Deep Learning-based Semantic Segmentation of 3D Point Clouds: a Case of Hydraulic Structures

Tianyang Chen[1,2], Wenwu Tang[1,2], Shenen Chen[3], Craig Allan[1,2], John Diemer[2], Tarini Shukla[1,3], Zachery Slocum[1,2], Navanit Sri Shanmugam[3], Chavan Vidya Subhash[3], and Matthew S. Lauffer[4]

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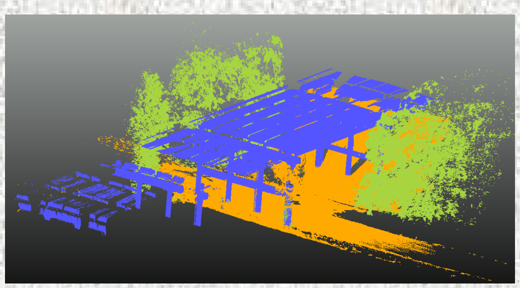
1. Center for Applied GIScience, the University of North Carolina at Charlotte
2. Dept. of Geography and Earth Sciences, the University of North Carolina at Charlotte
3. Dept. of Civil and Environmental Engineering, the University of North Carolina at Charlotte
4. Hydraulic Unit, North Carolina Department of Transportation

Introduction

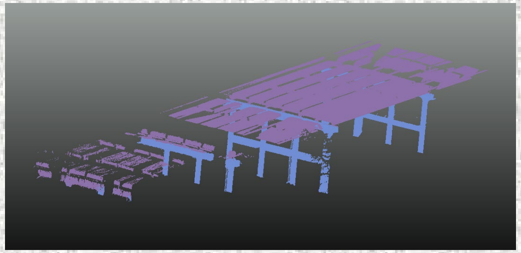
- **Research objective:**
  - Develop an approach to leverage the cutting-edge deep learning-based 3D classification algorithms to detect hydraulic structures (e.g., bridges and their components) from 3D point cloud (e.g., LiDAR scans).
- **Challenges:**
  - Limited availability of data, where volume is not comparable with benchmarks.
  - Imbalanced data, where classes are much unevenly distributed
- **This lightning talk:**
  - A showcase of how we address the challenges and a demonstration of the current results

Framework

Proposed approach to mitigate the challenge of imbalanced classes:
Model I: Detect bridge from a LiDAR scan
Model II: Detect different bridge components from point cloud of the detected bridge

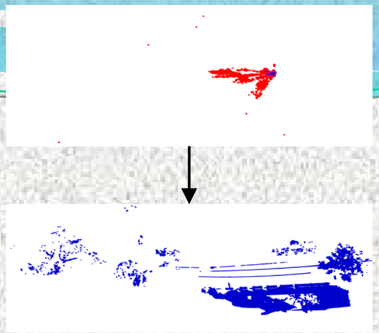


*Prediction results of **Model I** detecting bridge from the scene

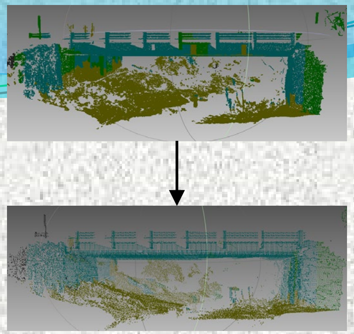


*Prediction results of **Model II** for bridge components

LiDAR data
↓
Pre-processing
↓
Model I to detect bridge
↓
Model II to detect bridge components
↓
Post-processing
↓
Output results



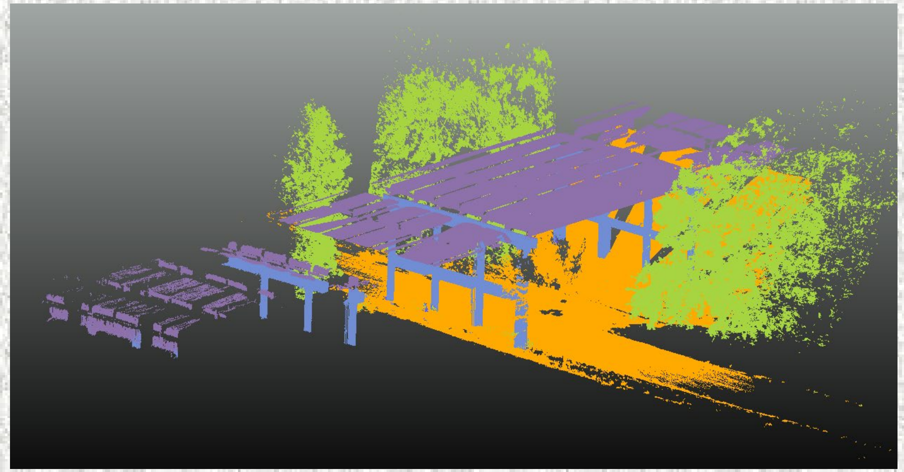
*Demo of outlier removal
Red are removed automatically



*Demo of Spatial sampling
From origin (top) to 1cm (bot)

Pre-processing to improve the quality of the data:
Step I. Outlier removal by Open3D, an open-source python lib, to remove noise
Step II. Spatial sampling to 1cm by CloudCompare command line, to reduce the data volume

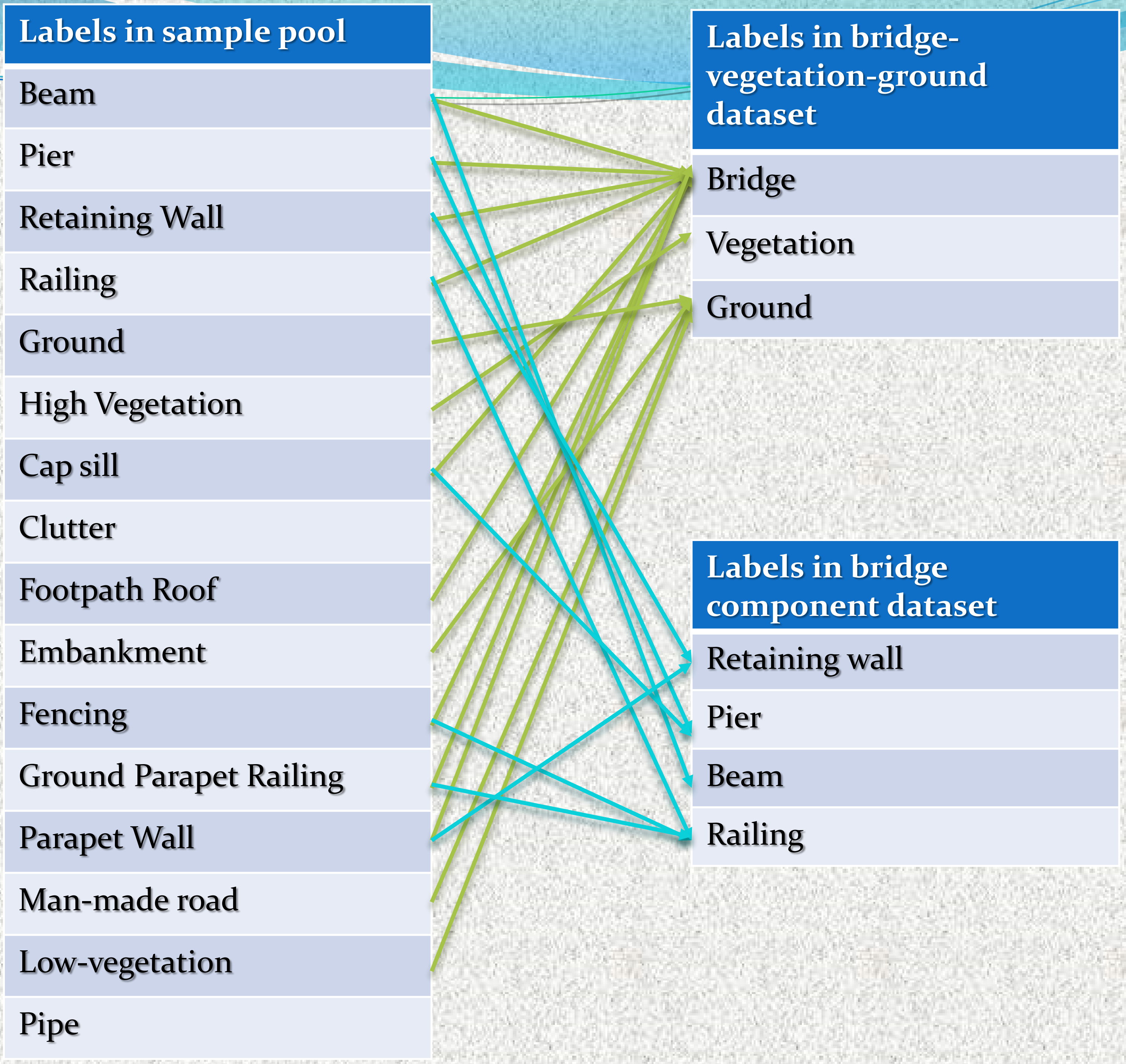
Post-processing to merge the prediction results from Model I and Model II.



*Demo of the results by combining results from **Models I and II**

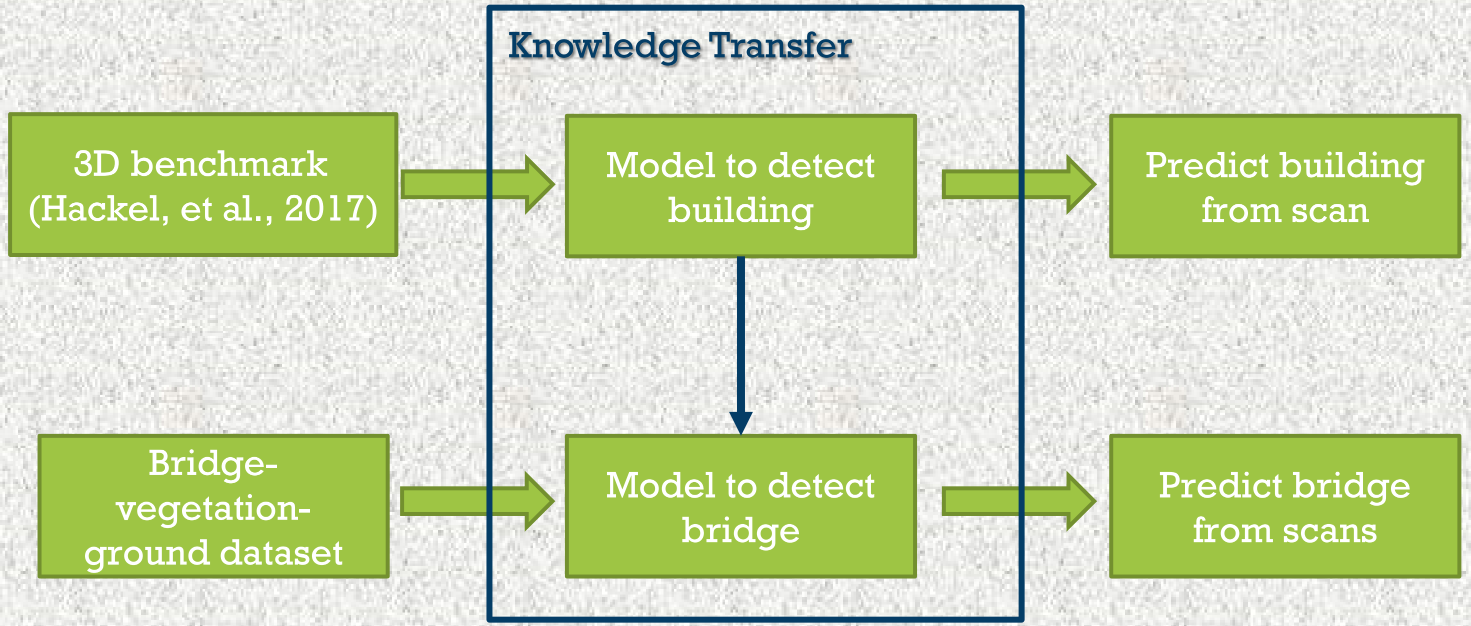
Class Aggregation and Datasets

- Annotated sample pool:
  - # annotated scans: 41
  - # classes: 16
- Two datasets were generated from the annotated sample pool:
  - 1. Bridge-vegetation-ground dataset with 3-categories: bridge, vegetation, and ground
  - 2. Bridge component dataset with 4-categories: wall, pier, beam, railing

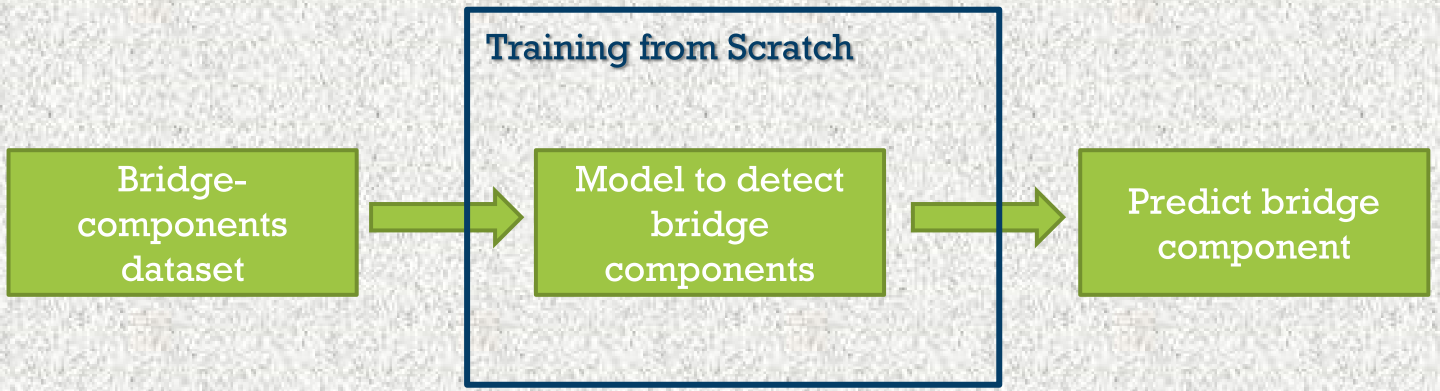


Training Deep Learning Models

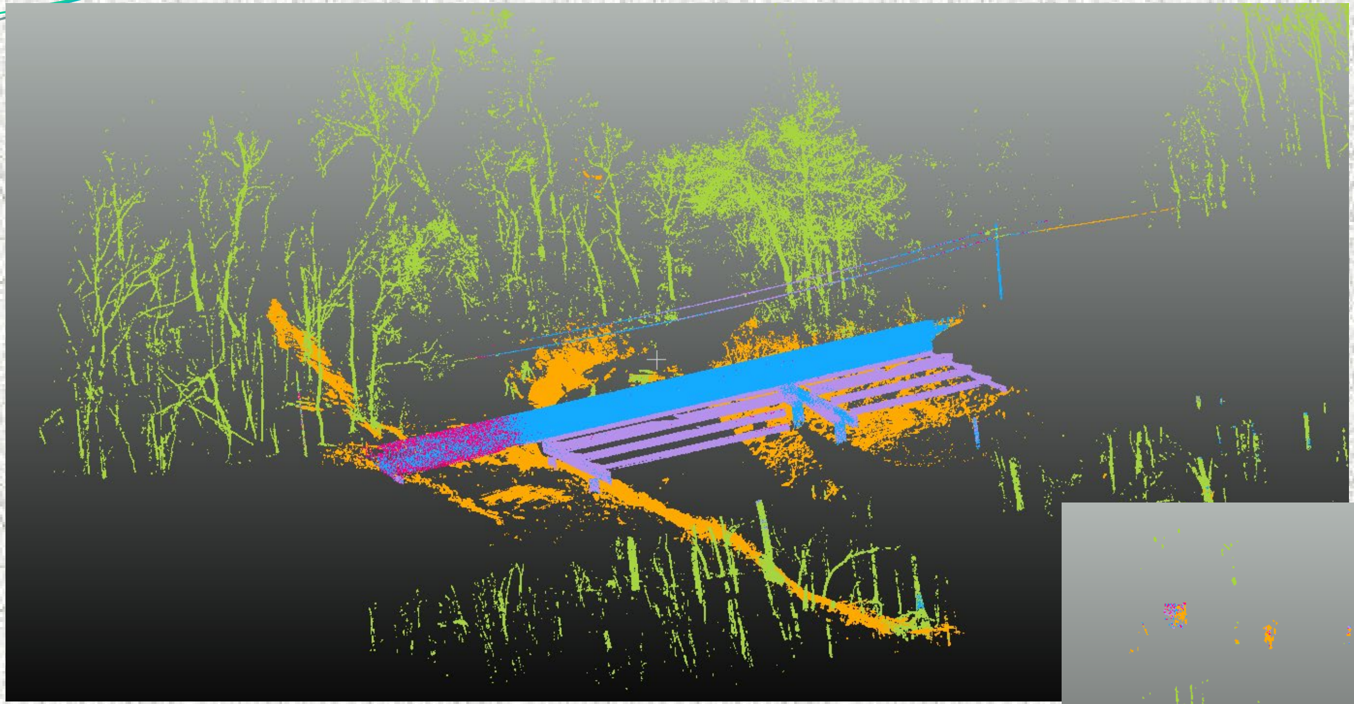
- Model I:
  - Deep neural network: ConvPoint (Boulch, 2020)
  - Dataset of Bridge-vegetation-ground
  - Transfer learning
  - Parameter tuning



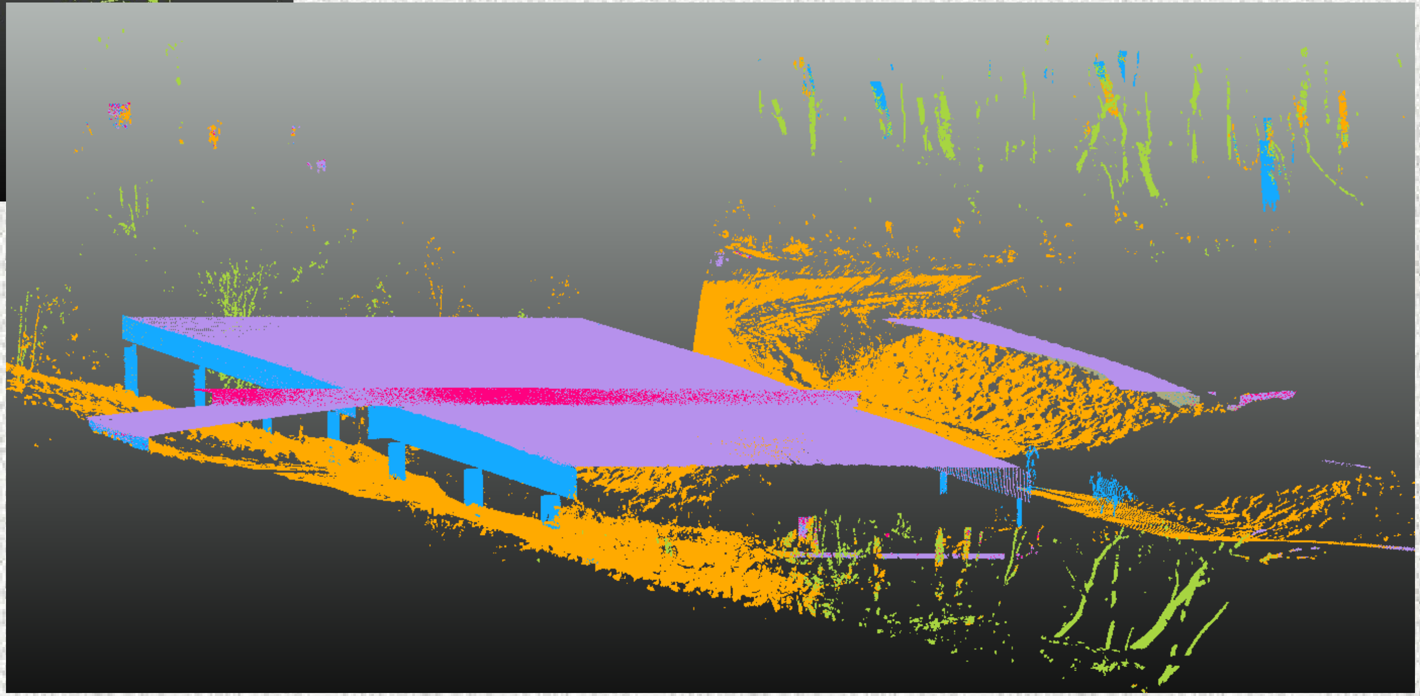
- Model II:
  - Deep neural network: ConvPoint (Boulch, 2020)
  - Dataset of bridge components
  - Training from scratch
  - Parameter tuning



Prediction Results on Raw LiDAR Data



Label		Color
Bridge components	Wall	
	Pier	
	Beam	
	Railing	
Vegetation		
Ground		



The proposed approach appears to <u>mitigate the effect from limited availability of data and imbalanced classes with in it</u>. It seems to be an adequate initial start for future application of the deep learning-based classification methods in 3D content.

Acknowledgement

- North Carolina Department of Transportation (NCDOT)
- Steering and Implementation Committee from NCDOT:
  - Matthew Lauffer, John W. Kirby, Tom Langan, Gary Thompson, Paul Jordan, Mark Swartz, Mark Ward, Derek Bradner, Brian Radakovic, Kevin Fischer
- This study is supported by the NCDOT project entitled "DeepHyd: A Deep Learning-based Artificial Intelligence Approach for the Automated Classification of Hydraulic Structures from LiDAR and Sonar Data"
  - PIs: Drs. Wenwu Tang, Shenen Chen, John Diemer, Craig Allan from the University of North Carolina at Charlotte

Reference

- Boulch, A. (2020). ConvPoint: Continuous convolutions for point cloud processing. Computers & Graphics.
- Hackel, T., Savinov, N., Ladicky, L., Wegner, J. D., Schindler, K., & Pollefeys, M. (2017). Semantic3d. net: A new large-scale point cloud classification benchmark. arXiv preprint arXiv:1704.03847.
- Olivas, E. S., Guerrero, J. D. M., Martinez-Sober, M., Magdalena-Benedito, J. R., & Serrano, L. (Eds.). (2009). Handbook of Research on Machine Learning Applications and Trends: Algorithms, Methods, and Techniques: Algorithms, Methods, and Techniques. IGI Global.

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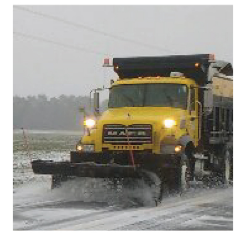



Engineered Water Repellency for Frost Heave Mitigation

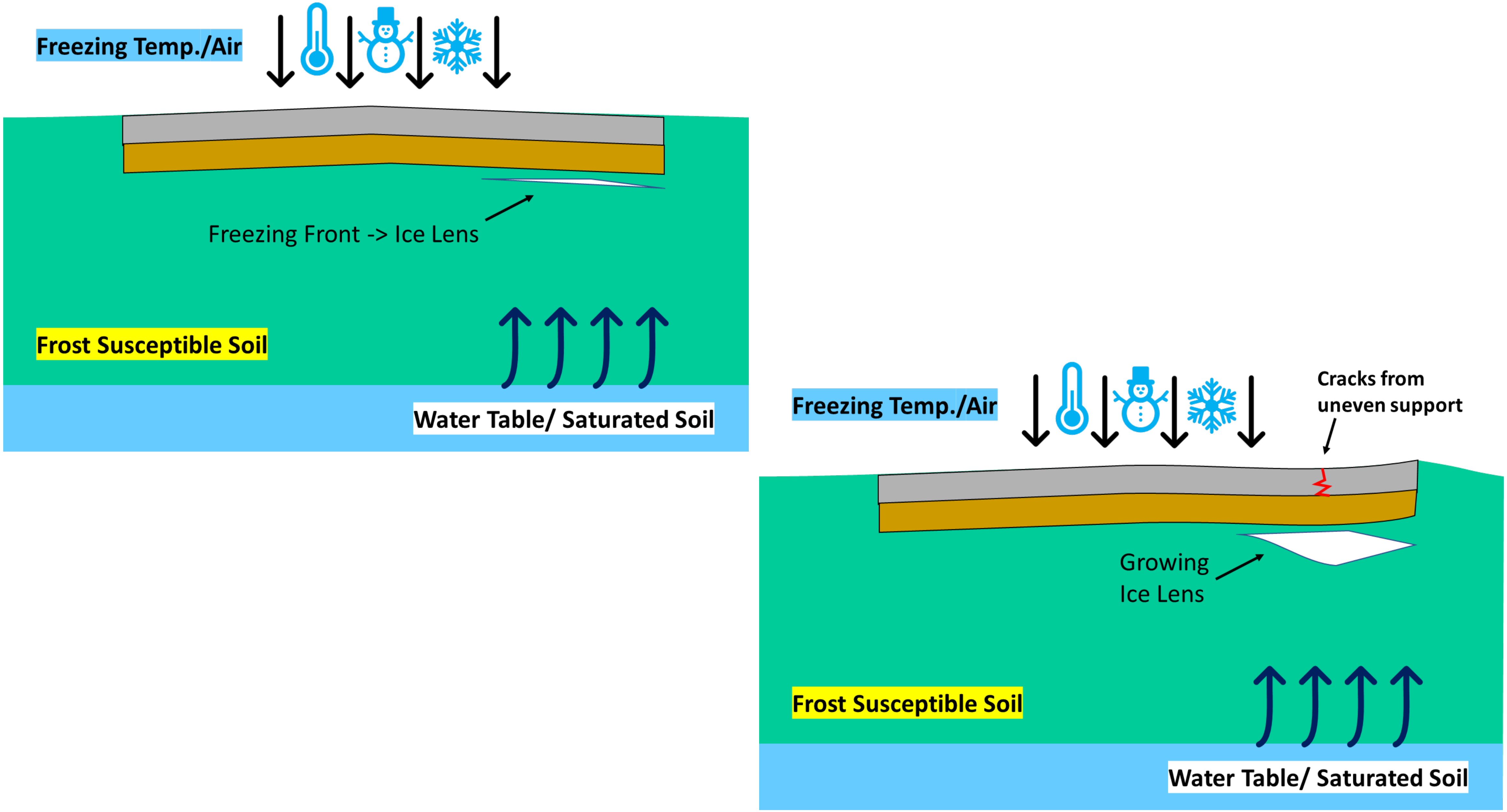
Micheal A. Uduebor
Ph.D. Student, Department of Civil and Environmental Engineering

UNC CHARLOTTE

October 2020

- Cold weather and frost action have a major effect on the design, construction, performance, and maintenance of roadways.
- Radical changes in moisture content cause excessive deformation during winter freezing and spring thawing.

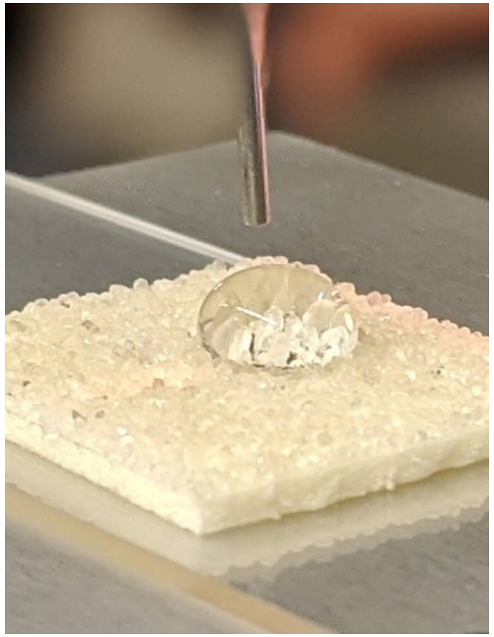
Images: hooninverse.com|mntransportationresearch.org|nphr.org|cartwellrvpark.wordpress.com

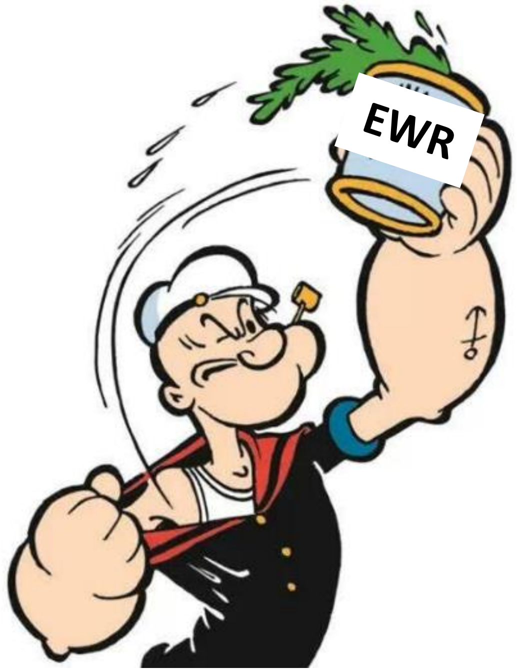

Freezing Temp./Air
Freezing Front -> Ice Lens
Frost Susceptible Soil
Water Table/ Saturated Soil
Freezing Temp./Air
Cracks from
uneven support
Growing
Ice Lens
Frost Susceptible Soil
Water Table/ Saturated Soil

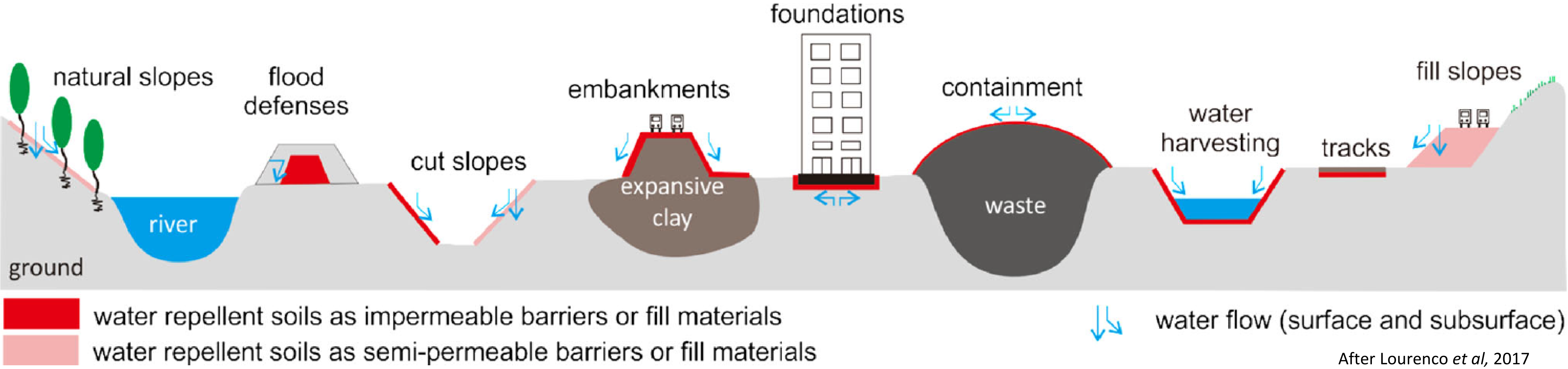
- National recurrent annual maintenance costs estimated at over 2 billion dollars
- Economic impacts: Vehicle damage, road closures, and weight restrictions.

Image: www.fosters.com

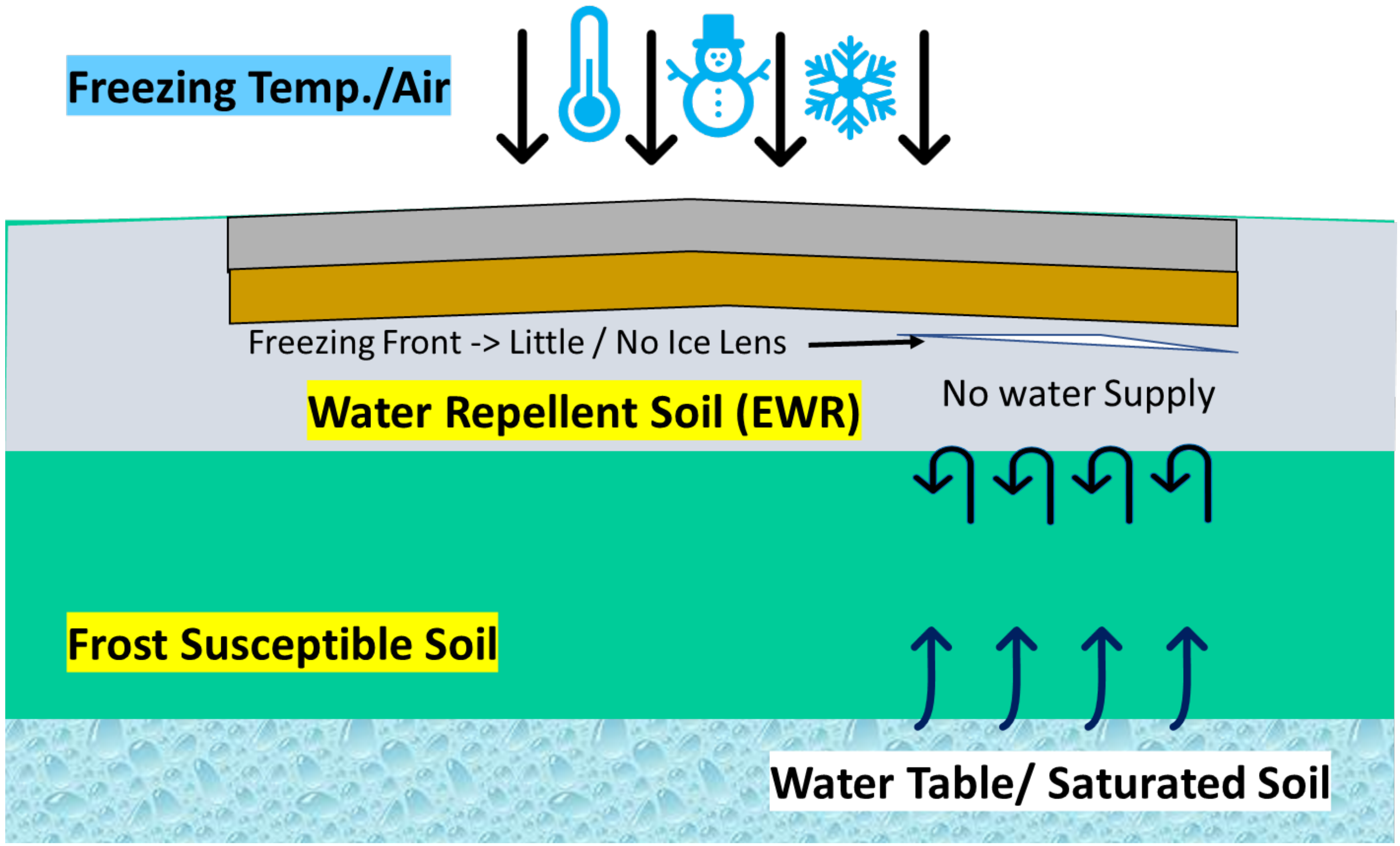
- Engineered Water Repellency (EWR)
- Soils are made hydrophobic using cost-effective and environmentally compatible polymers (Organosilanes).
- Varying Civil Engineering applications; Bridge decks, Slopes etc.







After Lourenco *et al*, 2017


Freezing Temp./Air
Freezing Front -> Little / No Ice Lens
Water Repellent Soil (EWR)
No water Supply
Frost Susceptible Soil
Water Table/ Saturated Soil


WATER TRUCK

- Multi-year project funded by the U.S. National Science Foundation and Iowa Department of Transport
- Involves laboratory, field, numerical studies.

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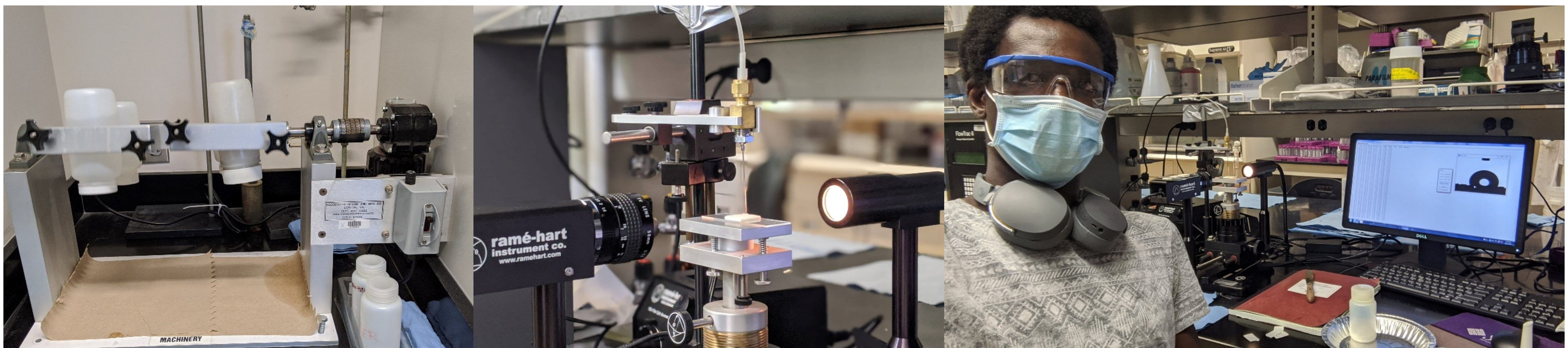


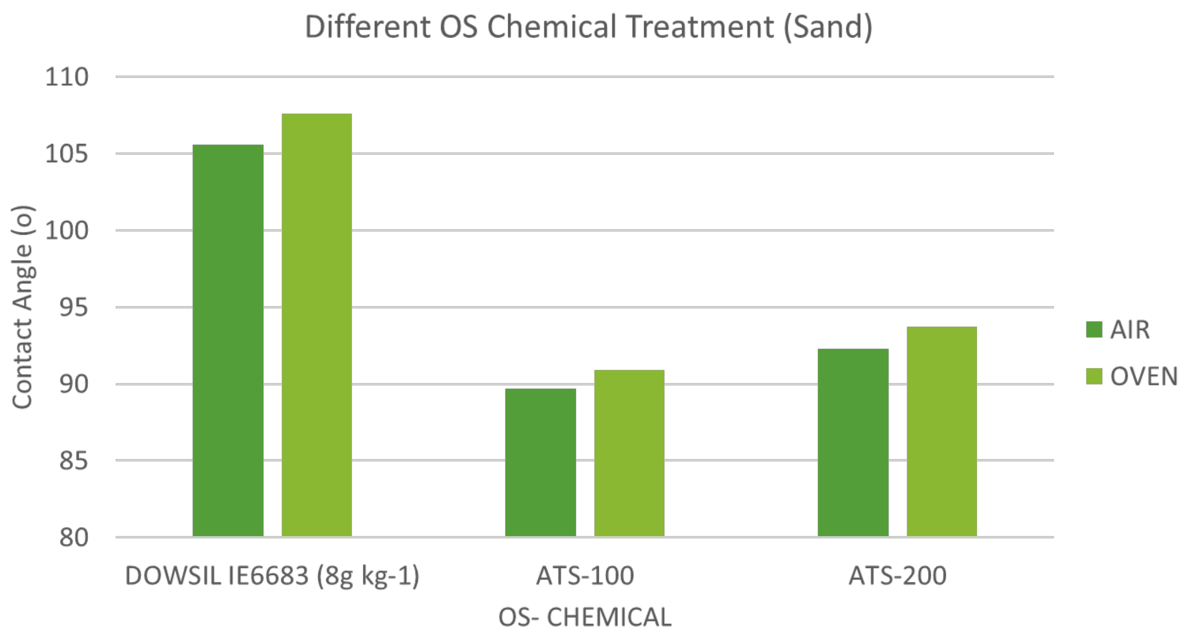
So far,

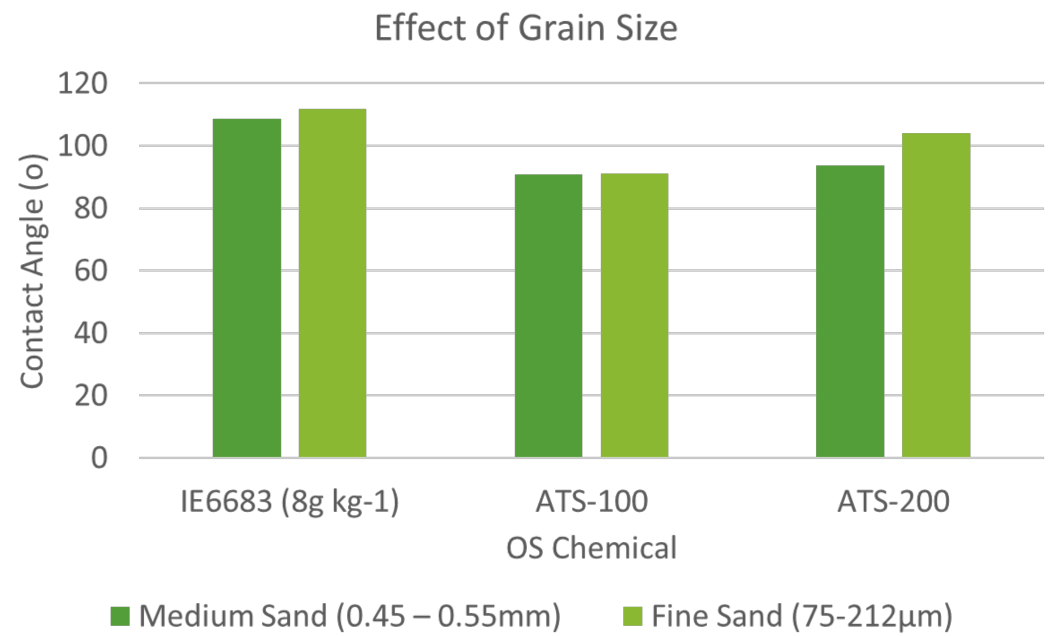
Organosilane Selection Considerations

- **Environmental safety**
  - Toxicity
  - Flammability
  - Solvent Type
  - Leaching
- **Effectiveness**
  - Surface Modification
  - % Dosage
  - Duration
- **Cost**
  - Treatment Cost/m^2/m^3
  - Shipping/Transport
- **Other considerations**
  - Handling
  - Familiarity of Use
  - Fit to Existing Methods/Machinery

So far,

Organosilane Treatment Effectiveness

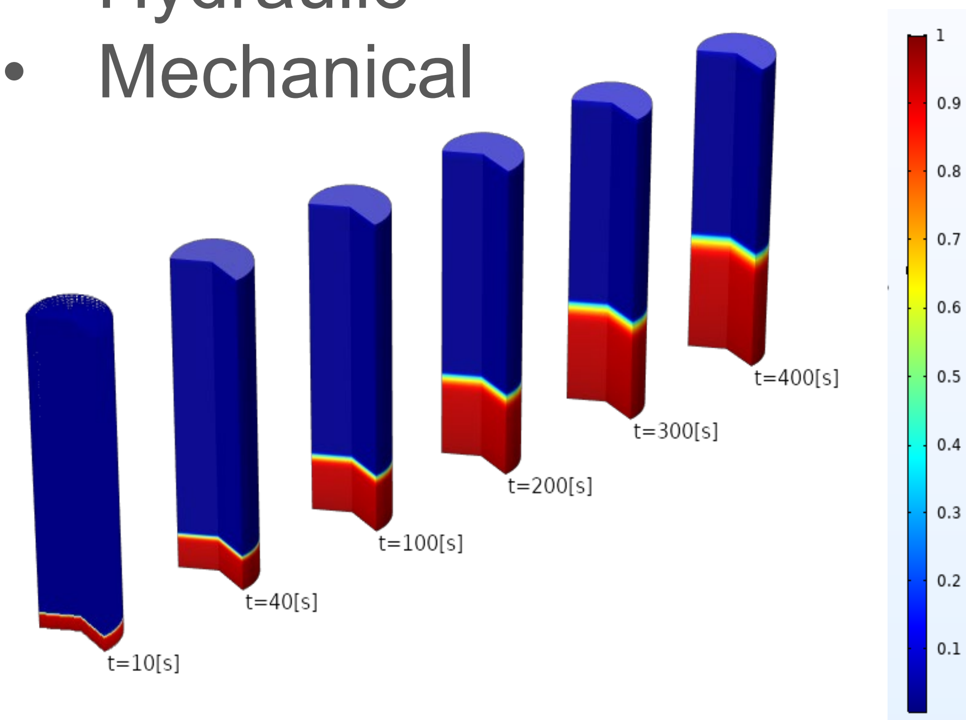


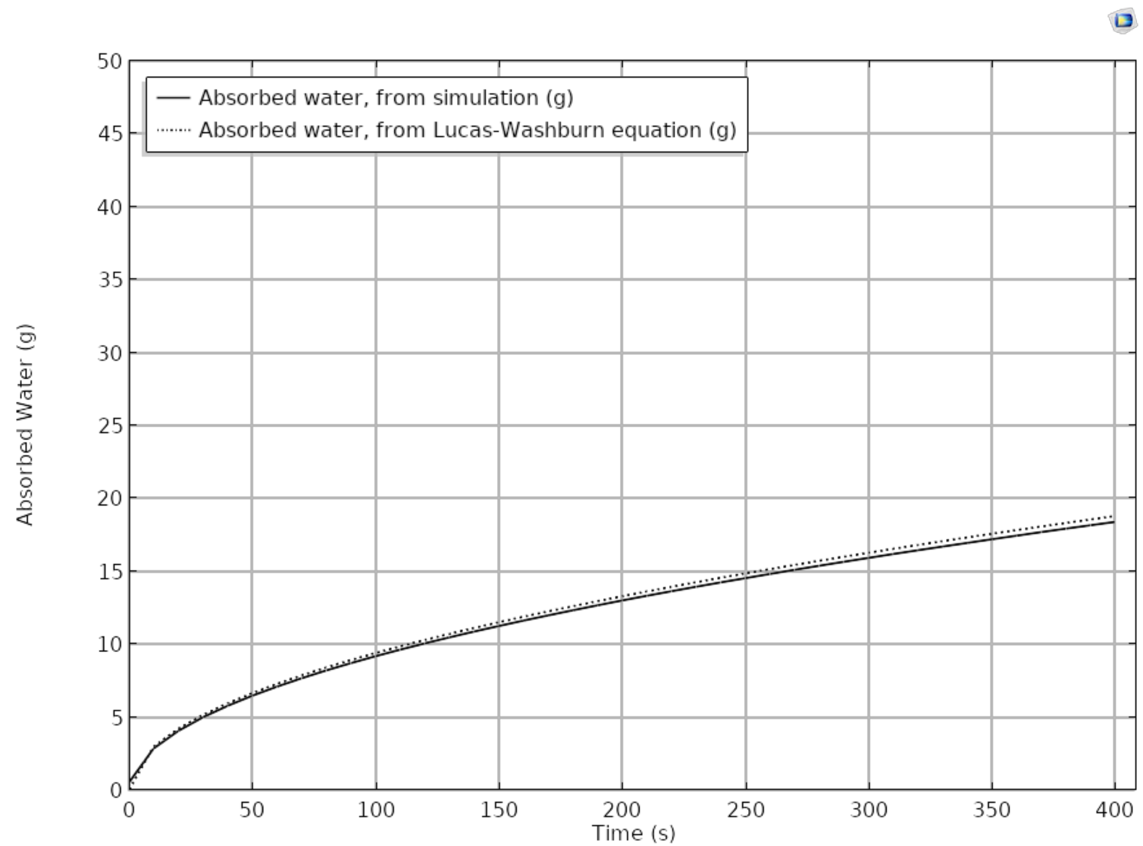


So far,

Numerical Modelling – Coupled Processes (COMSOL)

- Thermal
- Hydraulic
- Mechanical





Also,

- Decouple the mode of water transport in freezing soils.
- Osmotic or Matric or Both?

Goal

- Scientific and engineering insights for mitigating frost heave damage to road pavements and associated infrastructure.

Soil Sampling Acknowledgments:
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Jeff Winkler, Project Engineer R-2915C (U.S. 221)
Jim Holloway, Head Inspector

Thank you!

CONTACT/UPDATES

muduebor@uncc.edu
bit.ly/UNCC_EWR

Quantification of Bridge Pier Scour from 3D Point Cloud Data Using Spatial Interpolation

Navanit Sri Shanmugam[1], Shenen Chen[1], Wenwu Tang[2,3], Craig Allan[2,3], John Diemer[3], Vidya Subhash Chavan[1], Tianyang Chen[2,3],Tarini Shukla[1,3], Zachery Slocum[2,3], and Matthew S. Lauffer[4]

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Introduction

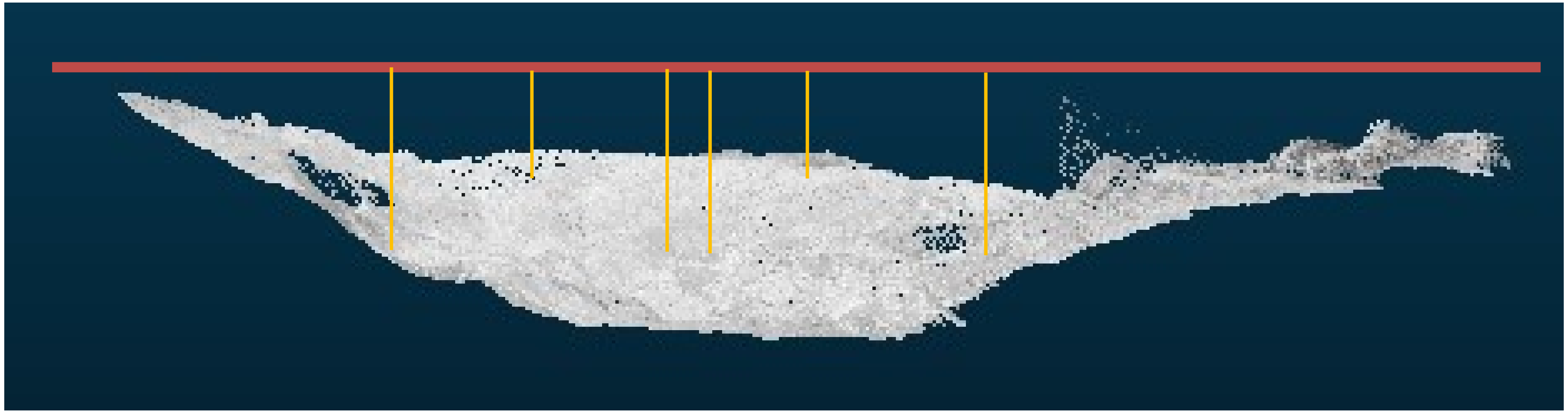
- Scour is the erosion of materials surrounding bridge foundation
- It is the leading cause for bridge collapse in the United States

- Objectives
  - To fill the data voids in a single scan 3D point cloud of a scour using spatial interpolation
  - To find the volume of soil eroded from the resulting point cloud

Data voids

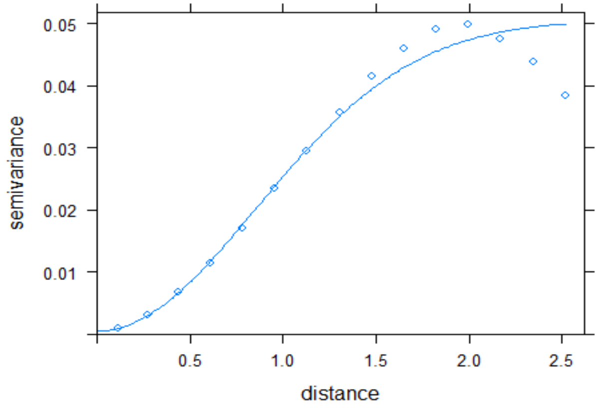
Methodology

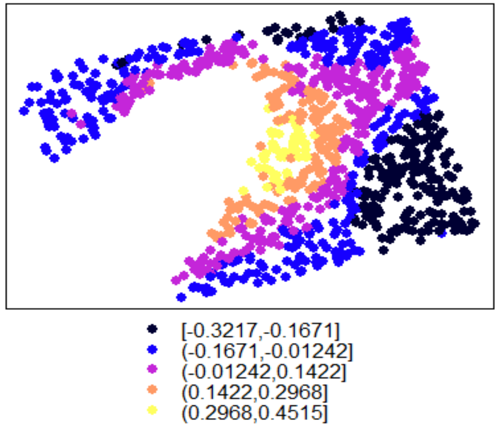
- Use LiDAR to scan scour surface (multiple scans such that no voids exist) [Device: FARO S 350]
- Segment out scour from the point cloud (single scan) [Software: CloudCompare]
- Define reference plane [Software: MATLAB]
- Calculate projections
- Calculate distances
- Remove recurring points
- Interpolate [Software: R Studio]
- Calculate volume of scour and compare with volume from stitched scour point cloud

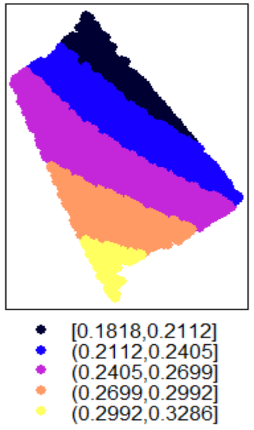


Results and Discussions

- Reference planes can be defined manually by selecting 3 points or automatically by including ground points in a different point cloud segment
- Scour data was random sampled to 1000 points
- Average interpolation error 0.02m compared to stitched point cloud
- Volume difference of 8.3%







Challenges and Future Work

- Input point cloud should contain only scour
- Dependent on reference plane
- Multiple points on a single projection line leads to loss of data
- Longer processing times as the number of points increases
- Calculate for multiple pier/scour simultaneously
- Record progression of scour over time from LiDAR scans of scour taken over months

Acknowledgements

- North Carolina Department of Transportation (NCDOT)

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Thank you!

Questions/Comments?