***

L = Low, M = Medium, H = High, RGB = Red Green Blue, DEM = Digital Elevation Model  
 mm/pix = millimeter/pixel, NA = Not Applicable, ND = Not Detected

\* = Based on detection of lower severity, \*\*Detection not always possible, \*\*\*Based on observation

Color cells = Distress not available

# Notable Results (Cont'd)

## AC Pavement Distress Detection Capabilities

ASTM Distress (PAVER™ Distress #)	Severity	Detection		Minimum Res (mm/pix)	
		RGB	DEM	RGB	DEM
Alligator cracking (41)	L	Yes	Yes	3.5	5.94
Bleeding (42)	NA				
Block cracking (43)	L	Yes	Yes	7.26	9.2
	M	Yes	Yes	7.26	19.6
	H	Yes	Yes	7.26	19.6
Corrugation (44)	NA				
Depression (45)	L	No	No	ND	ND
	M	No	Yes	ND	5.96
	H	Yes	Yes	4.06	16.02
Jet blast erosion (46)	NA				
Joint reflection cracking (47)	NA				
L&T cracking (48)	L	Yes	Yes	7.26	9.2
	M	Yes	Yes	7.26	19.6
	H	Yes	Yes	7.26	19.6
Oil spillage (49)	NA				

L = Low, M = Medium, H = High, RGB = Red Green Blue, DEM = Digital Elevation Model

mm/pix = millimeter/pixel, NA = Not Applicable, ND = Not Detected

\* = Based on detection of lower severity, \*\*Detection not always possible, \*\*\*Based on observation

Color cells = Distress not available

# Notable Results (Cont'd)

## AC Pavement Distress Detection Capabilities

ASTM Distress (PAVER™ Distress #)	Severity	Detection		Minimum Res (mm/pix)	
		RGB	DEM	RGB	DEM
Patching (50)	H	Yes	Yes	4.06	16.02
Polish aggregate (51)					
Raveling (52)	L	Yes	No	1.48	ND
	M	Yes	No	1.48	ND
	H*	Yes	No	1.48	ND
Rutting (53)	NA				
Shoving (54)	L	No	Yes	ND	5.94
	M	Yes	Yes	2.5	10
	H	Yes	Yes	2.5	10
Slippage cracking (55)					
Swell (56)	L	No	No	ND	ND
	M	No	No	ND	ND
	H				
Weathering (57)	L	No	No	ND	ND
	M	No	No	ND	ND
	H	No	No	ND	ND

L = Low, M = Medium, H = High, RGB = Red Green Blue, DEM = Digital Elevation Model

mm/pix = millimeter/pixel, NA = Not Applicable, ND = Not Detected

\* = Based on detection of lower severity, \*\*Detection not always possible, \*\*\*Based on observation

Color cells = Distress not available

# Notable Results (Cont'd)

## AC Pavement Distress Detection Capabilities

ASTM Distress (PAVER™ Distress #)	Severity	Detection		Minimum Res (mm/pix)	
		RGB	DEM	RGB	DEM
Patching (50)	H	Yes	Yes	4.06	16.02
Polish aggregate (51)					
Raveling (52)	L	Yes	No	1.48	ND
	M	Yes	No	1.48	ND
	H*	Yes	No	1.48	ND
Rutting (53)	NA				
Shoving (54)	L	No	Yes	ND	5.94
	M	Yes	Yes	2.5	10
	H	Yes	Yes	2.5	10
Slippage cracking (55)					
Swell (56)	L	No	No	ND	ND
	M	No	No	ND	ND
	H				
Weathering (57)	L	No	No	ND	ND
	M	No	No	ND	ND
	H	No	No	ND	ND

L = Low, M = Medium, H = High, RGB = Red Green Blue, DEM = Digital Elevation Model

mm/pix = millimeter/pixel, NA = Not Applicable, ND = Not Detected

\* = Based on detection of lower severity, \*\*Detection not always possible, \*\*\*Based on observation

Color cells = Distress not available

# Publications and Presentations on sUAS Research

## Publications

1. Sourav, M. A. A., Ceylan, H., Brooks, C., Dobson, R., Kim, S., Peshkin, D., & Brynick, M. (2024). Use of small unmanned aircraft systems in airfield pavement inspection: implementation and potential. *International Journal of Pavement Engineering*, 25(1), 2401630. <https://doi.org/10.1080/10298436.2024.2401630>
2. Sourav, M. A. A., Mahedi, M., Ceylan, H., Kim, S., Brooks, C., Peshkin, D., Dobson, R., & Brynick, M. (2022). Evaluation of Small Uncrewed Aircraft Systems Data in Airfield Pavement Crack Detection and Rating. *Transportation Research Record*, 0(0). <https://doi.org/10.1177/03611981221101030>
3. Vidyadharan, A., Carter, T., Ceylan, H., Bloebaum, C., Gopalakrishnan, K., & Kim, S. (2017). Civil infrastructure health monitoring and management using unmanned aerial systems. In *Airfield and Highway Pavements 2017* (pp. 207-216).
4. Sourav, M. A. A., Ceylan, H., Kim, S., & Brynick, M. (2024). Integration of Small Unmanned Aircraft Systems and Deep Learning for Efficient Airfield Pavement Crack Detection and Assessment. In *International Conference on Transportation and Development 2024* (pp. 884-893).
5. Sourav, M. A. A., Ceylan, H., Kim, S., Brooks, C., Peshkin, D., Dobson, R., & Brynick, M. (2023). Use of Digital Elevation Model for Detecting Airfield Pavement Distress. In *Airfield and Highway Pavements 2023* (pp. 254-265).

# Publications and Presentations on sUAS Research (Cont'd)

## Publications

6. Sourav, M. A. A., Mahedi, M., Ceylan, H., Kim, S., Brooks, C., Peshkin, D., Dobson, R., Brynick, M., & DiPilato, M. (2022). Small Uncrewed Aircraft Systems-Based Orthophoto and Digital Elevation Model Creation and Accuracy Evaluation for Airfield Portland Cement Concrete Pavement Distress Detection and Rating. In *International Conference on Transportation and Development 2022* (pp. 168-180).  
<https://doi.org/10.1061/9780784484371.016>
7. Sourav, M. A. A., Ceylan, H., Brooks, C., Peshkin, D., Kim, S., Dobson, R., Cook, C., Mahedi, M., & Jenkins, A. (2023). *Small Unmanned Aircraft System for Pavement Inspection*. (No. DOT/FAA/TC-23/50). United States. DOT. FAA. William J. Hughes Technical Center.
8. Sourav, M. A. A., Ceylan, H., Brooks, C., Peshkin, D., Kim, S., Dobson, R., Cook, C., & Brouillette, O. (2022). *Small Unmanned Aircraft System for Pavement Inspection: Task 4—Execute the Field Demonstration Plan and Analyze the Collected Data* (No. DOT/FAA/TC-22/35). United States. DOT. FAA. William J. Hughes Technical Center
9. Sourav, M. A. A., Ceylan, H., Brooks, C., Peshkin, D., Kim, S., Dobson, R., Cook, C., & Brouillette, O. (2022). *Practical Lessons Learned from Planning, Collecting, Processing, and Analyzing Small Unmanned Aircraft System Data for Airfield Pavement Inspection*. (No. DOT/FAA/TC-22/48). United States. DOT. FAA. William J. Hughes Technical Center.

# Publications and Presentations on sUAS Research (Cont'd)

## Presentations

1. Sourav, M. A. A., Ceylan, H. (2022). *Use of sUAS in Airfield Pavement Inspection*. Oral Presentation. ASCE T&DI Uncrewed Aircraft Systems Committee. 4<sup>th</sup> Quarter Virtual Meeting. December 12, 2022. Virtual.
2. Sourav, M. A. A., Ceylan, H., Kim, S., Brooks, C., & Peshkin, D. (2022). *Use of Drone in Airfield Pavement Distress Detection - A Possibility and A Future*. Poster Presentation. Mid-Continent Transportation Research Symposium. September 14–15. Ames, Iowa.
3. Sourav, M. A. A., Mahedi, M., Ceylan, H., Kim, S., Brooks, C., Peshkin, D., Dobson, R., Brynick, M., & DiPilato, M. (2022). *Small Uncrewed Aircraft Systems-based Orthophoto and Digital Elevation Model Creation and Accuracy Evaluation for Airfield Portland Cement Concrete Pavement Distress Detection and Rating*. Oral Presentation. ASCE International Conference on Transportation & Development 2022. May 31– June 3, 2022. Seattle, WA
4. Sourav, M. A. A., Mahedi, M., Ceylan, H., Kim, S., Brooks, C., Peshkin, D., Dobson, R., & Brynick, M. (2022). *Evaluation of Small Uncrewed Aircraft Systems Data in Airfield Pavement Crack Detection and Rating*. Poster Presentation. The Transportation Research Board (TRB) 100<sup>th</sup> Annual Meeting. January 8–12, 2023 in Washington, D.C.

# **UAS for Construction Inspection and Building Information Modeling (BIM)**

**Dr. Reihaneh (Rei) Samsami (P.E., CAPM)**

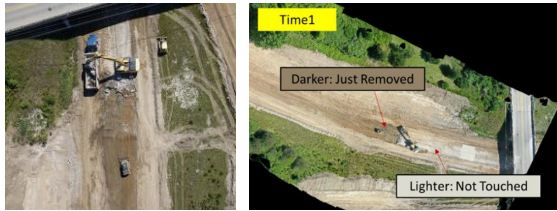
**Tagliatela Family Assistant Professor and MSCM Program Director  
Department of Civil and Environmental Engineering  
University of New Haven**

Email: [Rsamsami@newhaven.edu](mailto:Rsamsami@newhaven.edu)

LinkedIn: [www.linkedin.com/in/rsamsami](http://www.linkedin.com/in/rsamsami)

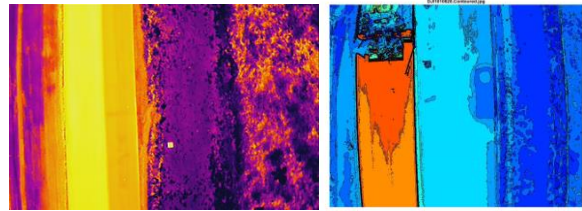
## 1. Automated Progress Monitoring

- UAS Data Collection Protocols
  - UAS Visual Data Analysis
    - Progress Metrics
- Fitting Metrics in The Workflow



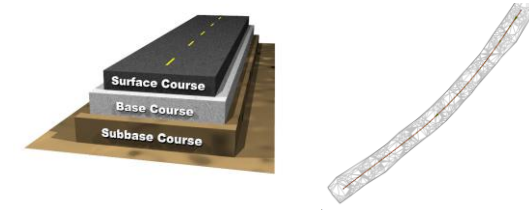
## 2. Automated Quality Inspection

- UAS Data Collection Protocols
  - UAS Thermal Data Analysis
    - Quality Control Metrics
- Fitting Metrics in The Workflow



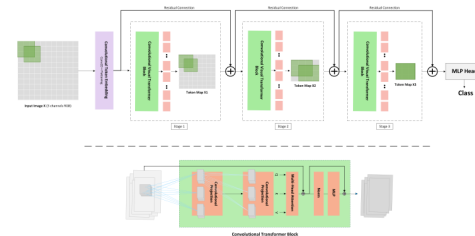
## 3. Automated As-Built BIM Development

- UAS BIM Parameters
- Information Analysis Techniques
- Supporting The Decision-making Workflows Using BIM



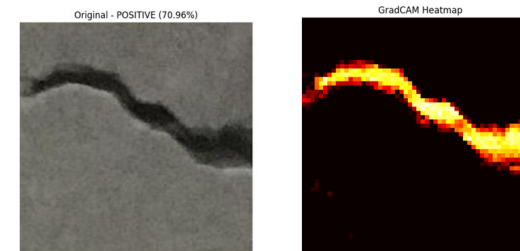
## 4. Automated Bridge Inspection

- Automated Data Collection
  - UAS Visual Data Analysis
- Crack Detection And Location
- Comparison between algorithms



## 5. Explainable AI

- Explainable AI for Better Transparency



A BRIEF LOOK AT RECENT RESEARCH AT

# SAMSAMI LAB



Dr. Rei Samsami



Dr. Colin Brooks



Dr. Amlan Mukherjee



Dr. Mo Nassar



Dr. Saida Elmi

# COLLABORATIVE EXCELLENCE: OUR TEAM IN ACTION



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## Integration of Unmanned Aerial Systems Data Collection into Day-to-Day Usage for Transportation Infrastructure – A Phase III Project Final Report, No. SPR-1713

### **Prepared by:**

C. Brooks<sup>1</sup>, C. Cook<sup>1</sup>, R. Dobson<sup>1</sup>, T. Oommen<sup>2</sup>, K. Zhang<sup>2</sup>, A. Mukherjee<sup>2</sup>, R. Samsami<sup>2</sup>, A. Semenchuk<sup>3</sup>, B. Lovelace<sup>4</sup>, V. Hung<sup>2</sup>, Y. Tan<sup>2</sup>, Y. Yang<sup>2</sup>, A. Jenkins<sup>1</sup>, J. Graham<sup>1</sup>, V.C. Lekha<sup>2</sup>, M. Billmire<sup>1</sup>, V. Barber<sup>1</sup>

<sup>1</sup>Michigan Tech Research Institute (MTRI), Michigan Technological University, 3600 Green Ct., Ste. 100, Ann Arbor, Michigan 48105

<sup>2</sup>Michigan Technological University (MTU), 1400 Townsend Drive, Houghton, Michigan, 49931

<sup>3</sup>Surveying Solutions Inc. (SSI), Standish, MI

<sup>4</sup>Collins Engineers Inc., St. Paul, MN

### **Project Manager:**

Steven J. Cook, P.E.  
Michigan Department of Transportation  
6333 Lansing Road  
Lansing, MI 48917

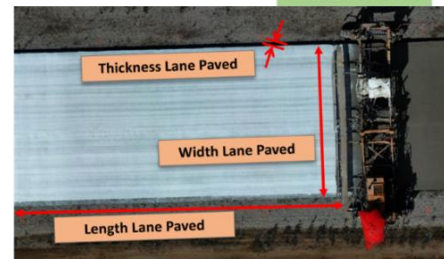
### **Research Manager:**

André Clover, P.E.  
Michigan Department of Transportation  
8885 Ricks Road  
Lansing, MI 48917

Revised version of June 11, 2022

# PROGRESS MONITORING

Development of a comprehensive methodology that integrates data collection, processing, analysis, and the derivation of progress estimation metrics for informed decision-making in construction projects.

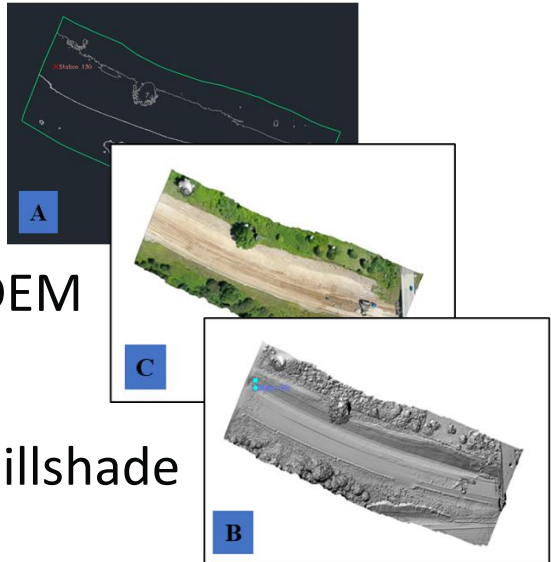


I-496: Reconstruction Project (Lansing, MI)

# PROGRESS MONITORING



DJI Mavic 2 Pro mdMapper 1000

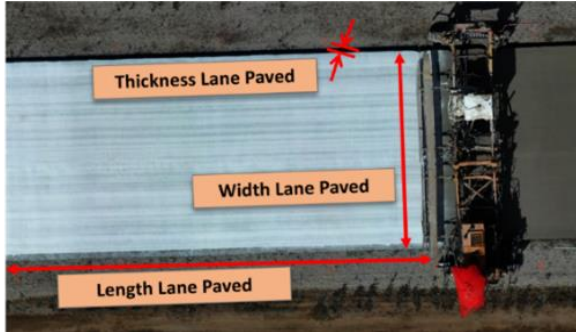


DEM

Hillshade

Geo-TIFF

Agisoft Photoscan



MDOT Standard Specifications for Construction

Construction Activity 602. Concrete Pavement(SY)

Image Processing  
Image Labeling

Pavement Removal Pay Item: SY	
Length (ft)	690.51
Width (ft)	22.80

$$\begin{aligned}
 \text{Estimated Production Rate} &= \frac{\text{Quantity Observed}}{\text{Duration}} \\
 &= \frac{690.51 \times 22.80}{4.133} \\
 &= 428.42 \left( \frac{SY}{Hr} \right)
 \end{aligned}$$

Earned Value Analysis

Project managers :  
Engineer's Opinion of Cost.  
Contractors: Future Biddings.

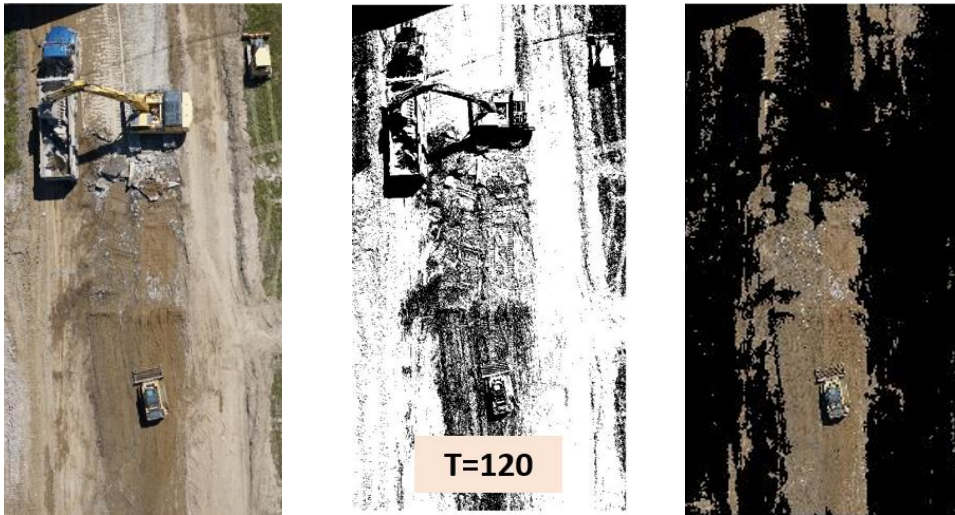
Take corrective actions to bring the project's performance back.

Detect the reasons for lower productivity rates and address them (weather conditions, site conditions, unplanned errors, and waiting time).

# DATA ANALYSIS & INFO RETRIEVAL

## Image Processing

Divide an image into “meaningful” regions; based on color, texture, etc.



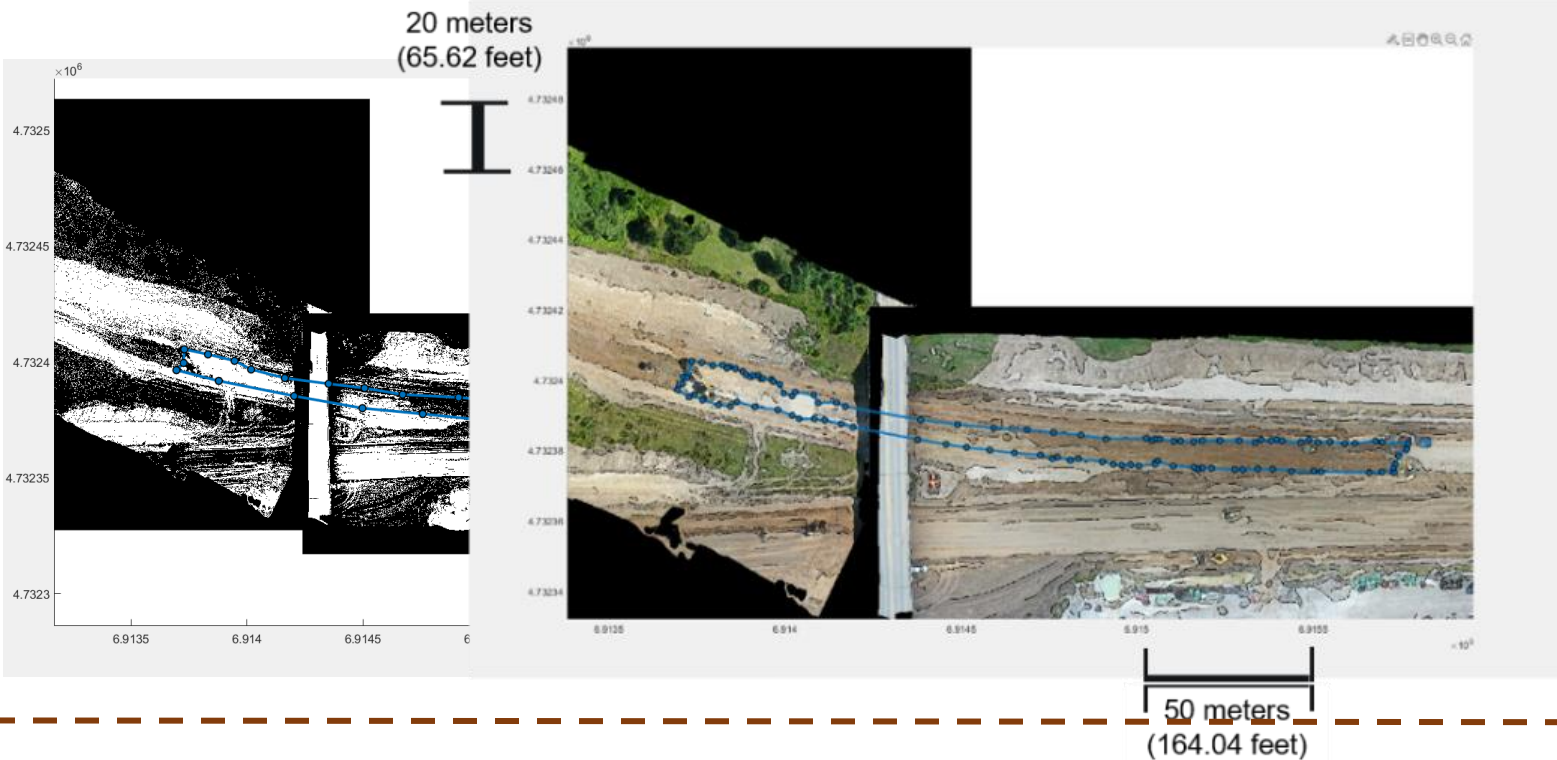
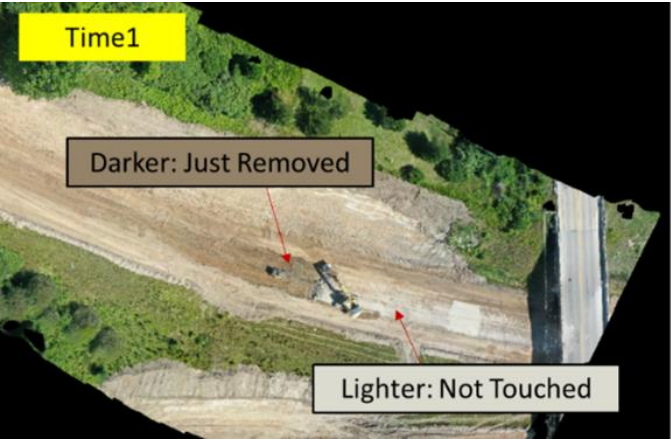
## Image Labeling

Detect objects of certain class (heavy equipment) using computer vision.



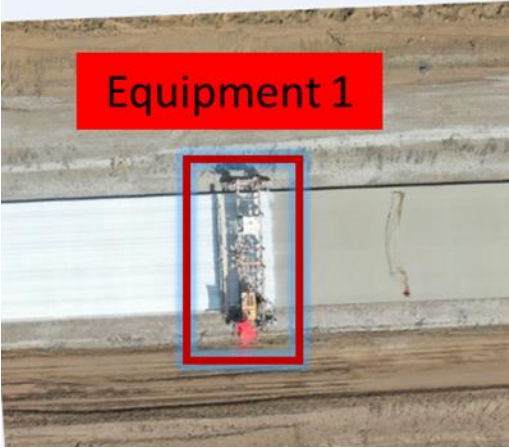
**Detect activities, Parameters, Equipment, Work quantities.**

# DATA ANALYSIS & INFO RETRIEVAL



Activity	Unit	Parameter	Measure	Parameter	Measure
Pavement Removal	SY	Length (ft)	690.51	Width (ft)	22.80

# DATA ANALYSIS & INFO RETRIEVAL



Activity	Unit	Parameter	Measure	Parameter	Measure
Concrete Pavement	SY	Length (ft)	973.52	Width (ft)	26.87

# HMA THERMAL SEGREGATION

Creation of data collection protocols and the application of thermal image analysis to improve HMA pavement inspections.

The collage consists of several images labeled A through F. Image A shows a drone on a blue landing pad. Image B shows an open equipment case. Image C shows a yellow and black data collection sheet. Image D shows a worker in a yellow vest applying material to a road surface next to a white pickup truck. Image E shows a thermal image of a road surface with a color scale. Image F shows a thermal image of a road with a car, overlaid on a photograph of the same road.

**I-69: HMA reconstruction project (Lansing, MI)**

# HMA THERMAL SEGREGATION

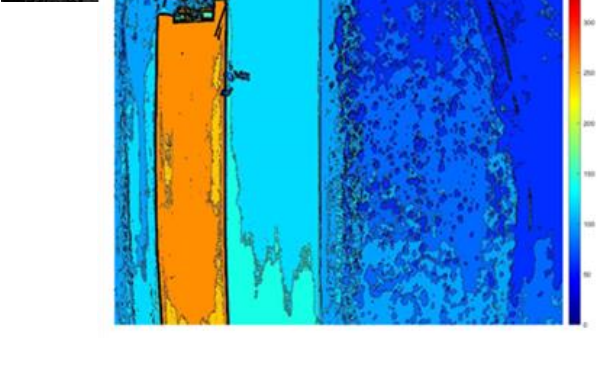
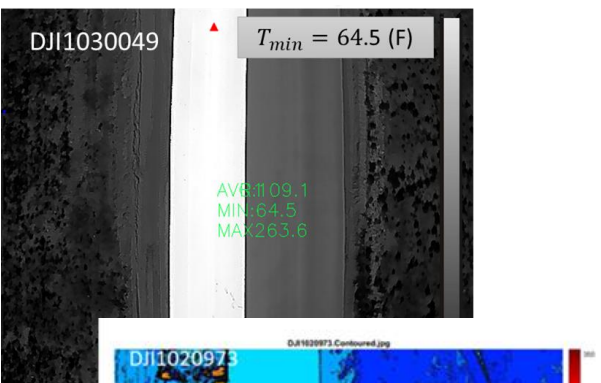


RJPG

Geo-TIFF



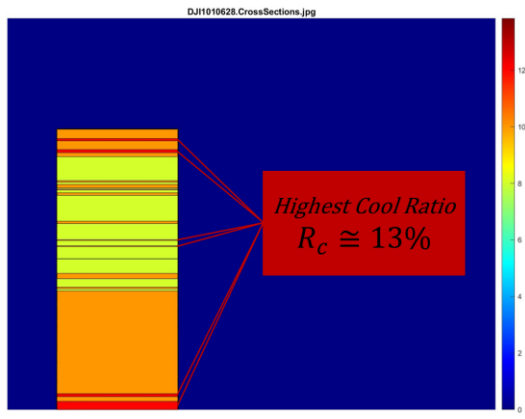
Mavic2 thermal images individually scaled.



Contouring

%R<sub>c</sub>: Cool Areas  
 %R<sub>ps</sub>: Potentially Segregated  
 %R<sub>hs</sub>: Highly Segregated

Image	%R <sub>c</sub>	%R <sub>ps</sub>	%R <sub>hs</sub>
DJI1010628	5.3	0.4	0.8
DJI1020973	1.7	0.4	0.8
DJI1030040	0.2	0.2	0.5
DJI1040849	1.4	1.8	2
DJI1050081	1.1	1.5	1.3
DJI1060783	0.7	1.2	1
DJI1070237	0.4	0.7	1.1
DJI1070435	0.7	0.4	1.6



Project managers & Inspectors

Fix the segregated areas or prevent future segregation.

Real-time results

MDOT MTM 324-07

# DATA ANALYSIS & INFO. RETRIEVAL

Intensity –Temperature relationship is defined for each single image.

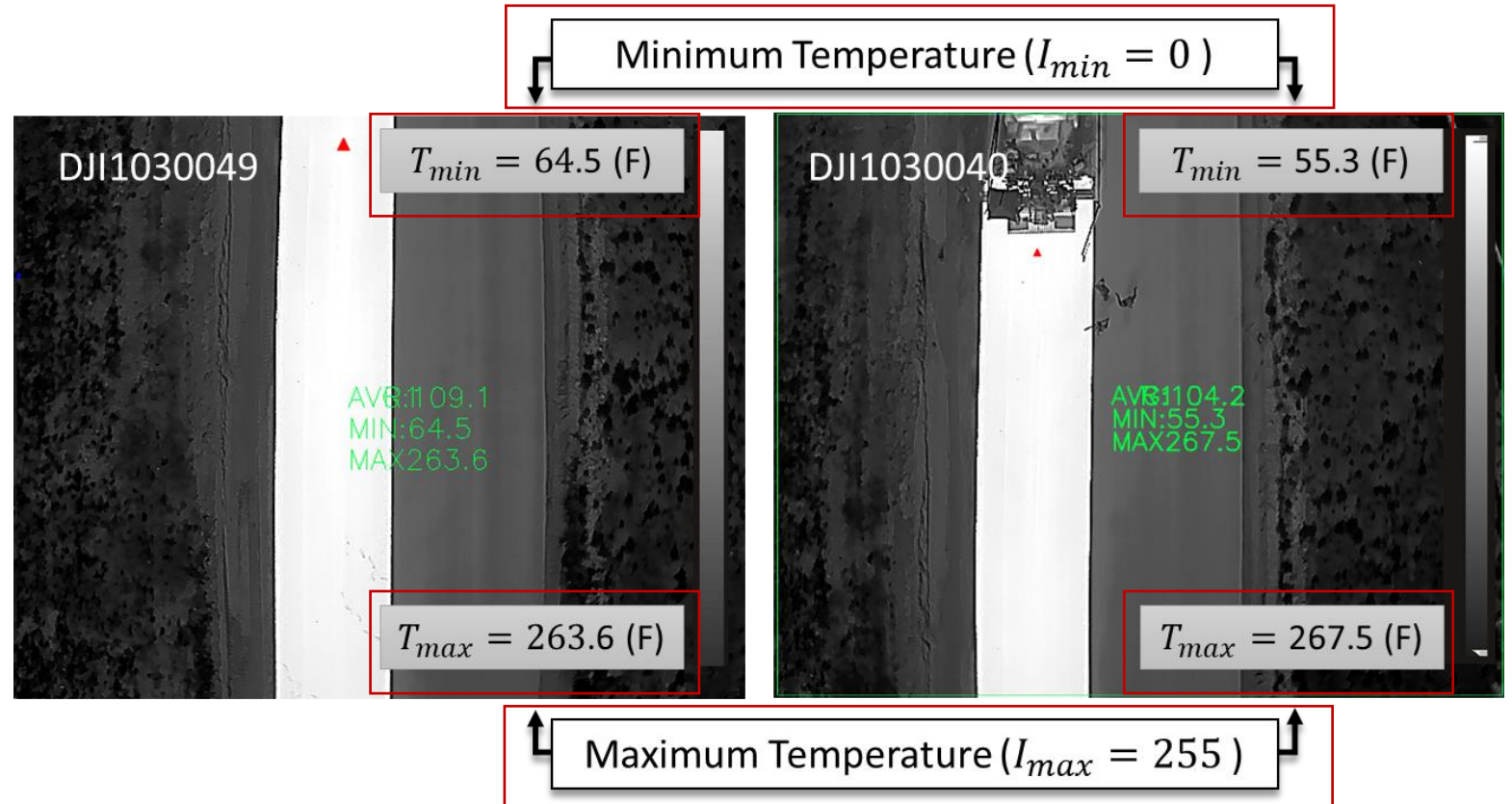


Images are universally scaled.



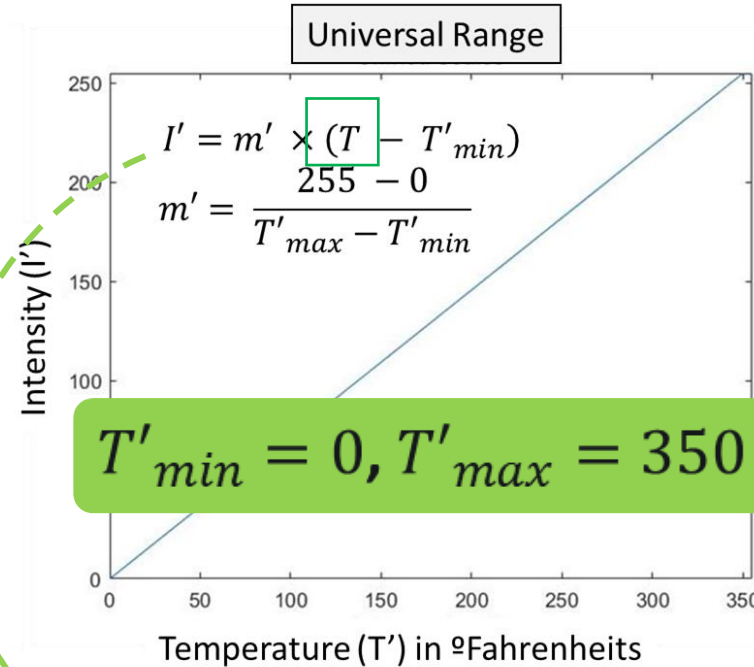
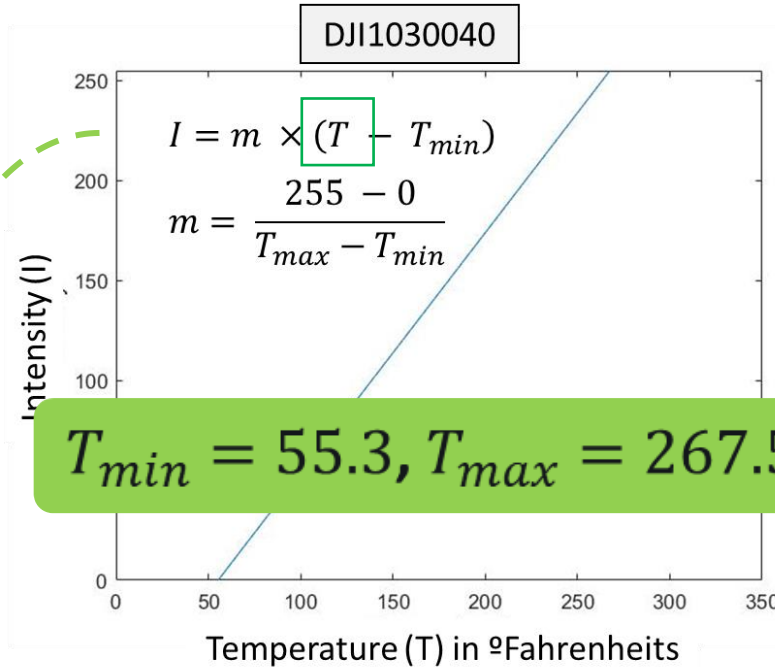
Cool Spots are visualized on each image.

Mavic 2 thermal images are each individually scaled.



# DATA ANALYSIS & INFO. RETRIEVAL

## Scaling

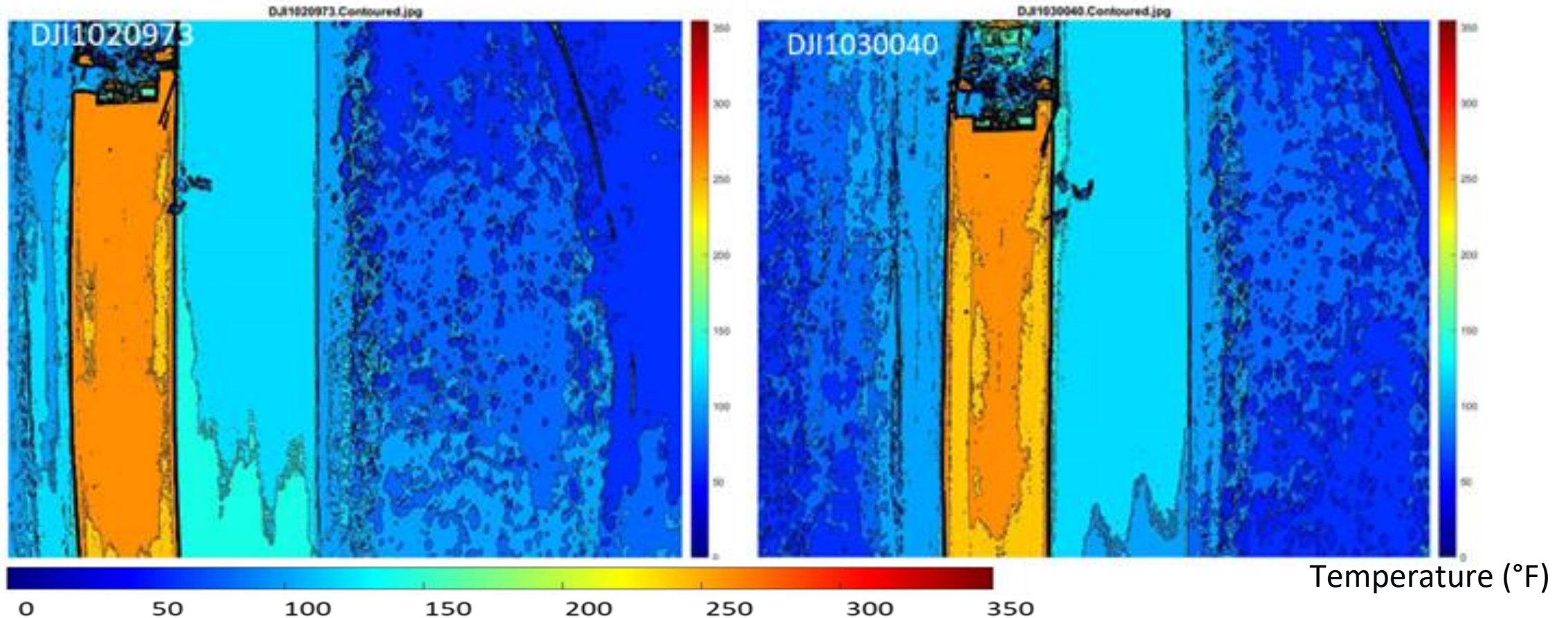


$$T = \frac{I}{m} + T_{min}$$

$$I' = m' \times \left( \frac{I}{m} + T_{min} - T'_{min} \right)$$

# DATA ANALYSIS & INFO. RETRIEVAL

## Contouring



# THERMAL SEGREGATION ESTIMATION

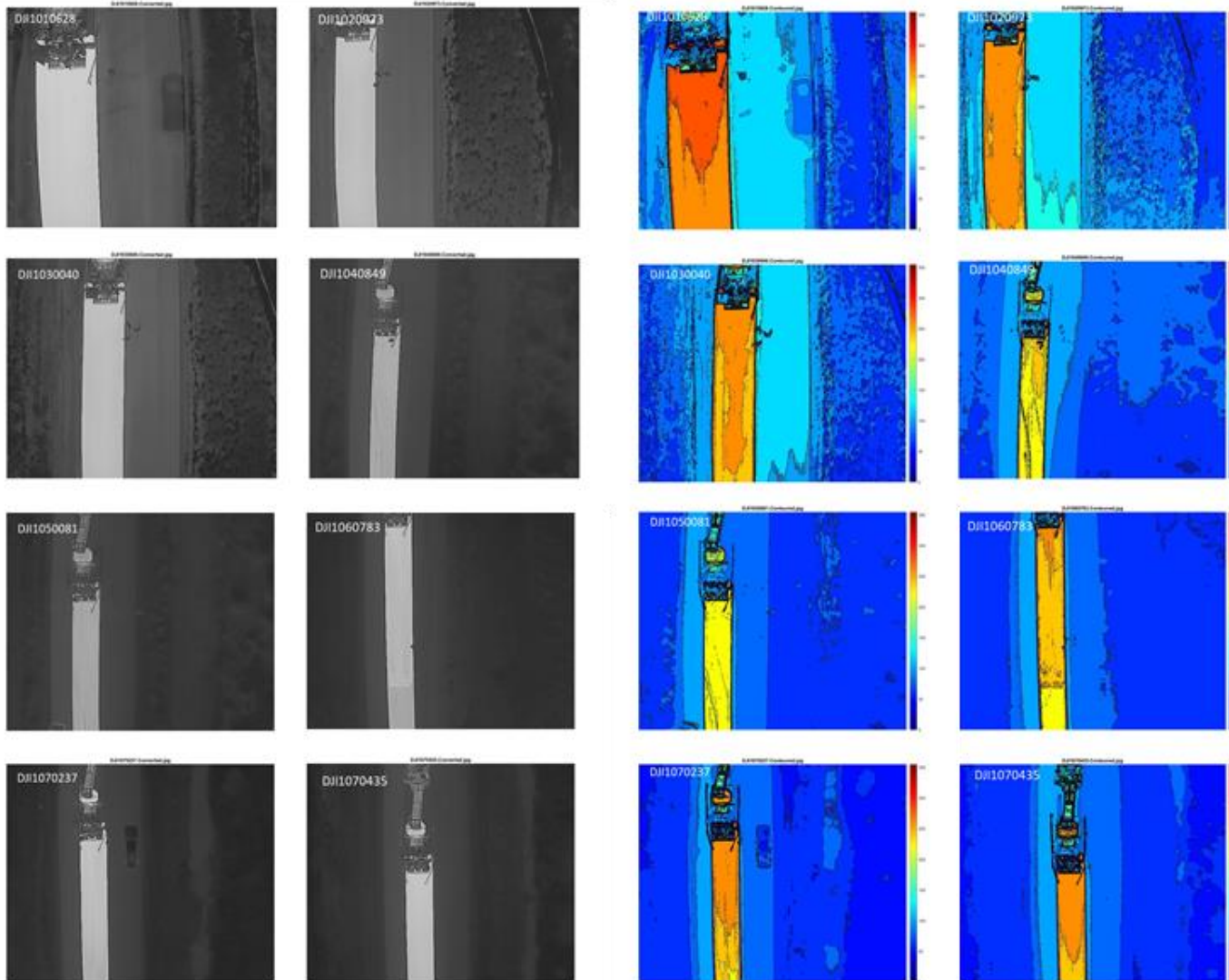
Thermal segregation metrics are defined.



Thermal segregation metrics are estimated using the scaled images.

No	Metric	Title	Category	Criterion
1	$R_c$	<b>Ratio of Cool Areas</b>	Temperature Range	Is laying temperature within the temperature window of <b>185°F-293°F</b> (85-145 °C) considered?
2	$R_{ps}$	<b>Ratio of Potentially Segregated Areas</b>	Temperature Differentials 1	Are temperature differentials larger than <b>19°F</b> (10 °C) causing Potentially Segregated spots?
3	$R_{hs}$	<b>Ratio of Highly Segregated Areas</b>	Temperature Differentials 2	Are temperature differentials larger than <b>36°F</b> (20 °C) causing Highly Segregated spots?

# THERMAL SEGREGATION ESTIMATION

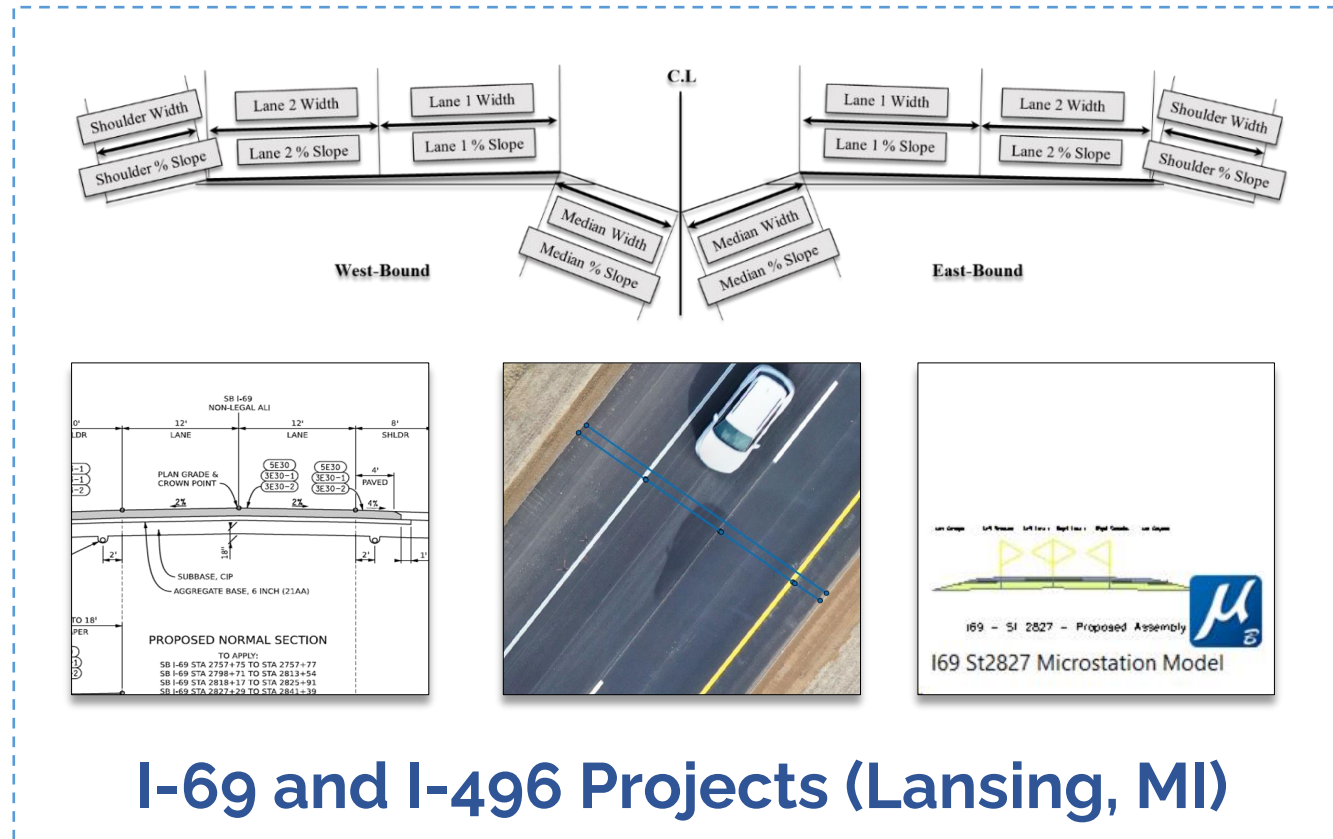


%R<sub>c</sub> : Cool Areas  
 %R<sub>ps</sub> : Potentially Segregated Areas  
 %R<sub>hs</sub> : Highly Segregated Areas

Image	%R <sub>c</sub>	%R <sub>ps</sub>	%R <sub>hs</sub>
DJI1010628	<b>5.3</b>	0.4	0.8
DJI1020973	1.7	0.4	0.8
DJI1030040	0.2	0.2	0.5
<b>DJI1040849</b>	1.4	<b>1.8</b>	<b>2</b>
DJI1050081	1.1	1.5	1.3
DJI1060783	0.7	1.2	1
DJI1070237	0.4	0.7	1.1
DJI1070435	0.7	0.4	1.6

# AS-BUILT BIM MODELING

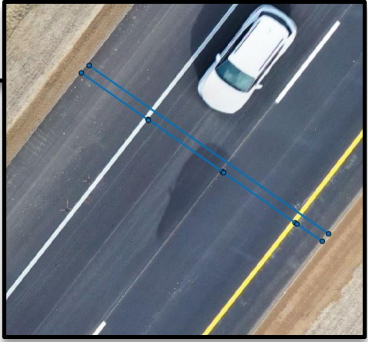
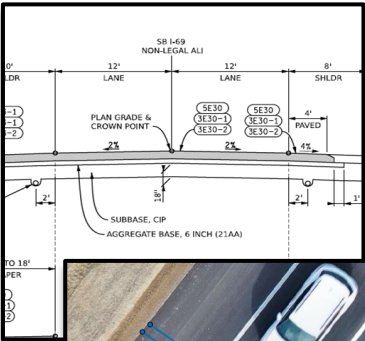
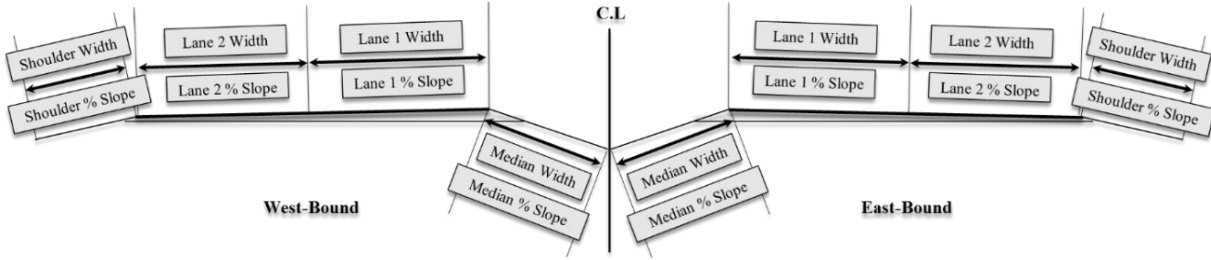
Integration of UAS data within BIM for as-built visualization of the project.



I-69 and I-496 Projects (Lansing, MI)

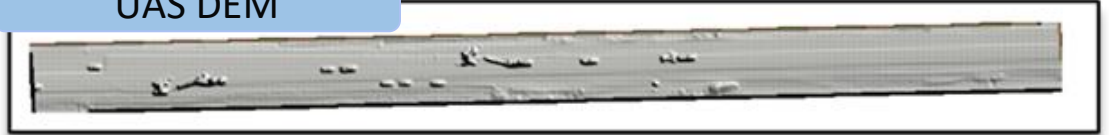
# AS-BUILT BIM MODELING

## Surface Parameters

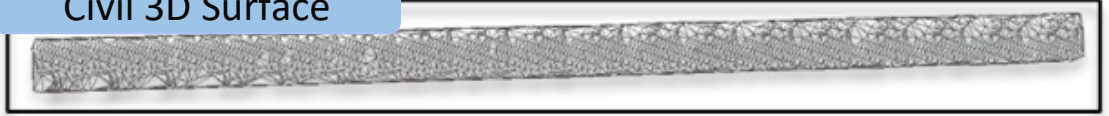


<b>Lane1</b>	Width	4.26 m
	Length	482 m
	% Slope	2%
<b>Lane2</b>	Width	3.69 m
	Length	482 m
	% Slope	2%
<b>Shoulder1</b>	Width	2.67 m
	Length	482 m
	% Slope	4%
<b>Daylight1</b>	Width	0.85 m
	Length	482 m
	% Slope	1:4

## UAS DEM



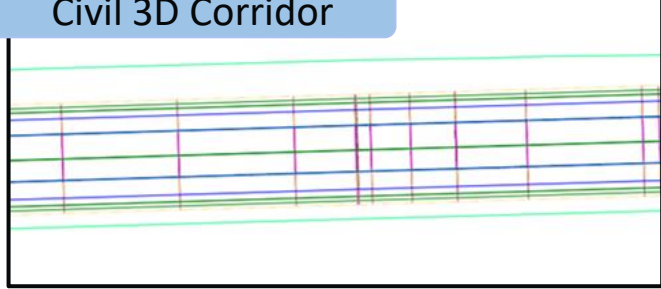
## Civil 3D Surface



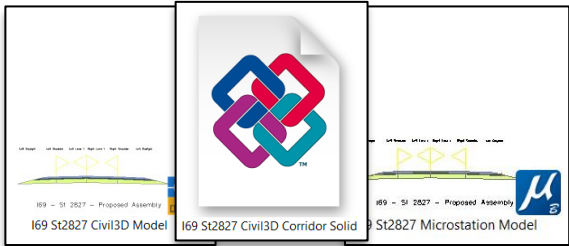
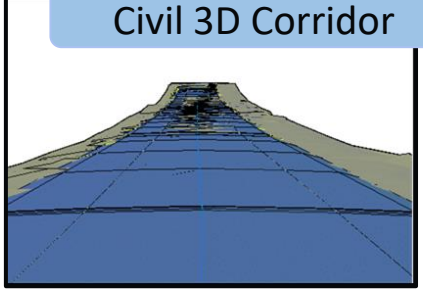
## Alignment



## Civil 3D Corridor



## Civil 3D Corridor



CIVIL 3D BIM  
CORRIDOR SOLID  
MICROSTATION BIM



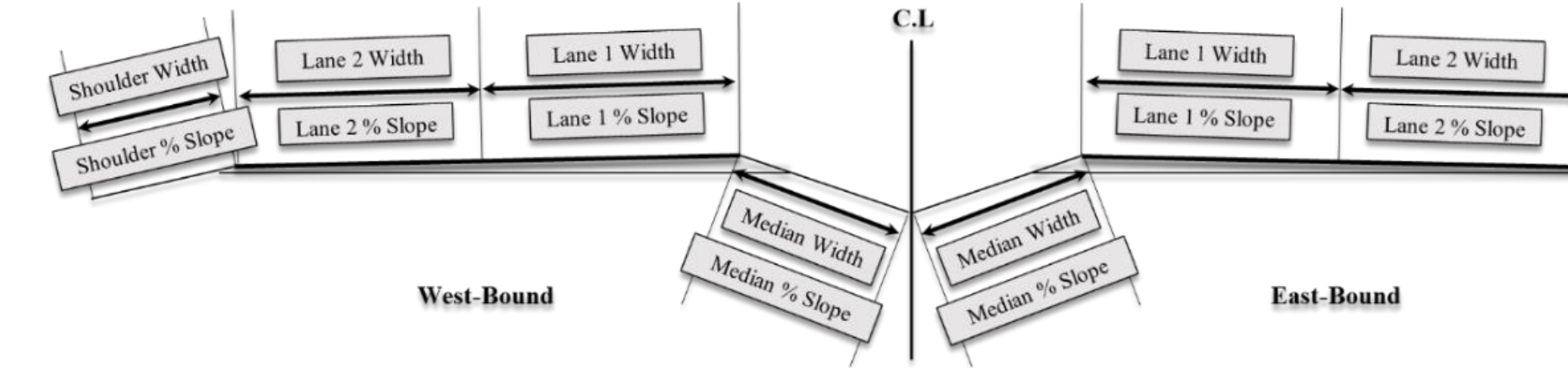
# PARAMETER DEFINITION & MAPPING

BIM parameters and their geometric constraints are defined.

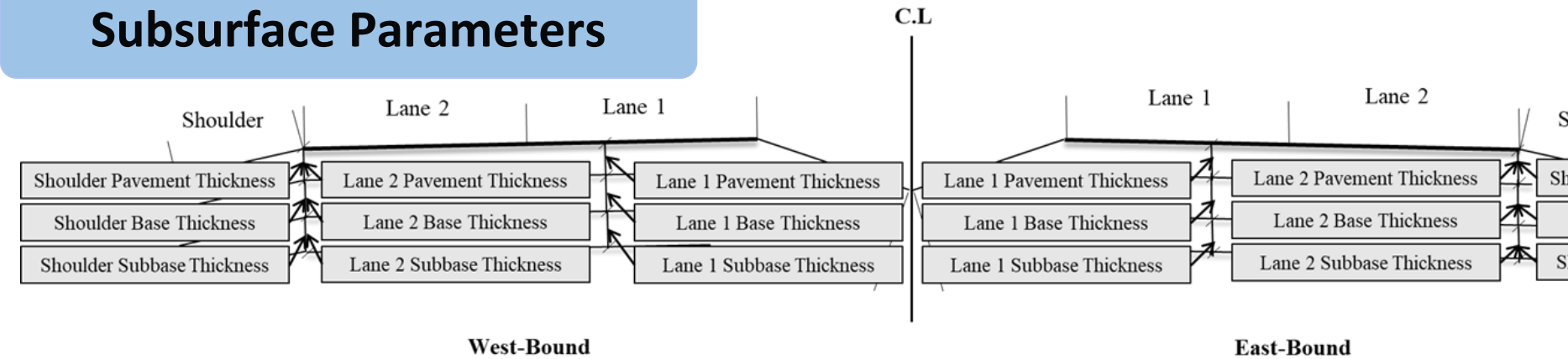
↓

UAS Geometry Parameters are mapped onto the BIM Parameters.

## Surface Parameters

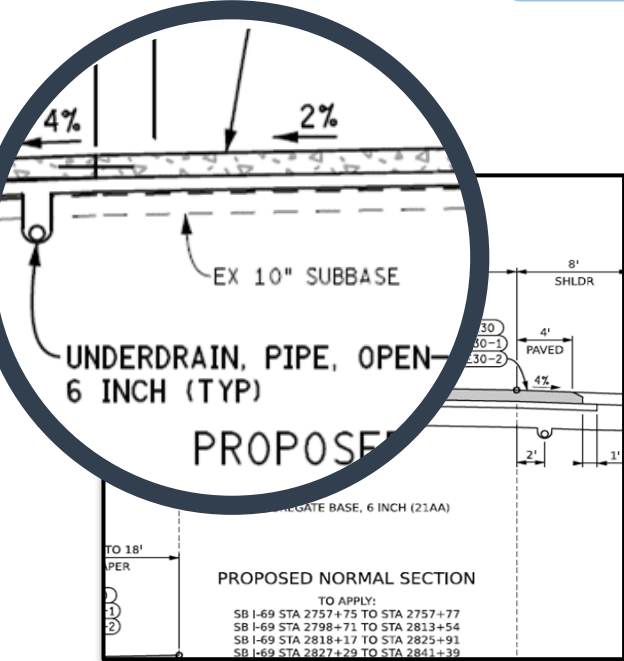


## Subsurface Parameters

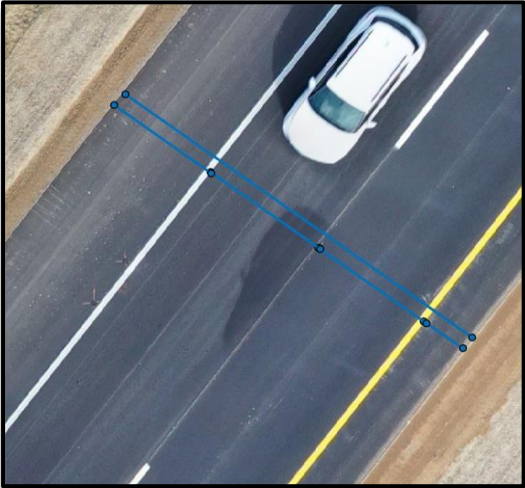


# PARAMETER DEFINITION & MAPPING

## INPUT



Project Plans



UAS Images

## OUTPUT

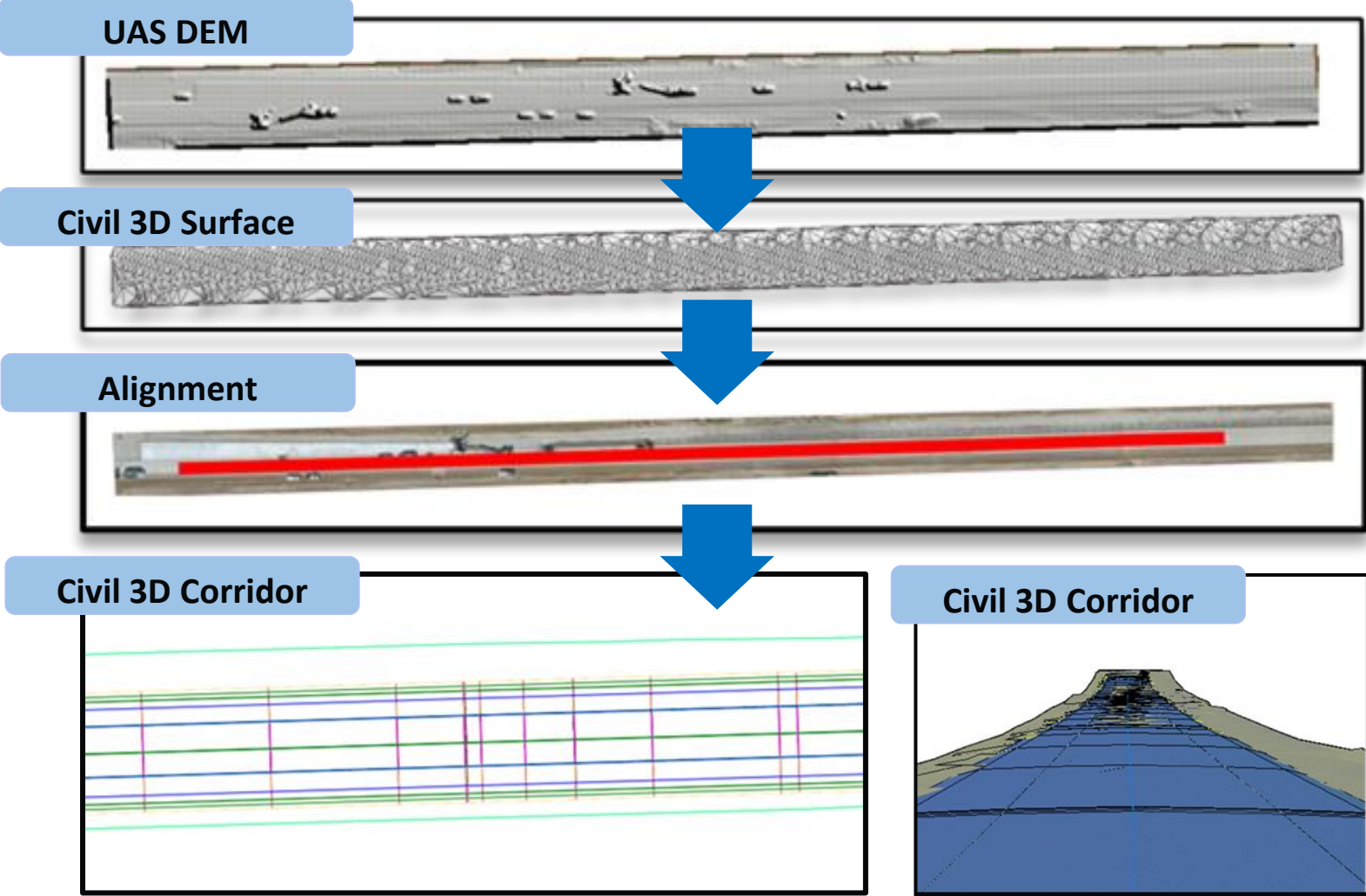
BIM PARAMETERS (MDOT I-496)	Surface	Lane 1	Width	4.26 m
			Length	482 m
			% Slope	2%
		Lane 2	Width	3.69 m
			Length	482 m
			% Slope	2%
Shoulder 1	Width	2.67 m		
	Length	482 m		
	% Slope	4%		
BIM PARAMETERS	Subsurface	Lane 1	Pavement Thickness	0.25 m
			Base Thickness	0.15 m
			Subbase Thickness	0.25 m
		Lane 2	Pavement Thickness	0.25 m
			Base Thickness	0.15 m
			Subbase Thickness	0.25 m
		Shoulder	Pavement Thickness	0.25 m
			Base Thickness	0.15 m
			Subbase Thickness	0.25 m

# AS-BUILT BIM DEVELOPMENT

Point data is extracted from DEM data and used to create surface.

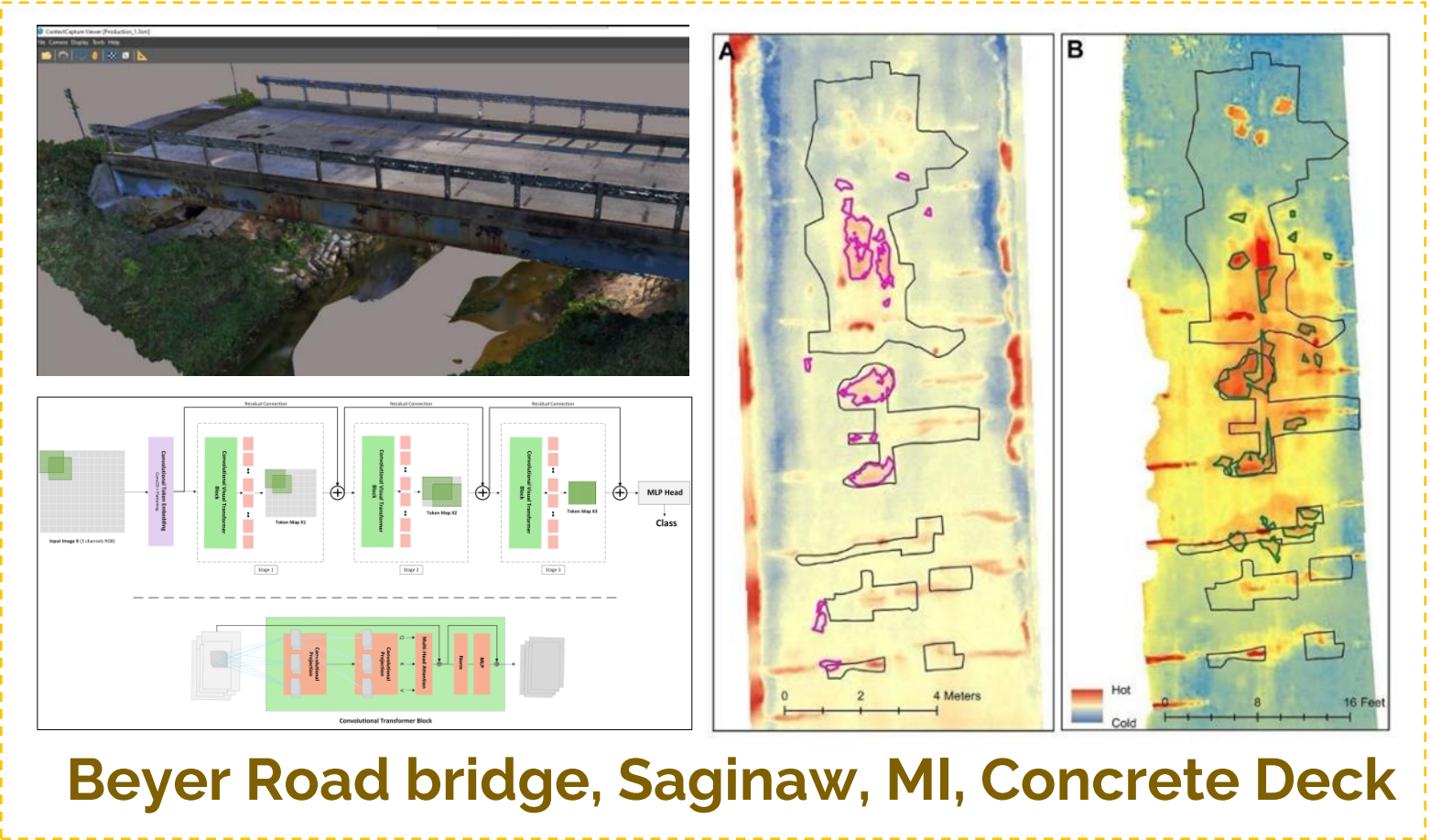
Hillshade image is used to extract the road alignment and create it on the surface.

BIM parameters are used to create an assembly and the corridor.



# BRIDGE INSPECTION

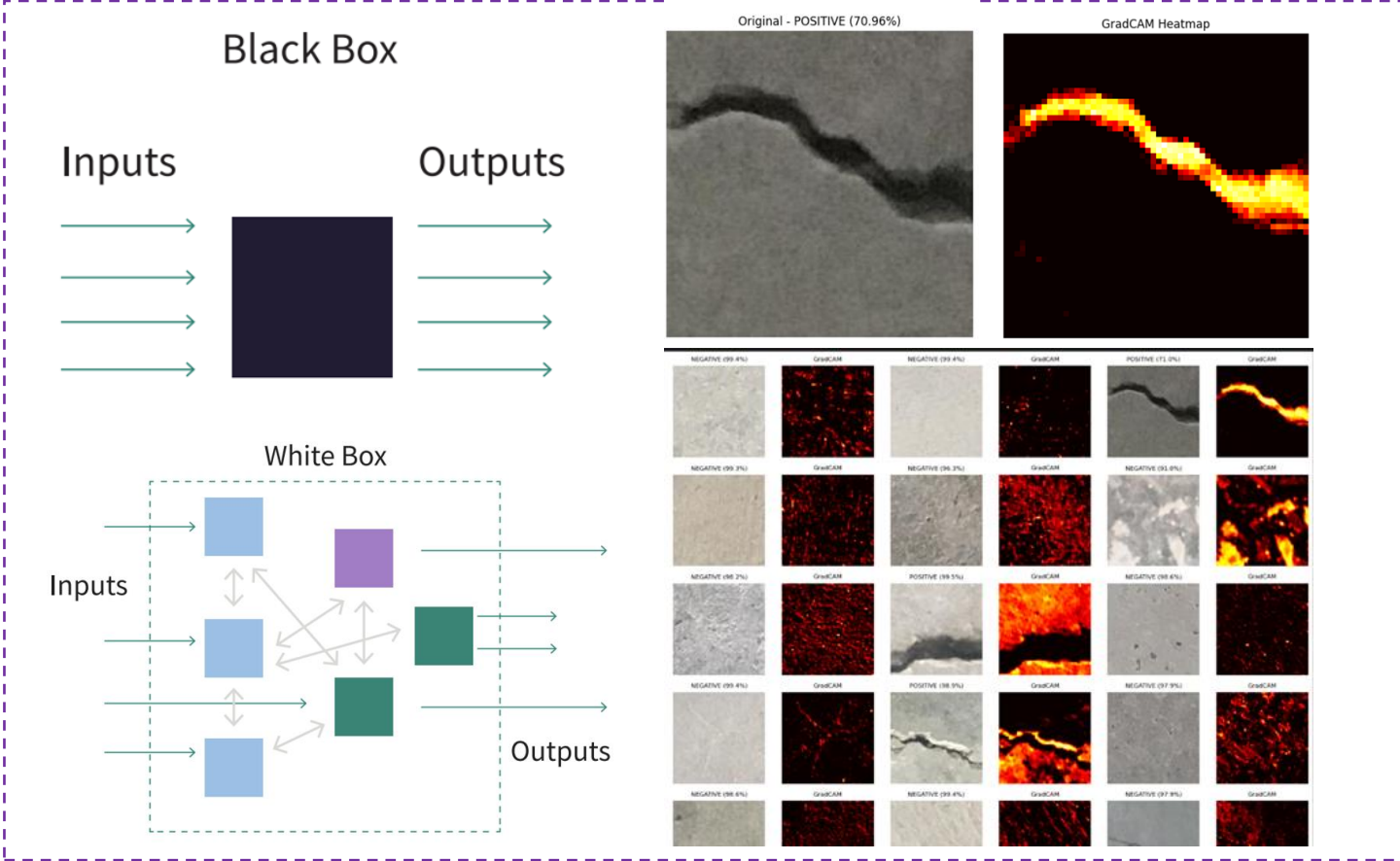
Developing new Deep Learning Models to detect and locate damages on a concrete bridge with high accuracy.



**Beyer Road bridge, Saginaw, MI, Concrete Deck**

# EXPLAINABLE AI

Identifying critical features influencing AI decisions, by offering explainability metrics.



# CHALLENGES

## Environmental & Site Conditions

- Weather dependency (wind, rain, lighting)
- Obstructions affecting line-of-sight and flight stability
- Variability in ground features complicating automated recognition

## Regulatory & Safety Constraints

- Airspace restrictions and FAA compliance
- Safety risks in active construction zones
- Need for certified pilots and trained personnel

## Data A

- Inconsistent i
- Difficulties ali
- with CAD/BIM
- Noise in poin

## Integration with BIM Workflows

- Limited interoperability with Civil 3D, MicroStation, or Revit
- Challenges mapping UAS data to as-designed parameters
- Time-consuming manual steps in creating usable BIM inputs

## Operational Limitations

- Battery life and flight duration constraints
- Need for frequent calibration and maintenance
- Difficulty scaling for large or complex job sites

olution  
S data

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olution  
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# CONCLUSION

- UAS technologies provide efficient, high-resolution data for construction inspection, quality control, and progress monitoring.
- Integration with BIM platforms enables as-built visualization and supports data-driven decision-making throughout the project lifecycle.
- Applications such as thermal segregation detection, automated bridge inspection, and explainable AI showcase the potential of intelligent inspection workflows.
- Challenges remain in areas like data accuracy, regulatory compliance, system integration, and workforce readiness, but ongoing research and field validation continue to bridge the gap.
- The future lies in scalable, explainable, and integrated AI-BIM solutions that enhance safety, productivity, and sustainability in civil infrastructure projects.



# UAS Have Changed Ohio DOT Bridge Inspection

# Ohio UAS Center Report



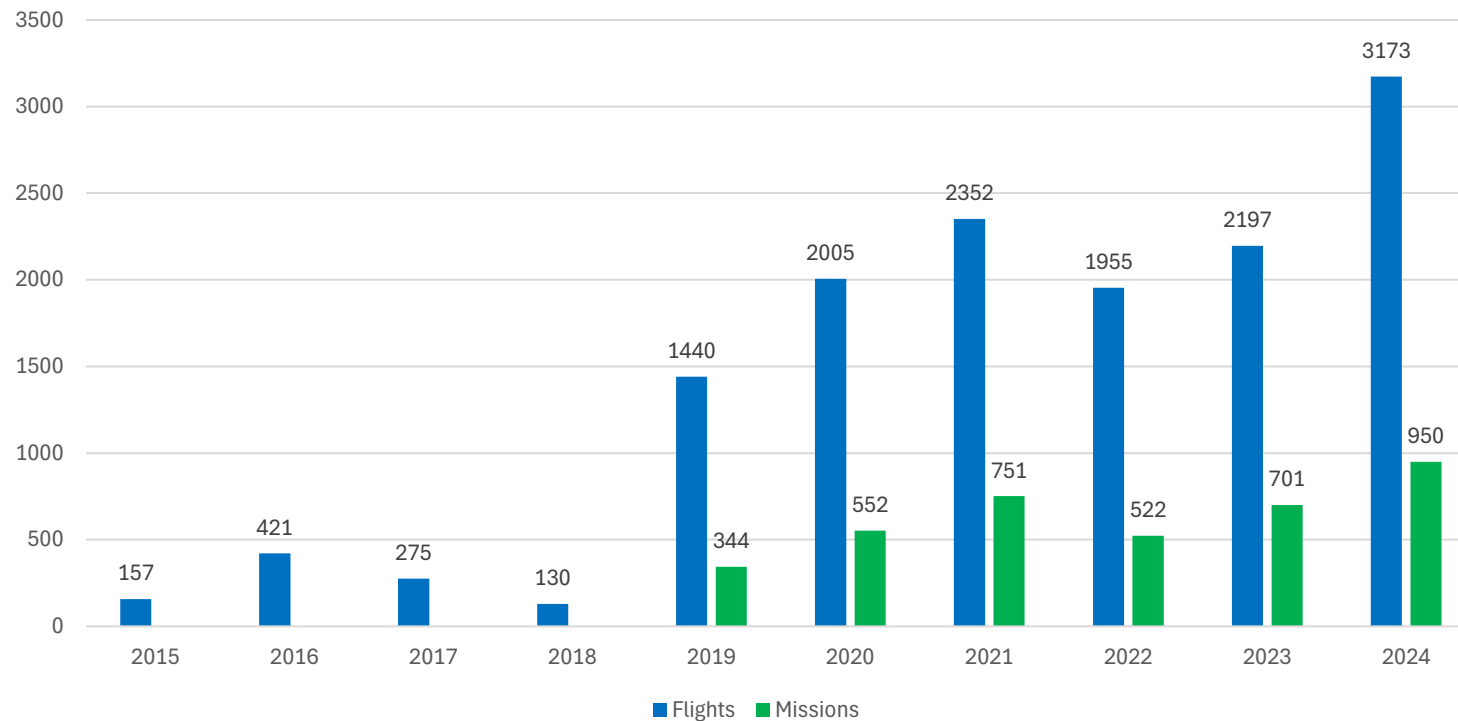
**DriveOhio**

UAS Center

## Total Flights and Missions since 2015

## 44 Pilots in 2024

Last 10 years comparison



#	Year	Flights	Missions
1	2015	157	
2	2016	421	
3	2017	275	
4	2018	130	
5	2019	1440	344
6	2020	2005	552
7	2021	2352	751
8	2022	1955	522
9	2023	2197	701
10	2024	3173	950
Total		14105	3820

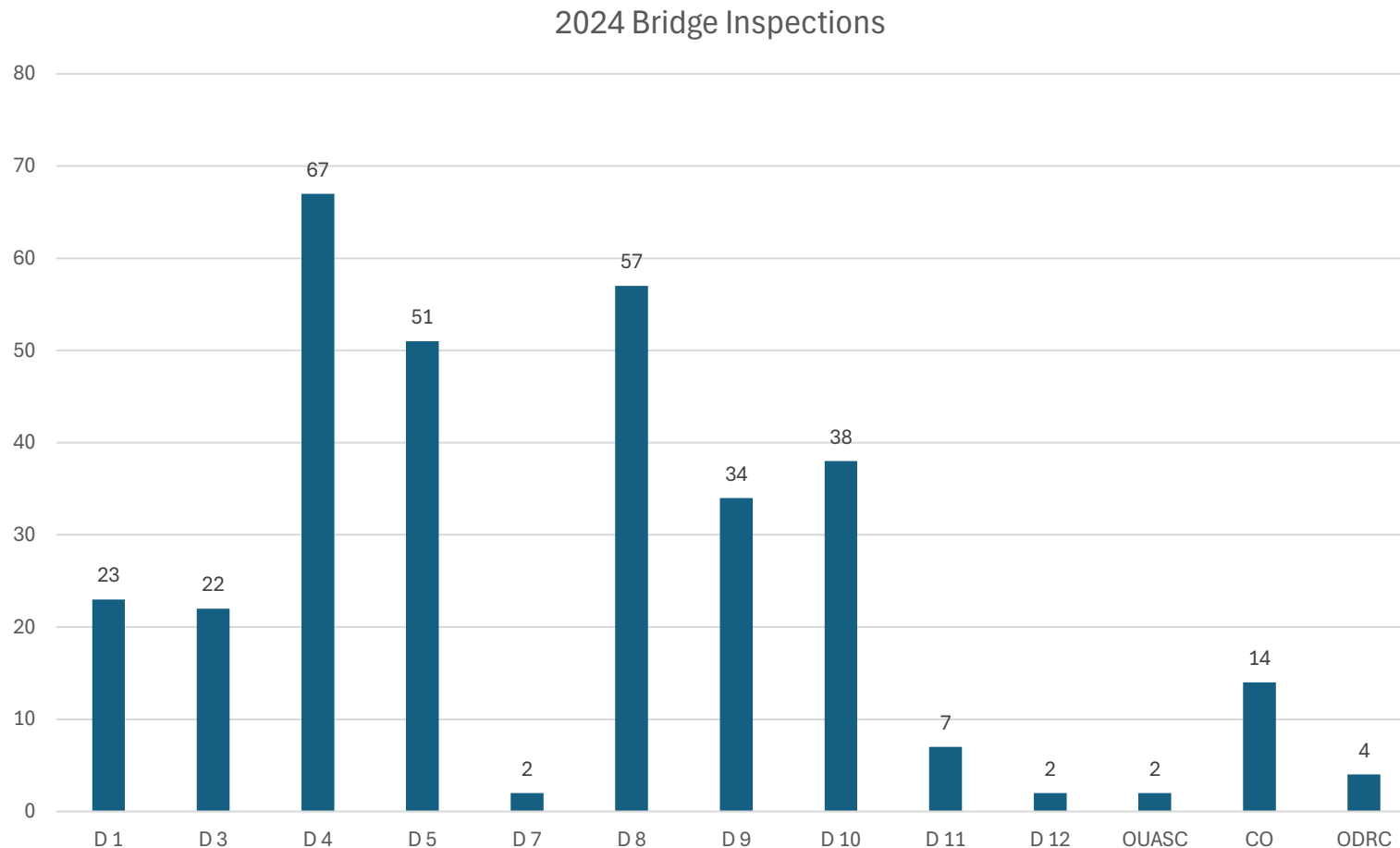
# UAS Center Report



**DriveOhio**

UAS Center

## Bridge Inspection Flights by Districts - 2024



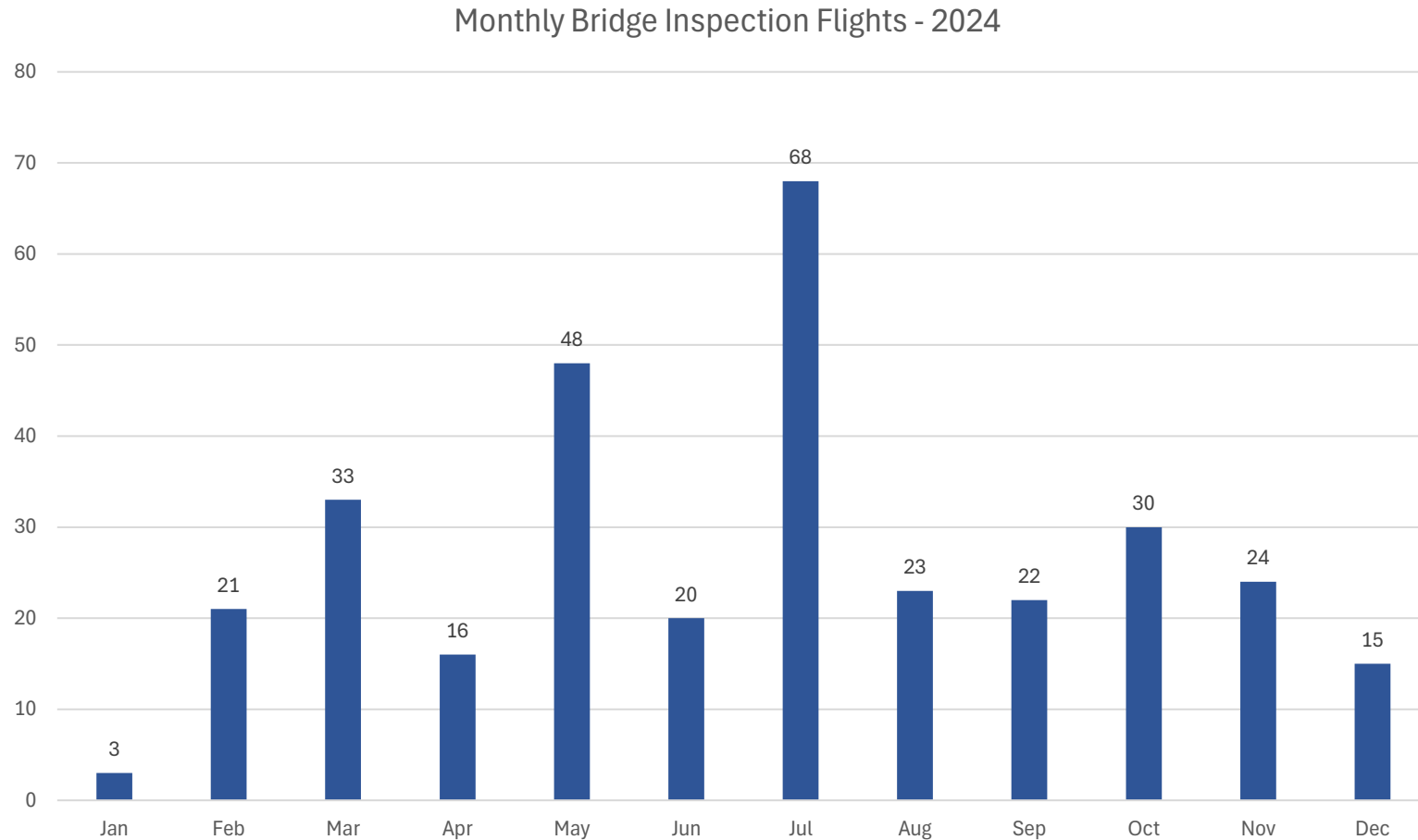
# UAS Center Report



**DriveOhio**

UAS Center

## Bridge Inspection Flights by Month - 2024



# UAS Center Report

## Bridge Inspectors - 2024



**DriveOhio**

UAS Center

	Pilot	# Flight	Total Miles
1	Adam Spong	40	21.02
2	Jeremy Patterson	39	11.00
3	Kevin Kennedy	38	11.94
4	Jenn Donley	36	17.24
5	Matt Stefanik	33	18.20
6	David Krazl	32	19.68
7	Jason Guth	21	15.37
8	Mike Butler	19	9.11
9	Stephanie Lentz	17	7.79
10	Andrew Hart	15	14.19

	Pilot	# Flight	Total Miles
11	Craig Penix	7	1.50
12	Daniel Breda	7	3.57
13	Eric Debolt	7	1.93
14	Joshua Reel	5	2.73
15	Jamie Davis	4	1.94
16	Scott McClure	2	0.86
17	Brian Meade	1	2.10
	<b>Grand Total</b>	<b>323</b>	<b>160.17</b>

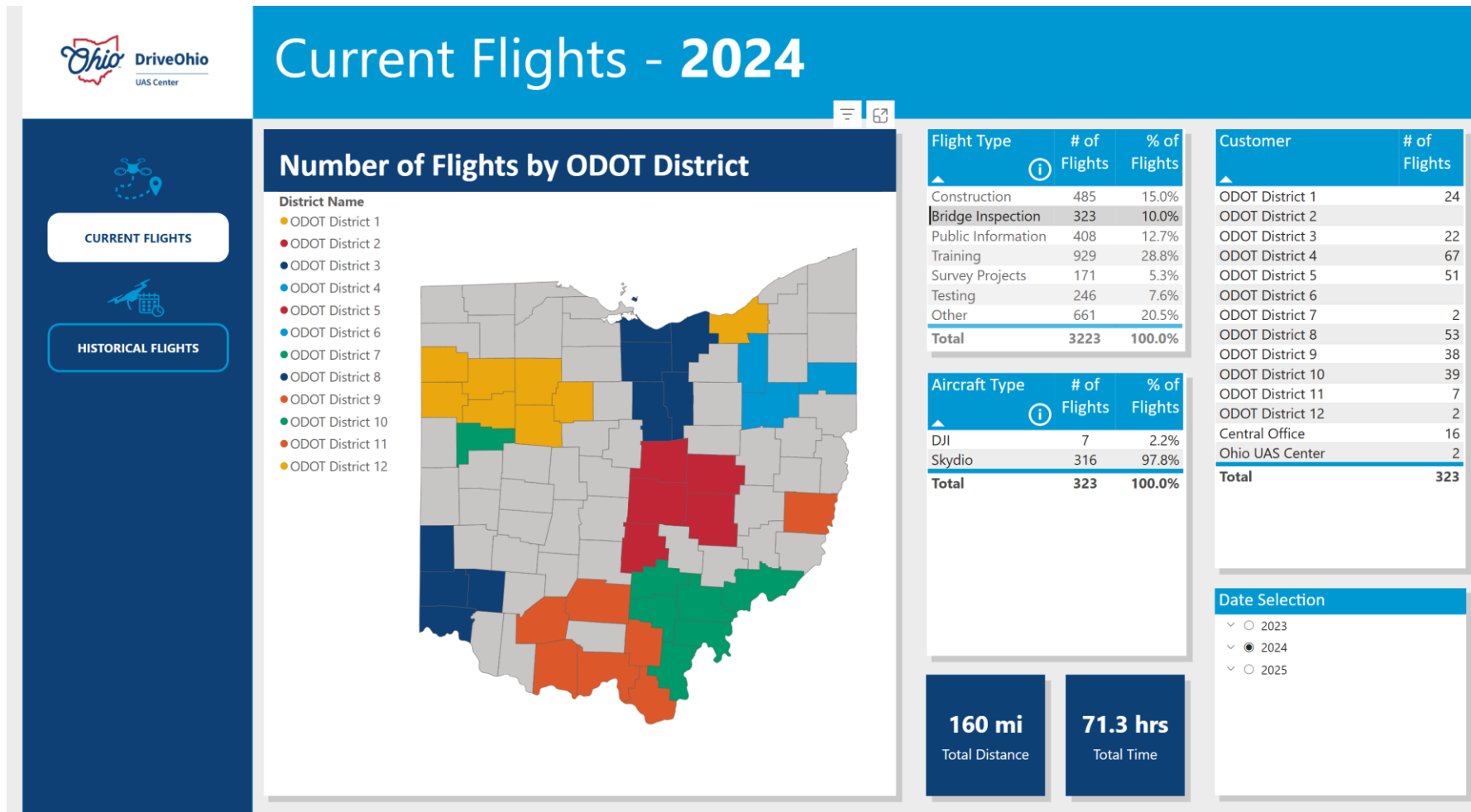
# UAS Center Report



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UASC Dashboard link - [Microsoft Power BI](#)



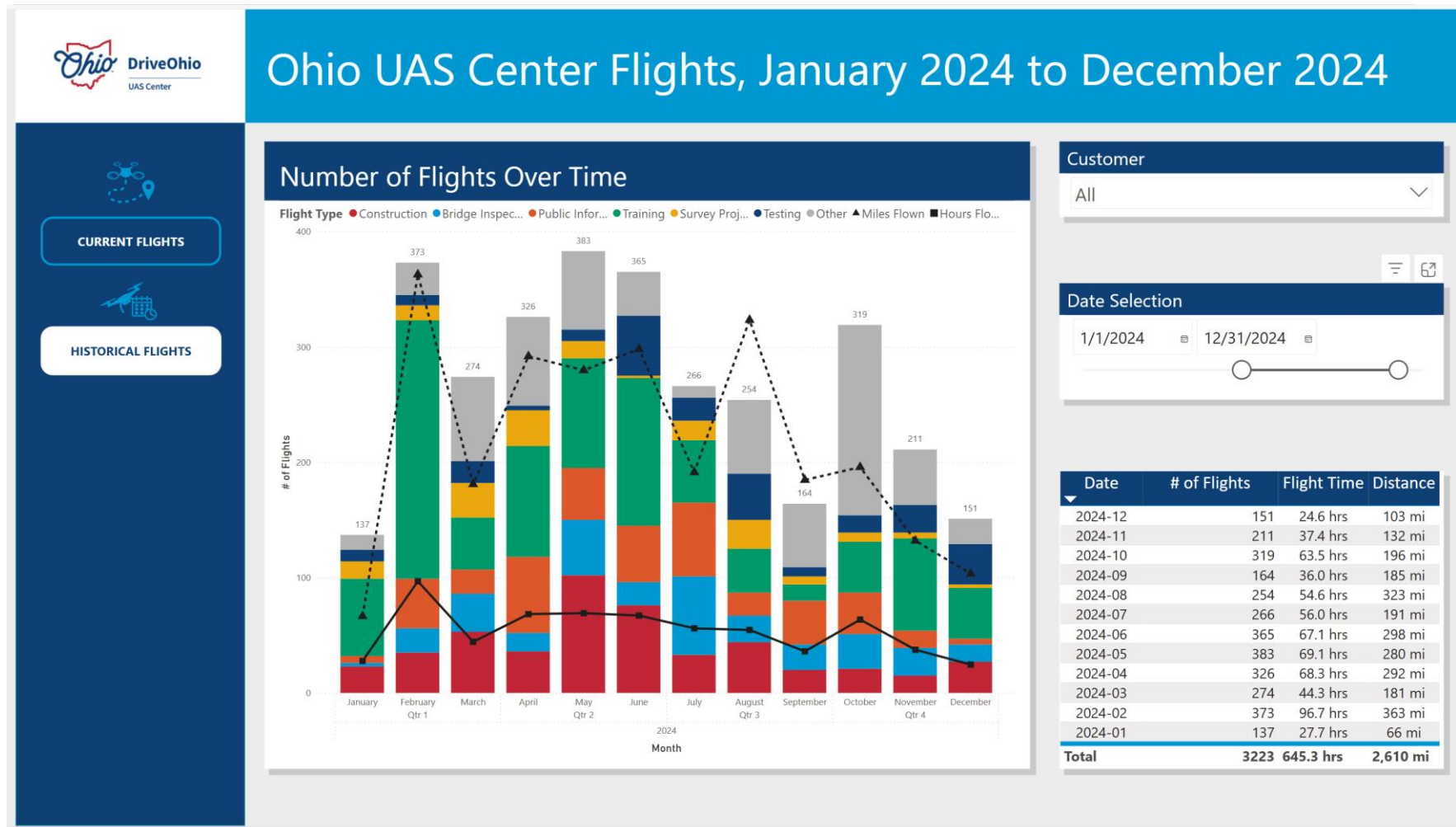
# UAS Center Report



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UAS Center

UASC Dashboard link - [Microsoft Power BI](#)



● Bridge Inspe...

# Bridge Inspections - ROI Calculations



## Snooper Inspections

LABOR



6 Employees



48 Total Labor Hours



\$2,018 Total Payroll

EQUIPMENT



\$625 for Snooper



\$500 for Other



\$1,125 for Total Cost

**\$3,143**

(\$4,182 nights/weekends)



## Drone Inspections

LABOR



2 Employees



8 Total Labor Hours



\$427 Total Payroll

EQUIPMENT



\$45 for Drone



\$50 for Pickup



\$95 for Total Cost

**\$522**

(\$735 nights/weekends)

**\$2,621 in Savings**

(\$3,417 nights/weekends)









# The JMB Problem

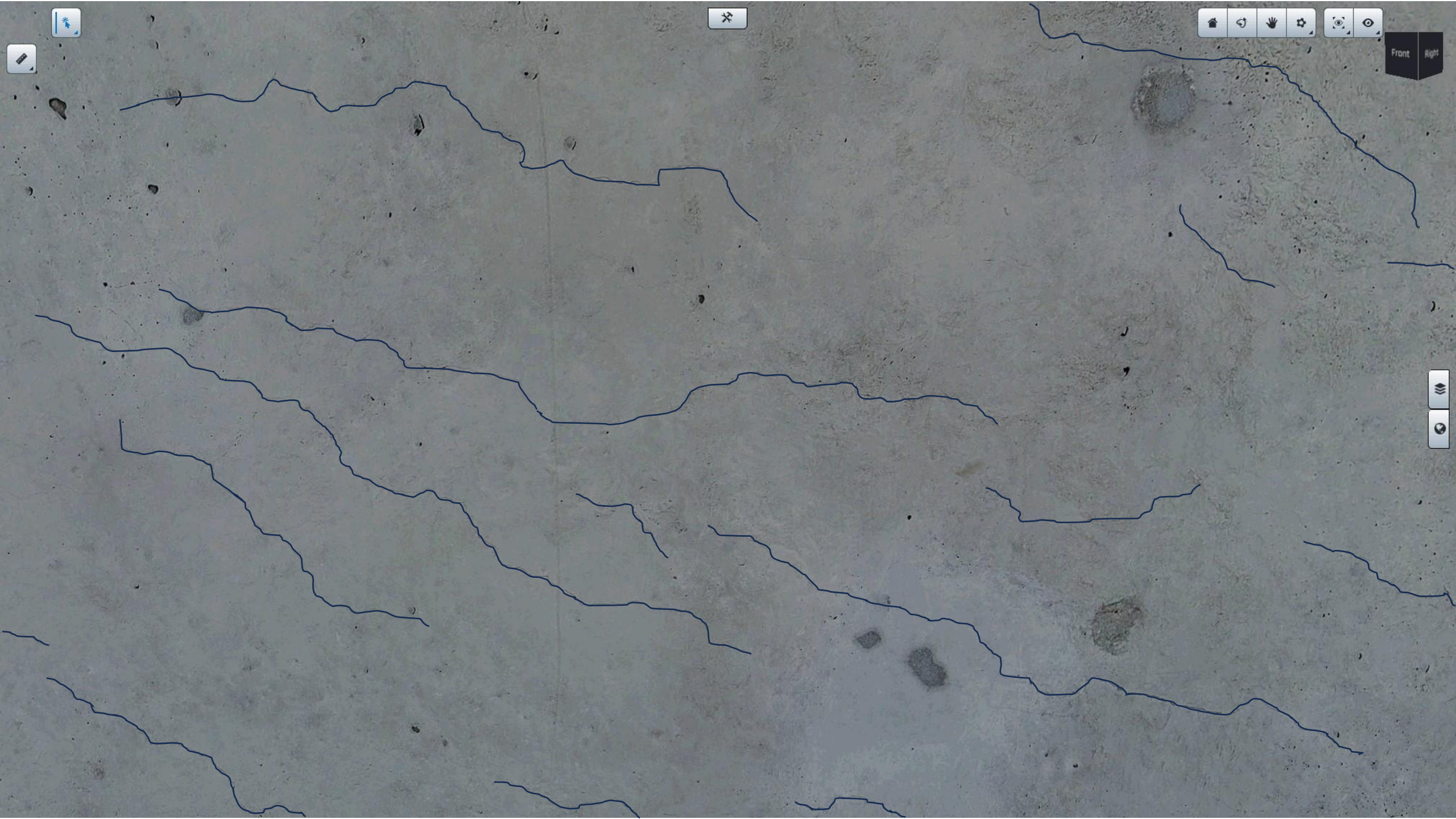




2,252 ft

239 ft

2016

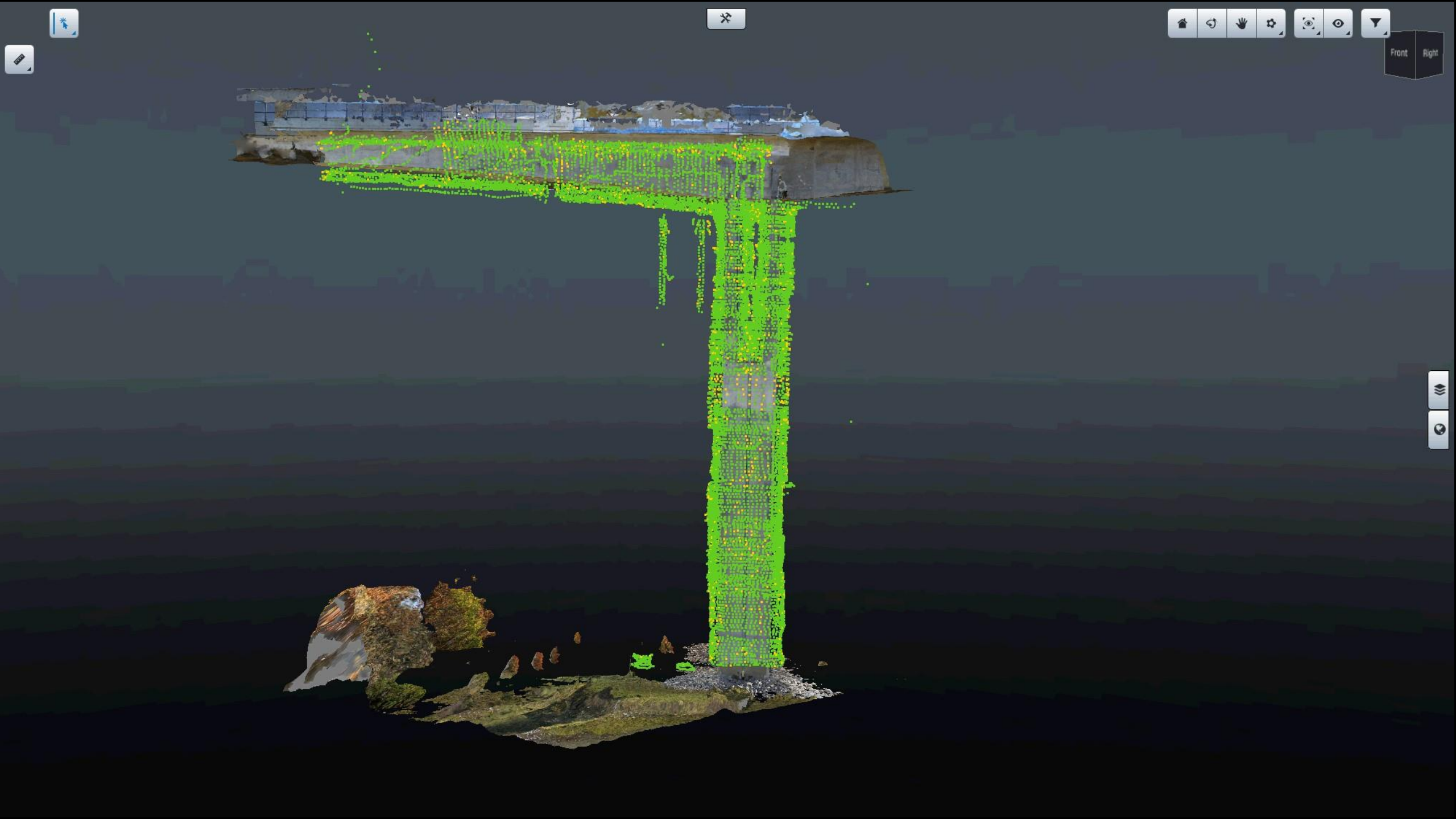




Q015/W

Front





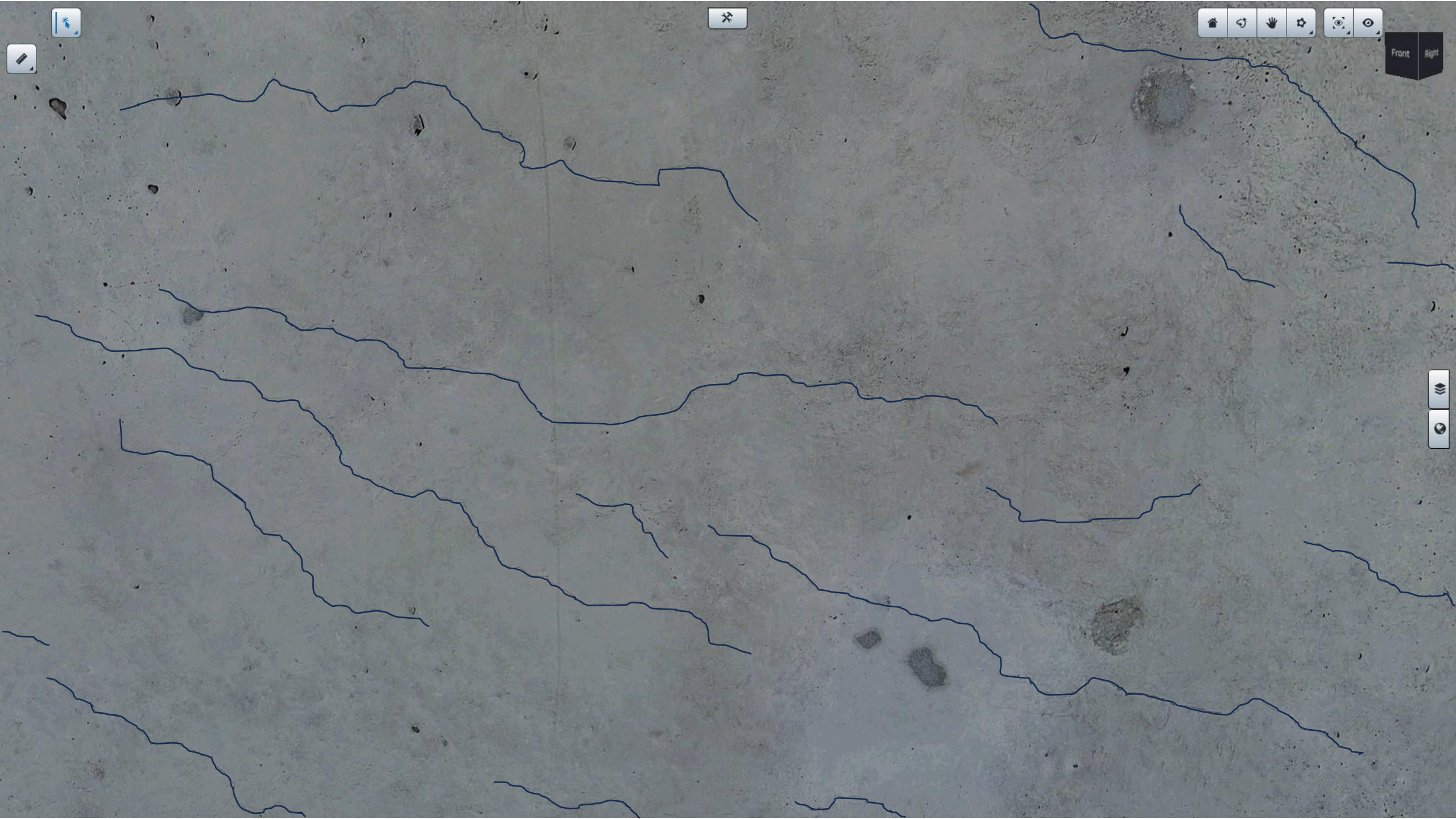
Front Right





Front Right

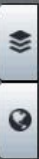




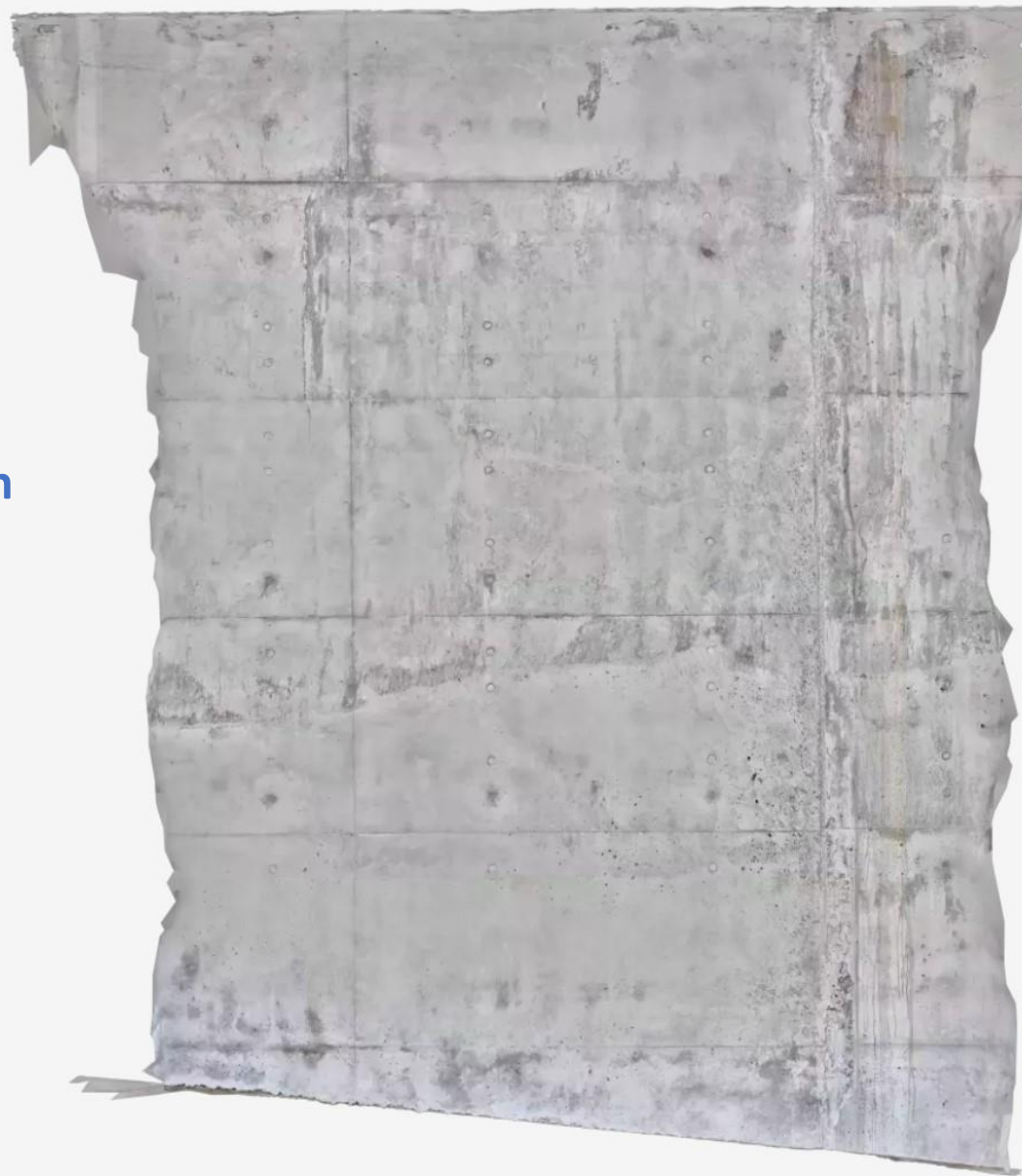
X  
Q015W



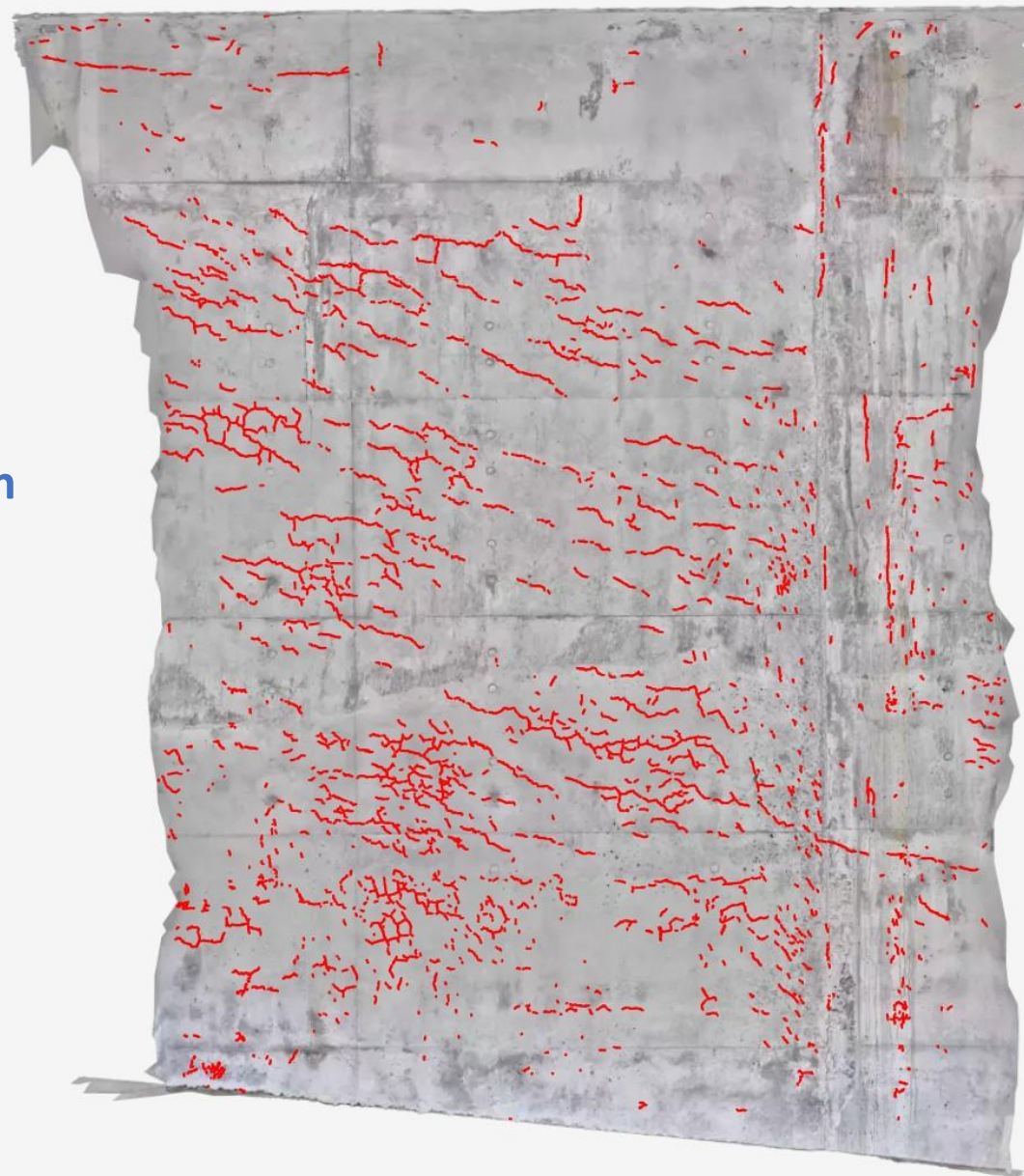
P2 NE SF  
2.4' x 0.008"



**gNext  
AI Crack Detection  
Demo**



**gNext  
AI Crack Detection  
Demo**





**DriveOhio**

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UAS Center

Thank You

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# Today's presenters



**Dr. Colin Brooks**  
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**Dr. Halil Ceylan**  
[hceylan@iastate.edu](mailto:hceylan@iastate.edu)



**Dr. Reihaneh Samsami**  
[rsamsami@newhaven.edu](mailto:rsamsami@newhaven.edu)



*Sciences  
Engineering  
Medicine*



**Jamie Davis**  
[jamie.davis@dot.ohio.gov](mailto:jamie.davis@dot.ohio.gov)



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ACADEMIES**

# Upcoming events for you

**May 8, 2025**

TRB Webinar: Navigating Current and Future Freight Challenges

**May 15, 2025**

TRB Webinar: Statewide Approaches to the Development of Comprehensive Transit Information Systems

<https://www.nationalacademies.org/trb/events>

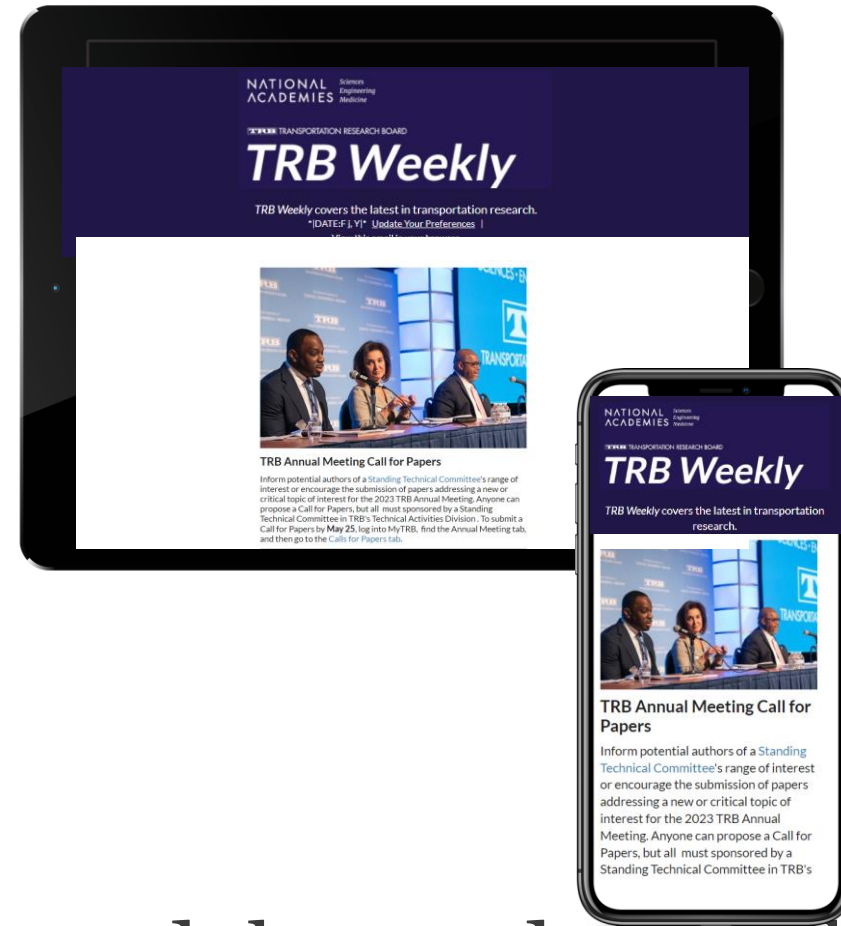


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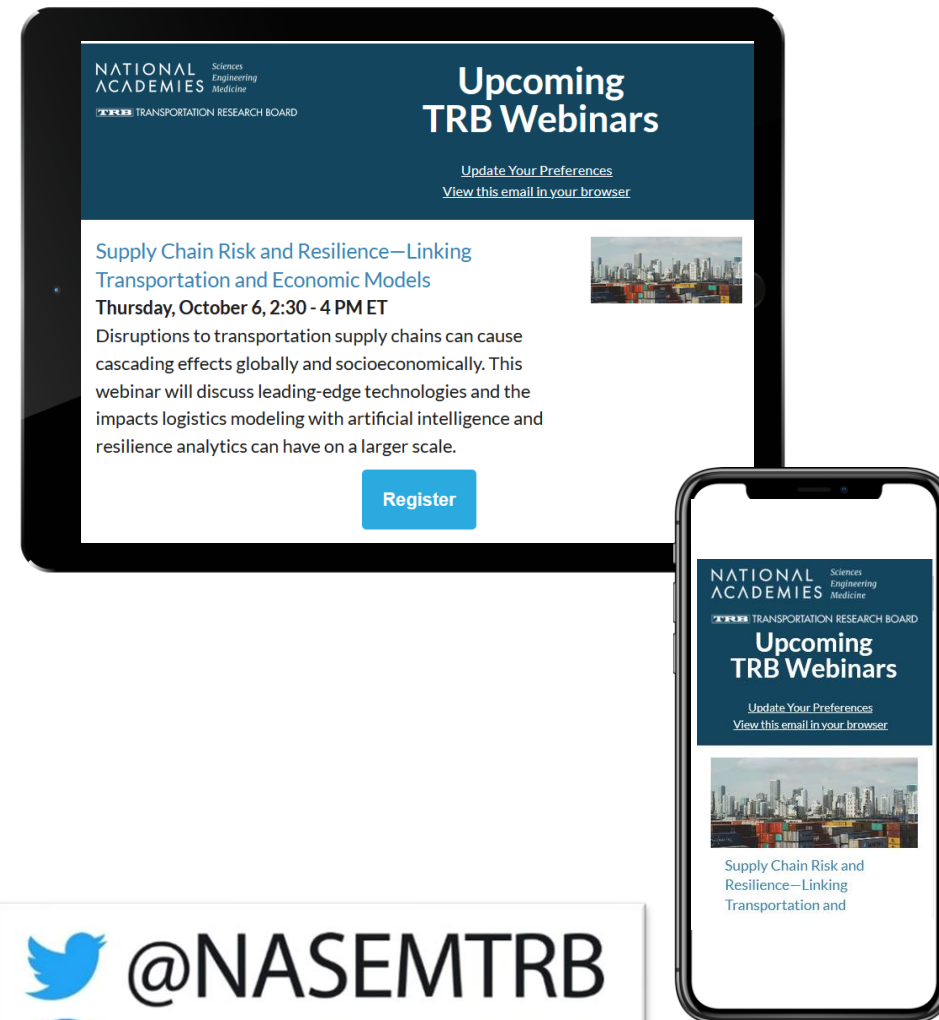
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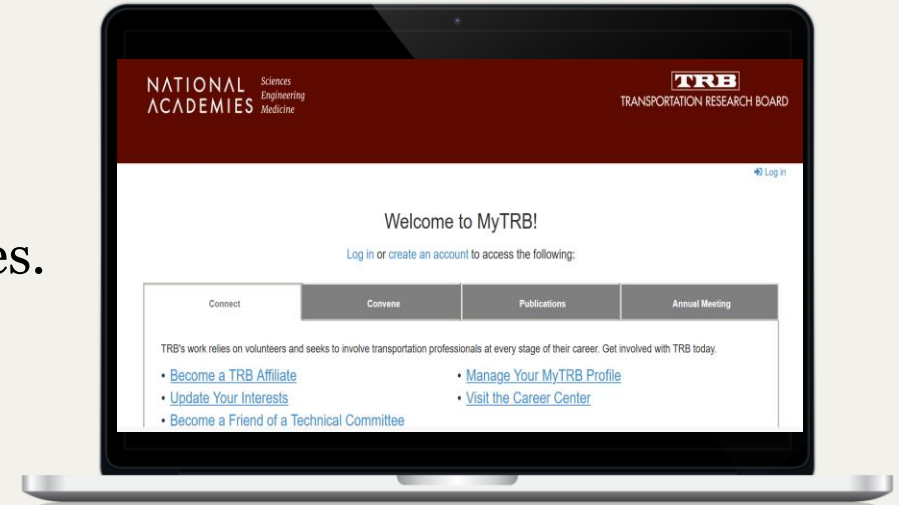


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