NORTH CAROLINA
Department of Transportation

NCDOT’s Stormwater Research Program

Andrew McDaniel, PE

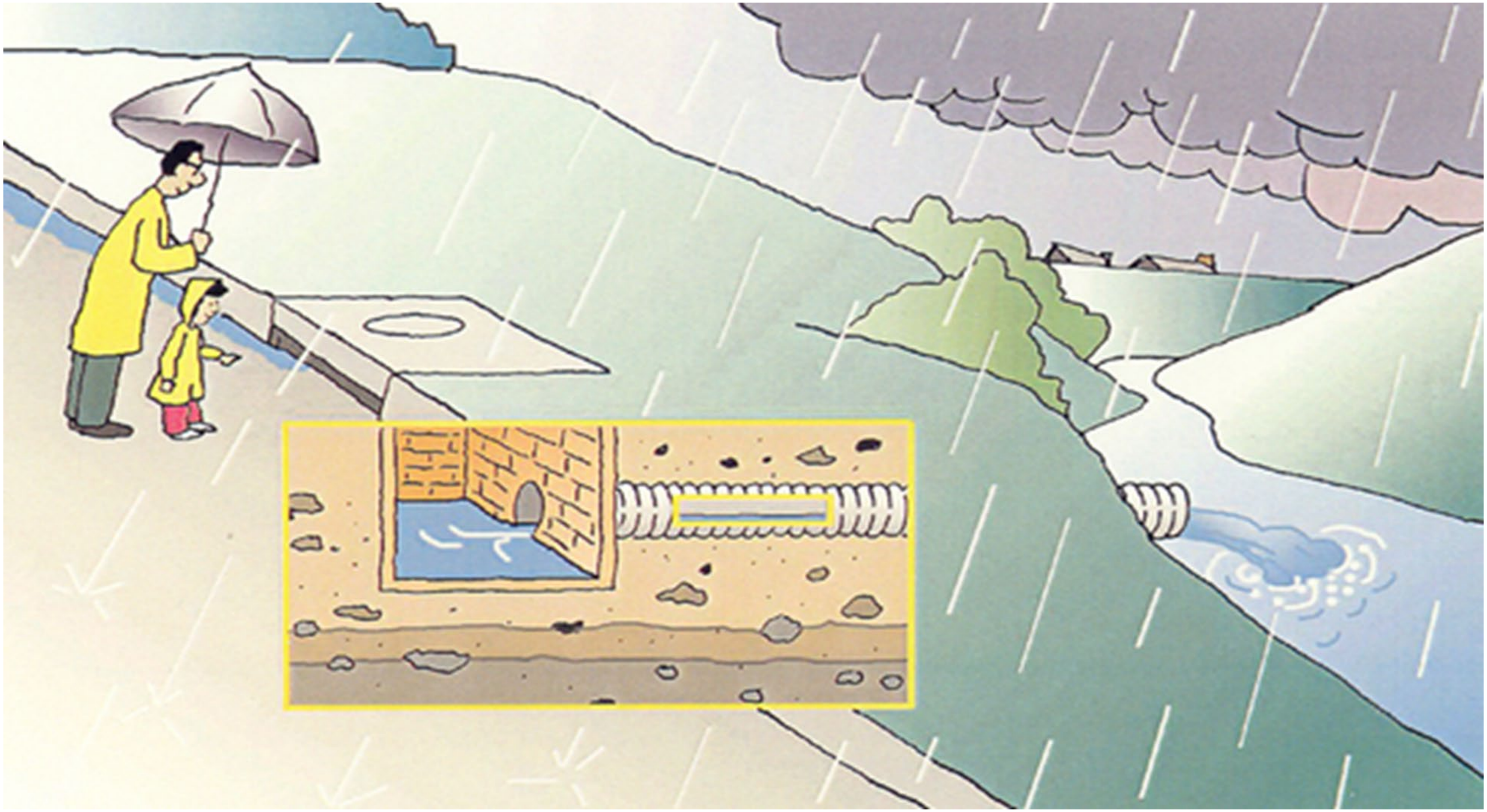
May 7, 2019

NCDOT

Highway Stormwater

PROGRAM

Stormwater Runoff



Clean Water Act Permit

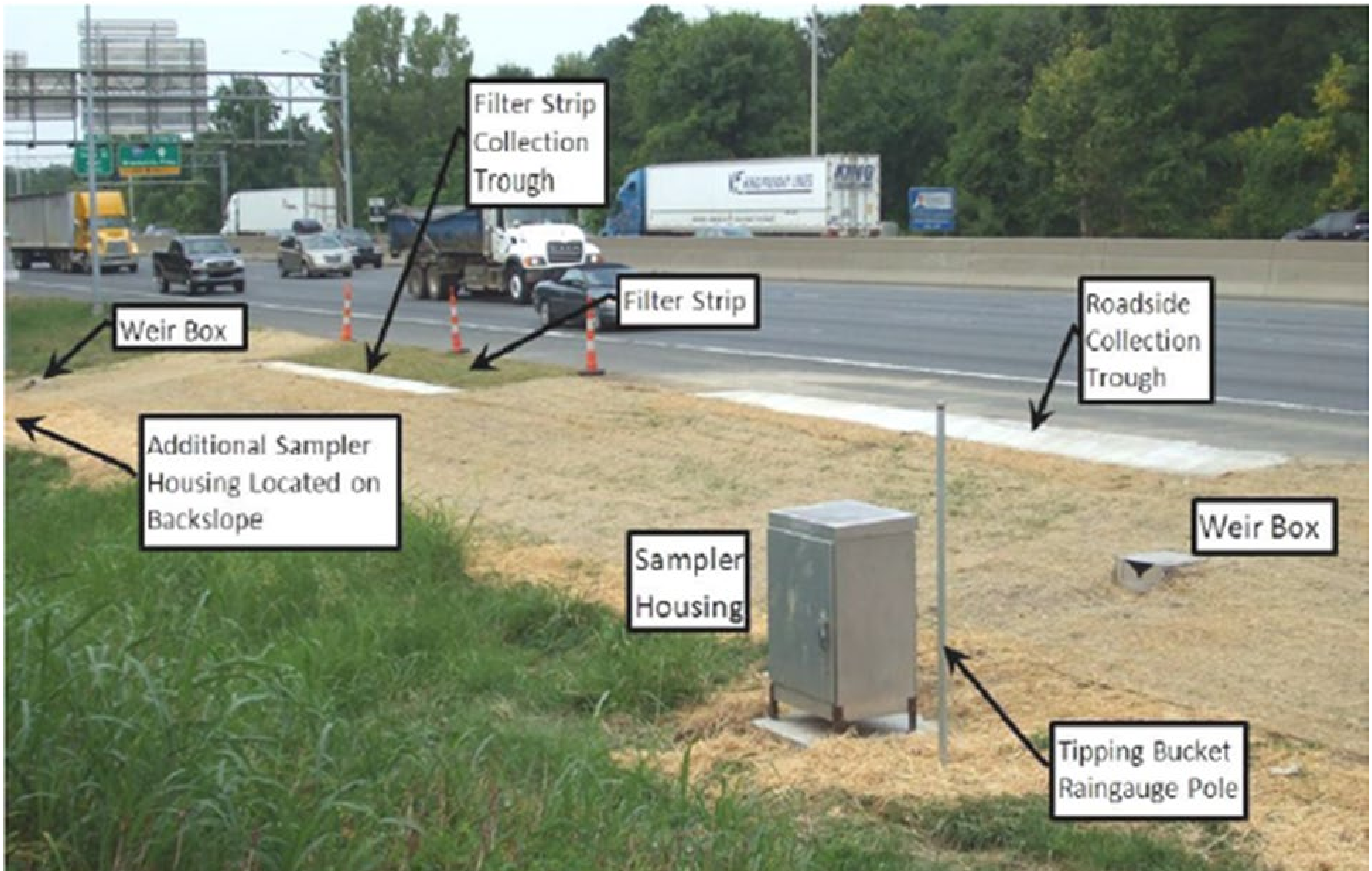
Stormwater Research Program

- Characterize Stormwater Runoff
- Evaluate Performance of BMP Designs
- Optimize BMP Designs
- Develop New BMPs
- Develop Technical Guidance

Just How Much Stormwater Research?

- Over **71** sites monitored across NC
- Over **2,751** storm events
- Over **33,579** event mean concentrations
- **162** different analytes

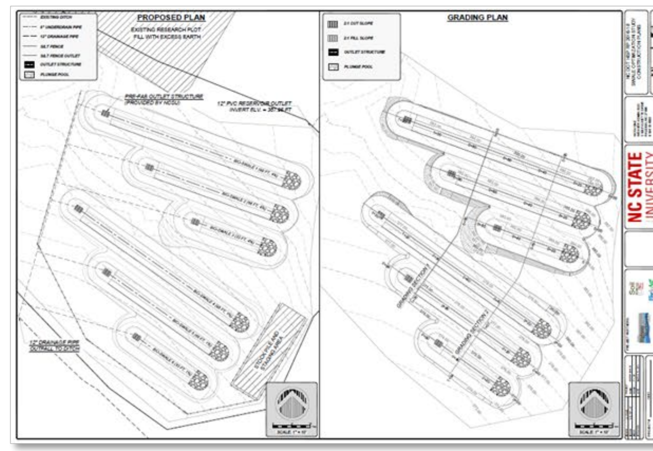
Characterizing Roadway Runoff



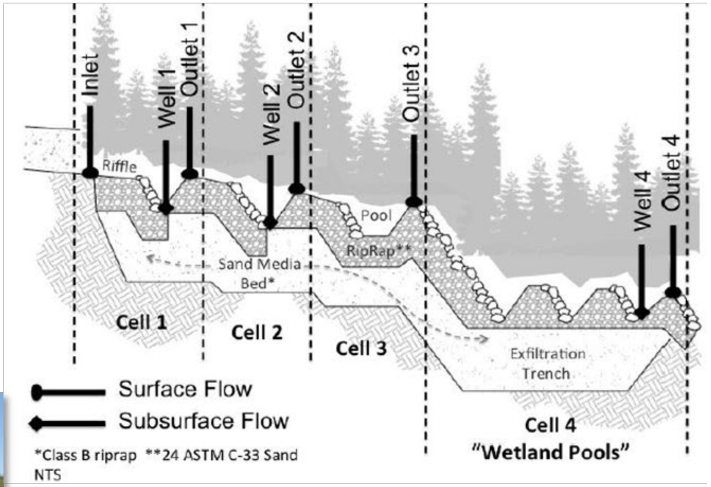
Swale Research

Minimize Bacterial Contamination

Bioswale Design Optimization



New BMPs – Biofiltration Conveyance



Undersized BMPs

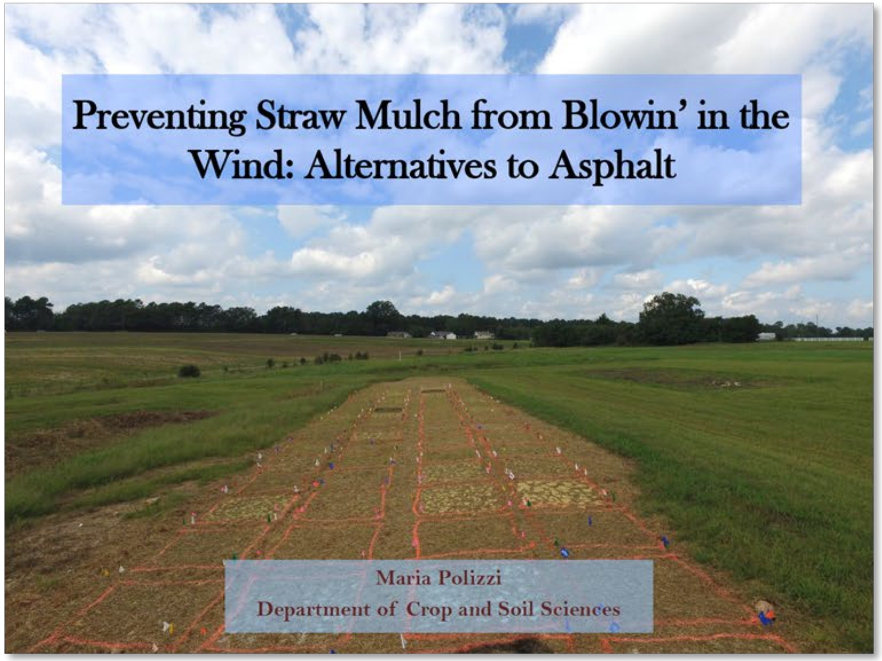
Erosion Control Research Projects

Evaluating of Flocculants: Optimizing Characteristics and Screening Methods – RP 2015-16

Comparing Low-Cost Methods for Stabilizing Diversions and Ditches – RP 2014-21

Straw Mulch Binding Agents

Performance Standards for Straw Mulch Binding Agents – RP 2015-17



Future Research Needs

How do we increase the ecological uplift of the roadway corridor?

- Integration of ecosystem services
- Entirely new types of BMPs
- Achieve triple bottom line benefits:
  - Environmental improvement
  - Societal benefits
  - Financial gains

Example: Pollinator Habitat Zones

NCDOT

Highway Stormwater

PROGRAM

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Selection, Installation, and Evaluation of Zoysiagrasses for NC Roadsides

Grady Miller, PhD

Susana Milla-Lewis, PhD

Concept

- Chemical and mechanical vegetation control on >1000 miles of median rail is time consuming and expensive.
- Reduced maintenance can translate into increased safety due to lower need for worker presence.

Project #2018-02
2017-2020

Concept

- Zoysiagrass is known to be a thick sod-producing, low-growing turfgrass that once established has minimum weed invasion.
- Limited zoysiagrass seed available.
- Zoysiagrass sod is currently most expensive grass to purchase.

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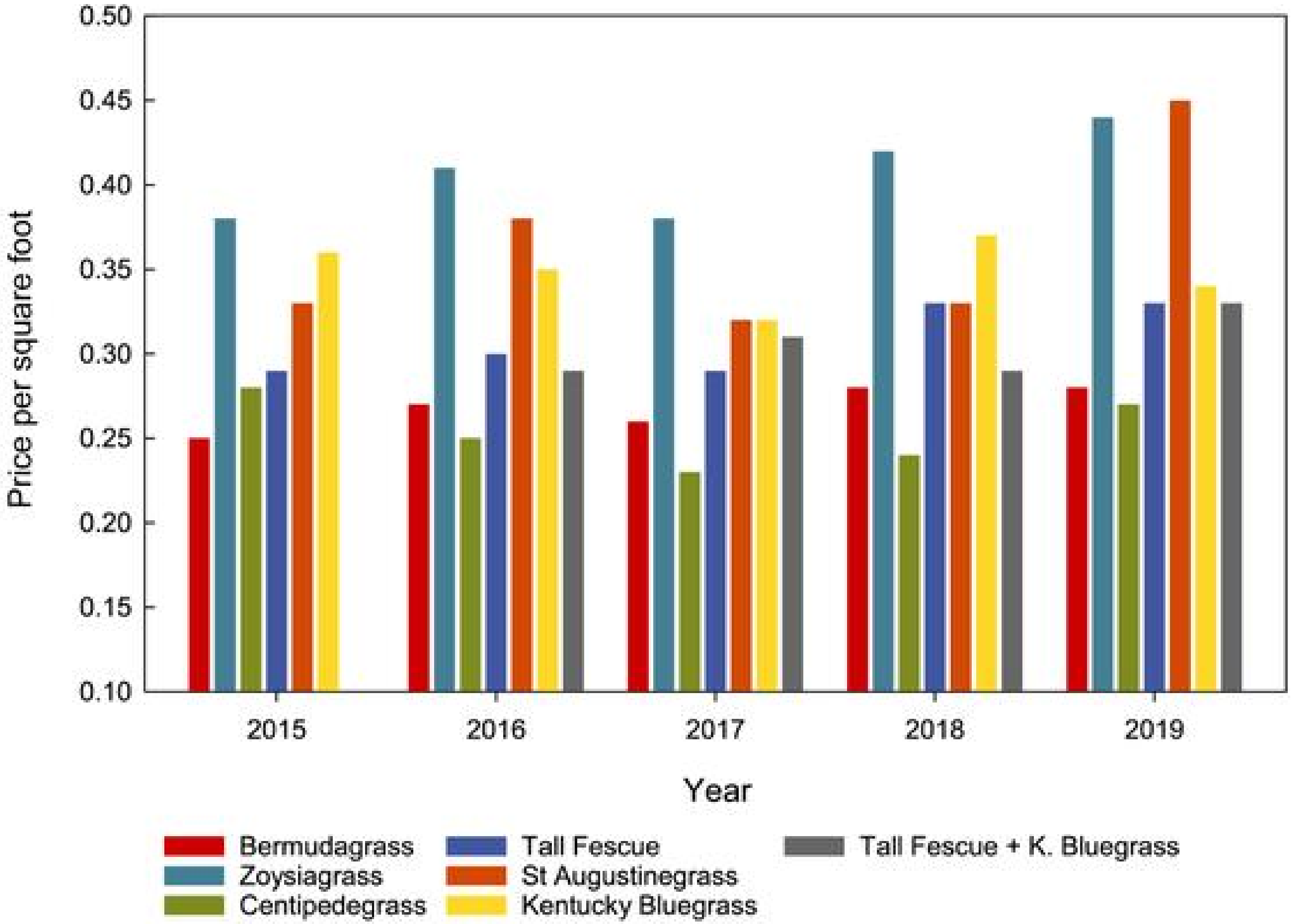
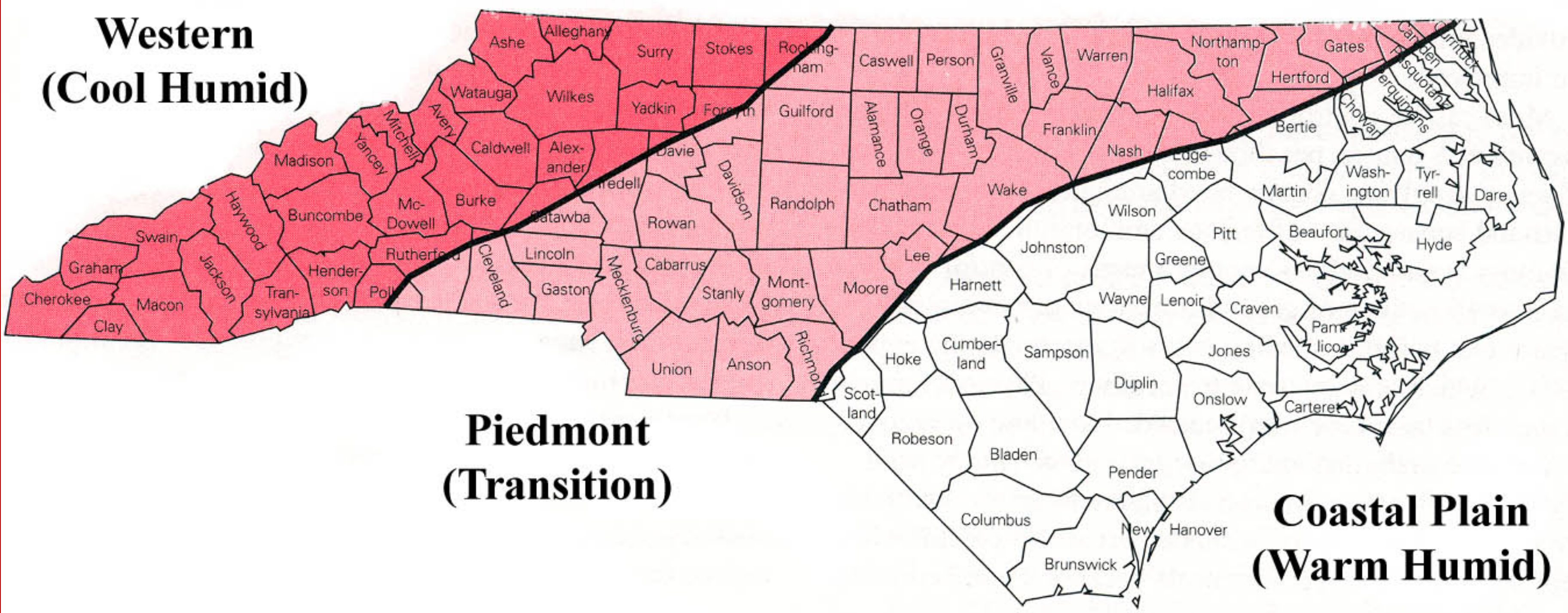


Zoysiagrasses Adapted for all of NC's Climatic Zones



Questions:

- What zoysiagrasses are available?
- Development work on new germplasm with specific characteristics desirable for roadside use?
- Large-scale planting equipment evaluation (timing factor of 2)?
- Best method and timing (factor of 6) for zoysiagrass establishment?

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Available zoysiagrass cultivars grown in nine southern states.

Grass/State	AL	MS	GA	KY	NC	SC	TN	TX	VA
Innovation*					X				
BK-7	X								
Carrizo								X	
Cavalier			X		X	X		X	
Common									
Compadre			X		X				X
Crowne					X			X	
Cutlass								X	
Diamond						X	X	X	
El Toro	X		X		X	X	X	X	
Emerald	X		X		X		X	X	
Empire	X	X	X		X	X		X	X
Geo	X		X		X	X	X	X	
Jamur	X	X	X		X	X		X	
L1F			X			X			
Leisure Time			X		X	X			
Meyer	X	X	X	X	X		X	X	X
Palisades		X	X			X	X	X	
Toccoa Green*								X	
Royal			X			X	X	X	
SoLo							X		
BA-189*								X	
Volunteer							X		
Y2 (Leisure Time)								X	
Zenith			X	X	X	X		X	
Zeon	X		X		X	X	X	X	X
Zorro		X	X		X	X	X	X	
Total Number	8	5	15	2	14	13	11	19	4

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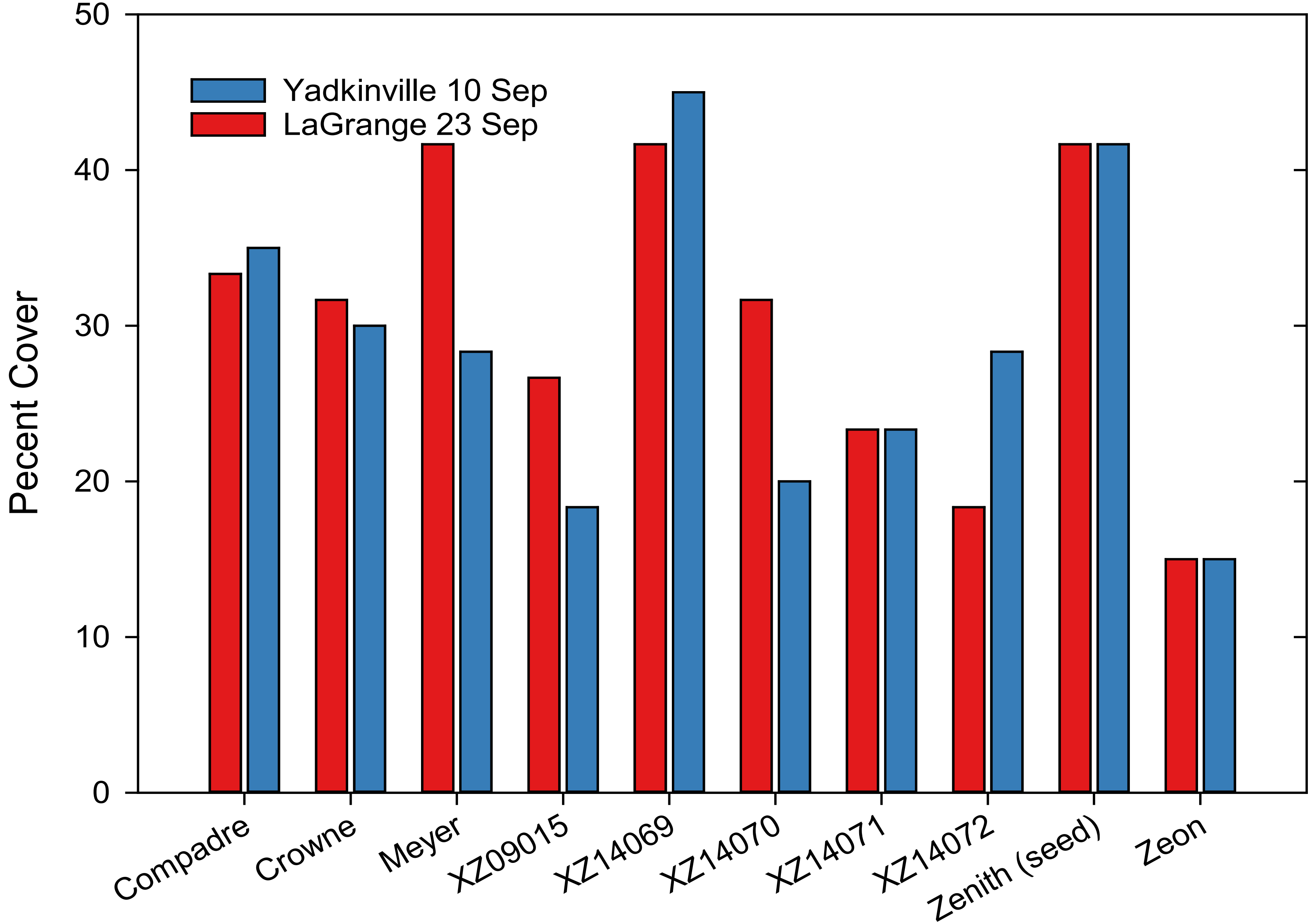
Developmental Germplasm Evaluation Preliminary Results



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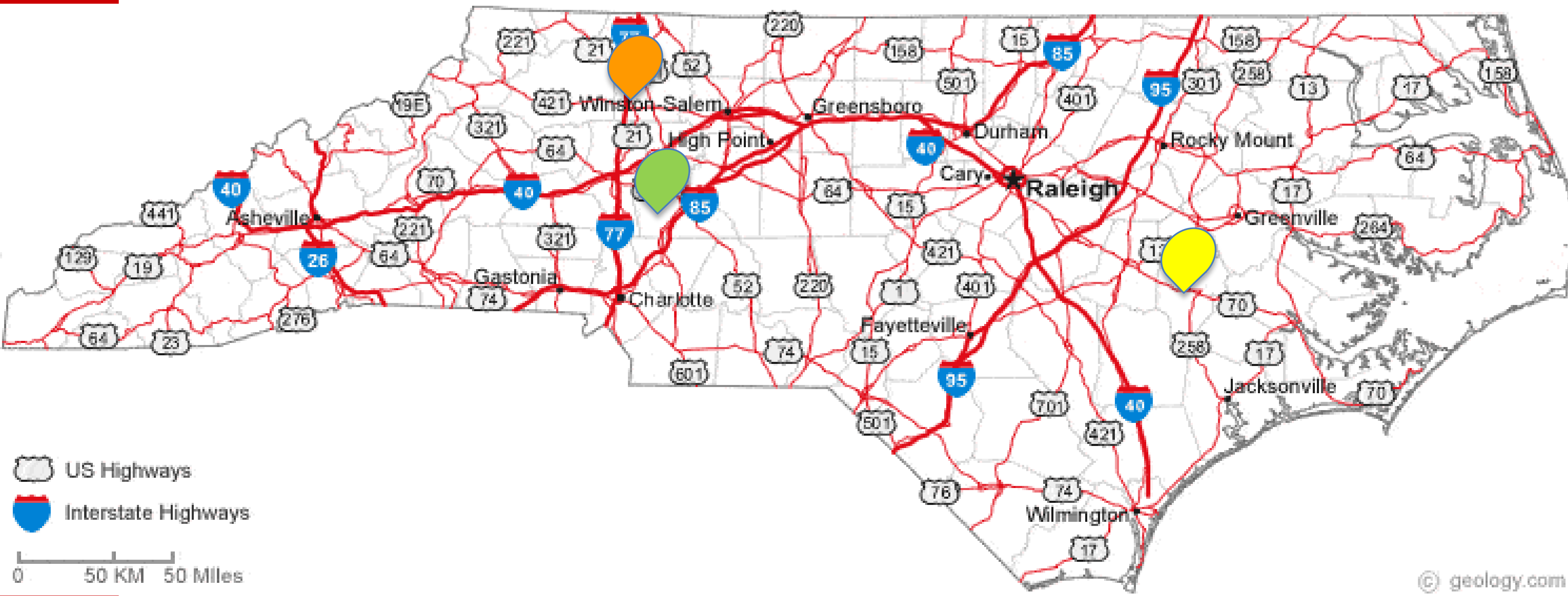

Wilkesboro (West) Site – Date/Method

Salisbury (West) Site - Equipment

LaGrange (East) Site - Date/Method & Equipment

DOT Equipment Evaluation—Goldsboro Year 2

N ^

Seed vs sprig

270 feet

Rep 1			Rep 2			Rep 3			Rep 4				
Mat	Straw	Control	Straw	Mat	Control	Straw	Control	Mat	Mat	Control	Straw	Old	Fall 2018
Control	Mat	Straw	Control	Straw	Mat	Mat	Straw	Control	Mat	Straw	Control	New, Disk	
Mat	Control	Straw	Control	Mat	Straw	Straw	Control	Mat	Control	Mat	Straw	New, No Disk	
Straw	Control	Mat	Straw	Mat	Control	Mat	Control	Straw	Mat	Control	Straw	New, Disk	Spring 2019
Mat	Control	Straw	Control	Straw	Mat	Mat	Control	Straw	Mat	Straw	Control	New, No Disk	
Control	Straw	Mat	Mat	Straw	Control	Control	Mat	Straw	Straw	Mat	Control	Old	

Seed vs sprig

Highway 70


STRICKLAND
BROS.
DANGER


SPRIG-EASE 150


FINN

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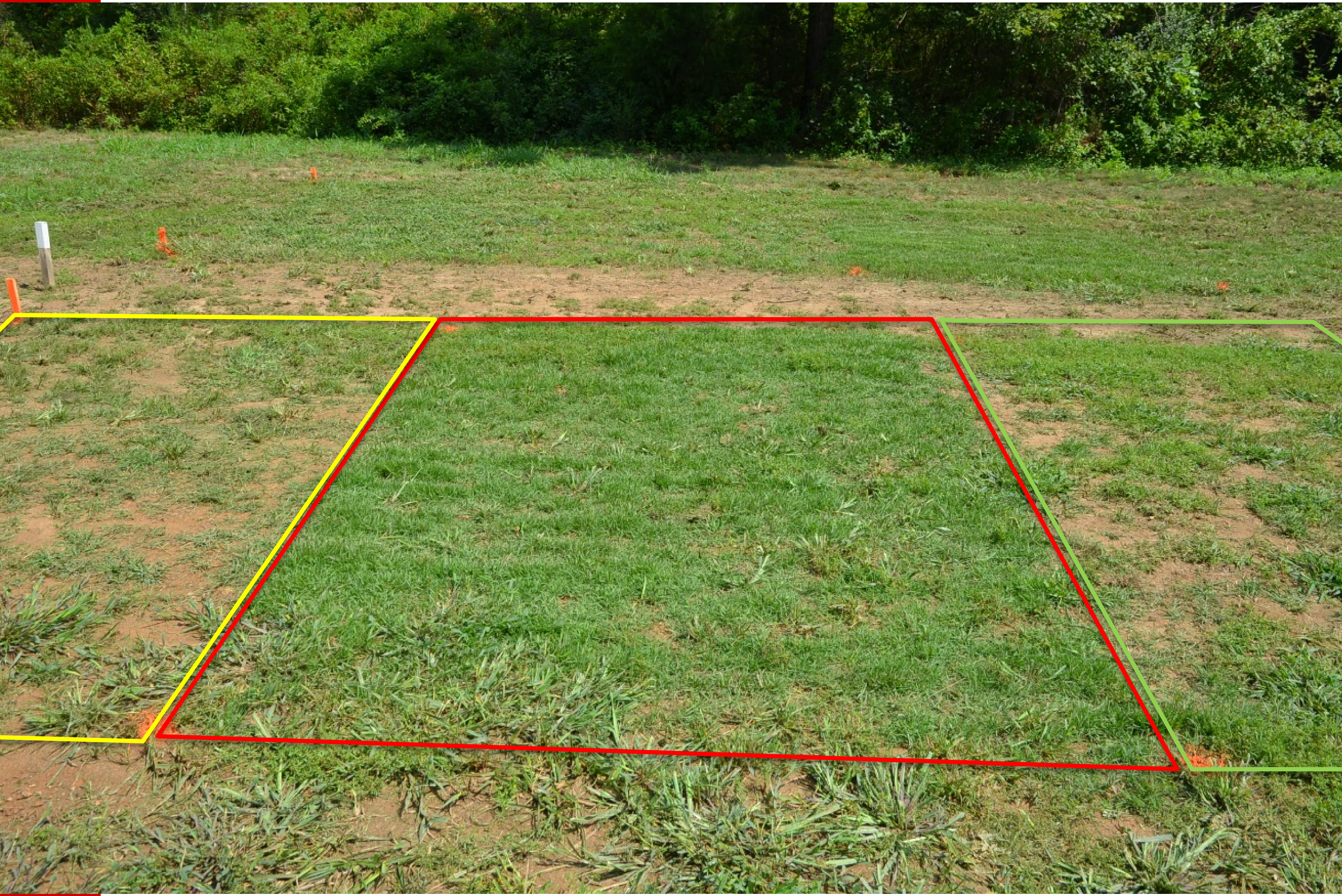
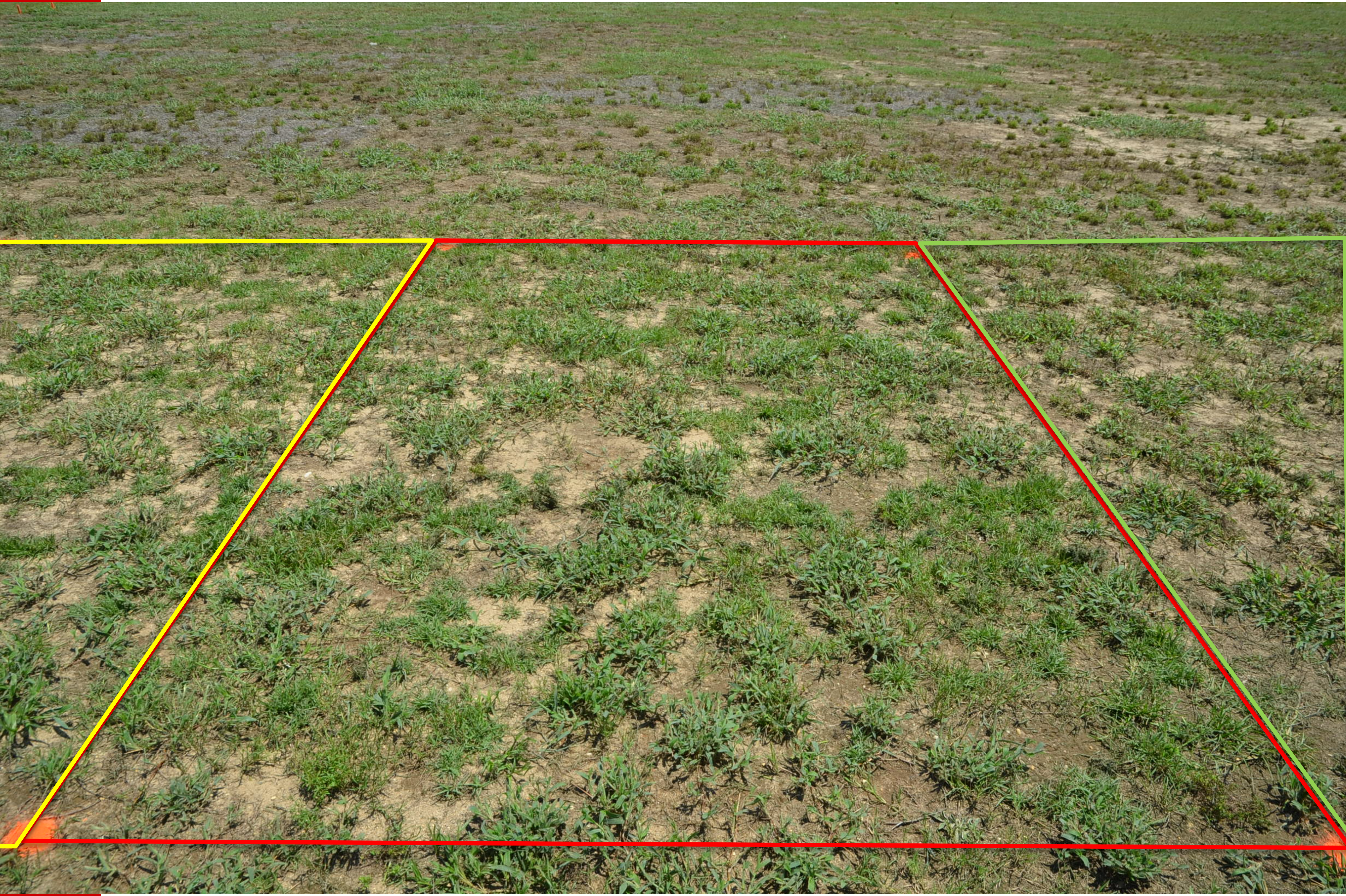
UNIVERSITY

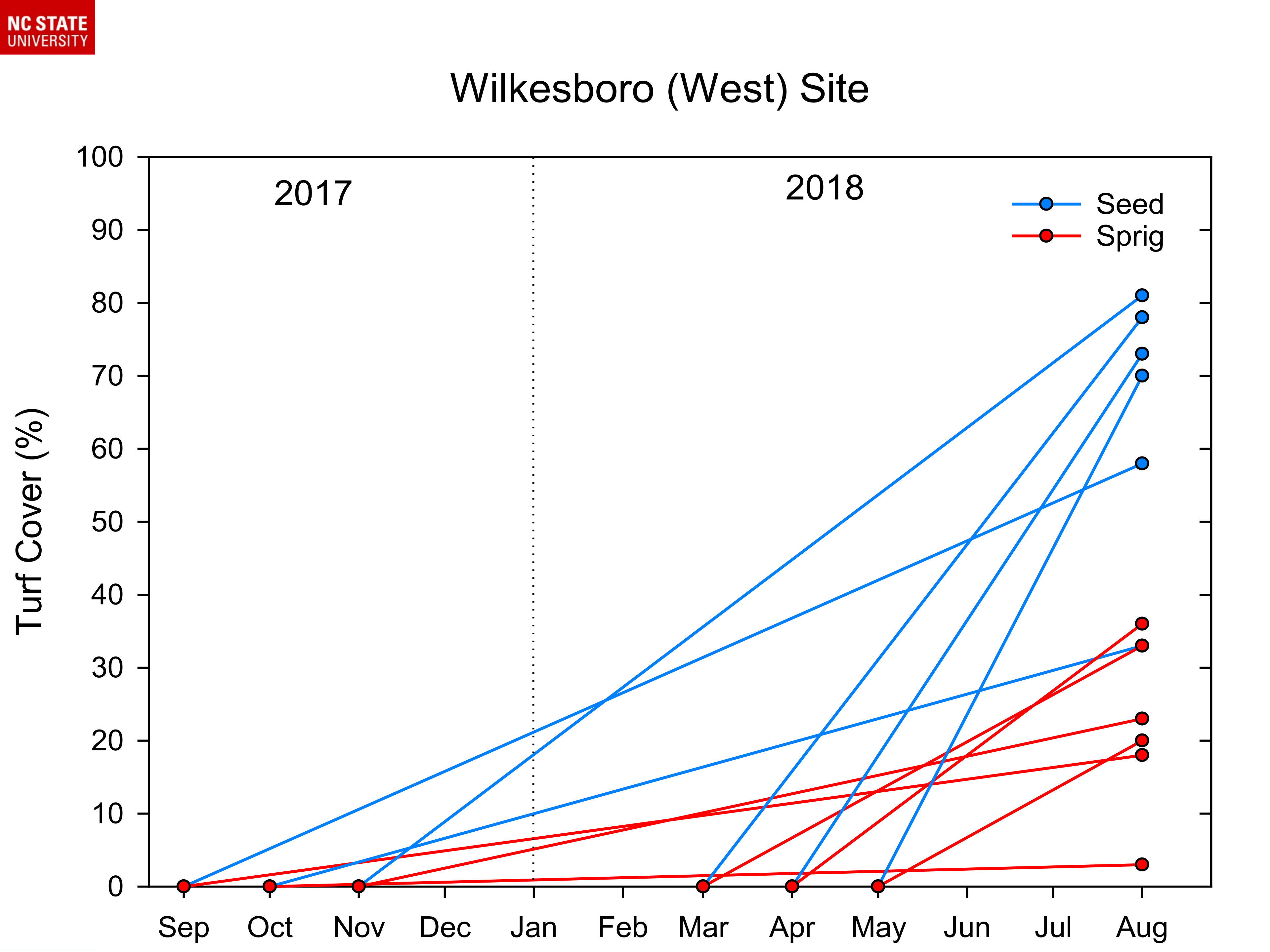
Method & Timing Study

Seed vs Sprigs

3 spring, 3 fall plantings



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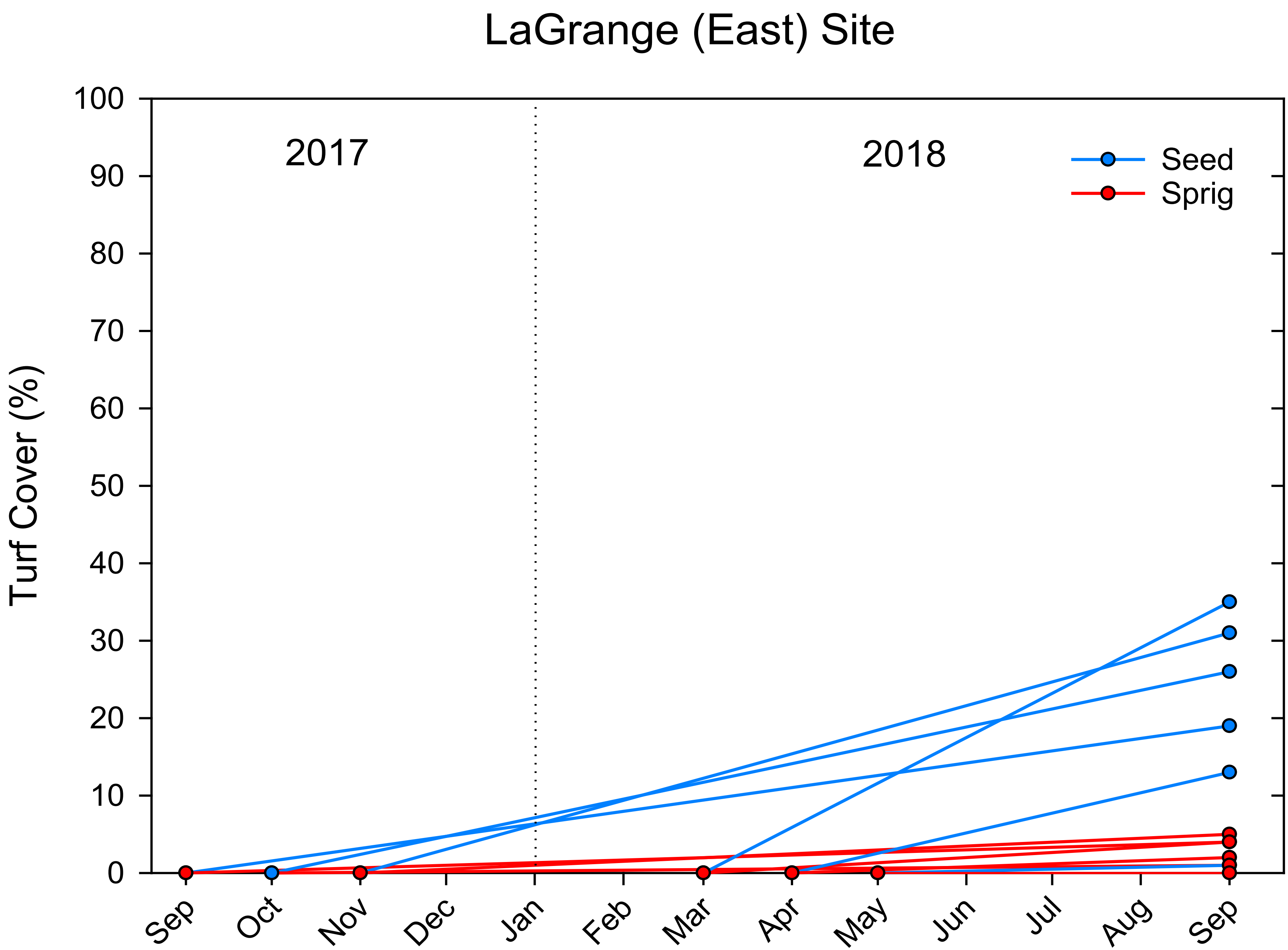
Wilkesboro (West) Site
2017
2018
Seed
Sprig
Turf Cover (%)
0
10
20
30
40
50
60
70
80
90
100
Sep
Oct
Nov
Dec
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug


LaGrange (East) Site
Turf Cover (%)
100
90
80
70
60
50
40
30
20
10
0
2017
2018
Seed
Sprig
Sep
Oct
Nov
Dec
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep

Preliminary Conclusions

- Zoysiagrass may be an alternative roadside vegetation
- Planting will continue to be a challenge – soil conditions and water availability
- Seeding may be the best route for roadside establishment (economically)
- New germplasm may reduce the challenges
- Fall versus spring establishment may not provide an advantage (or significant disadvantage).

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T H A N K S

<u>NC-DOT</u>

Derek Smith

Kevin Clemmer

Rick Seagroves

Robert Simpson

<u>NCSU Technical Work</u>

Drew Pinnix

Ben Gragg

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DeepHyd: A Deep Learning-based Artificial Intelligence Approach for the Automated Classification of Hydraulic Structures from LiDAR and Sonar Data

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NC Department of Transportation

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NCDOT Research & Innovation Summit

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  - 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 <u>"DeepHyd: A Deep Learning-based Artificial Intelligence Approach for the Automated Classification of Hydraulic Structures from LiDAR and Sonar Data"</u>
  - PIs: Drs. Wenwu Tang, Shenen Chen, John Diemer, Craig Allan from the University of North Carolina at Charlotte

Introduction

- Point cloud data, collected through Geiger and terrestrial LiDAR and bathymetric sonar technologies, provide rich information in terms of hydraulic structures and associated site conditions (Chen 2012; Prendergast and Gavin 2014; Bisio 2017).

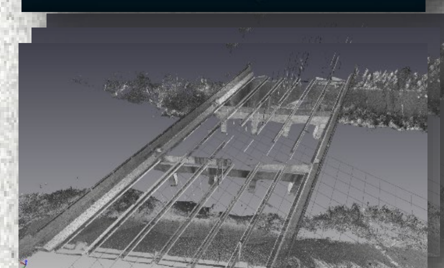
LiDAR 2D image of a bridge

LiDAR 3D scan from the same bridge

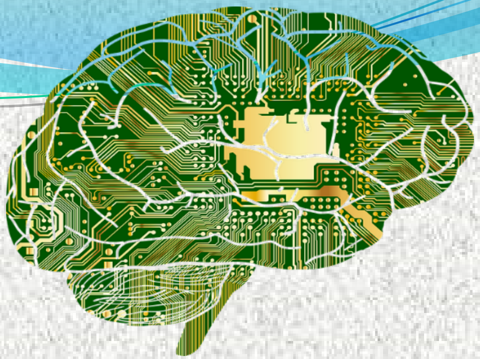
The bridge is located in Gaston County, NC

Current Issues

- However, **the efficient processing and classification** of point cloud data and their classification to generate **3D hydraulic features** of interest represent a grand challenge because
  - The volume of the point cloud data involved is often huge (a **big data analytics challenge**; see Tang and Feng 2017),
  - Hydraulic features of interest are often **complicated** in terms of their shape and the occurrence of temporal site and structural changes (see Chen 2012; Watson, Chen et al. 2011).



Proposed Solutions



- Potential Solutions: Deep Learning!!!
  - Combine unsupervised and supervised learning for a hierarchical representation of features of interest (Erhan et al. 2010; LeCun et al. 2015)
    - **Outperform** conventional machine learning algorithms (see Zheng, Tang, and Zhao, 2019)
    - Ideal for **feature detection and classification** (Yu et al. 2015)

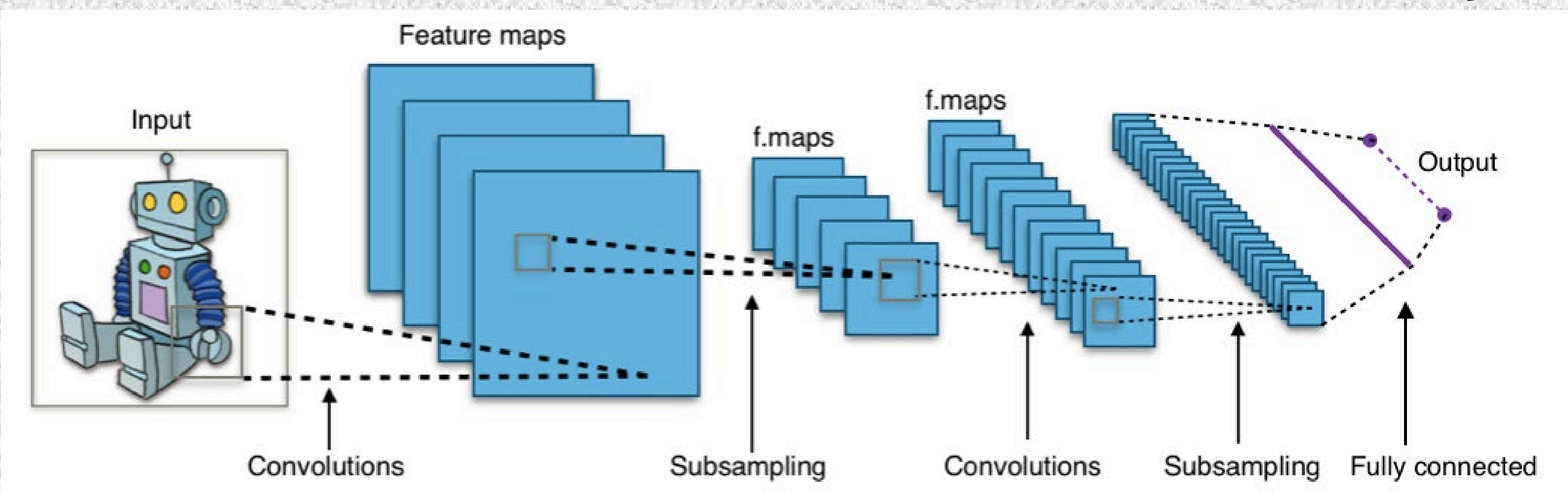


Image source: https://upload.wikimedia.org/wikipedia/commons/8/81/Deep_learning.png
https://en.wikipedia.org/wiki/File:Typical_cnn.png

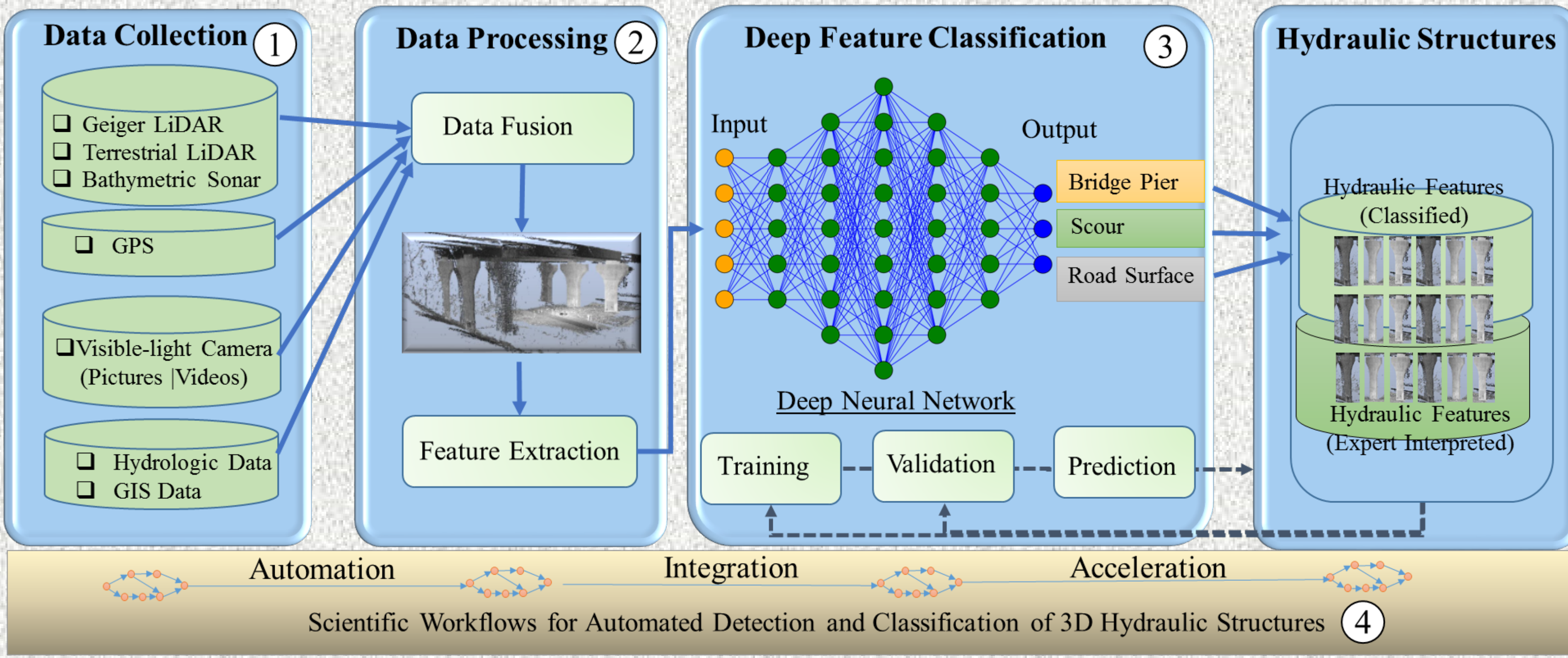
Proposed Solutions contd:

- Potential Solutions: Deep Learning!!!
  - Increasing applications for operations of **unmanned systems:**
    - **Autonomous vehicles (self-driving cars)**
    - **Unmanned aerial systems (e.g., drones)**

Image source: https://commons.wikimedia.org/wiki/File:Google_self-driving_car_in_Mountain_View.jpg
https://c.pxhere.com/images/7a/8f/3f18ae11e4cecc35044c840bca70-1446051.jpg!d

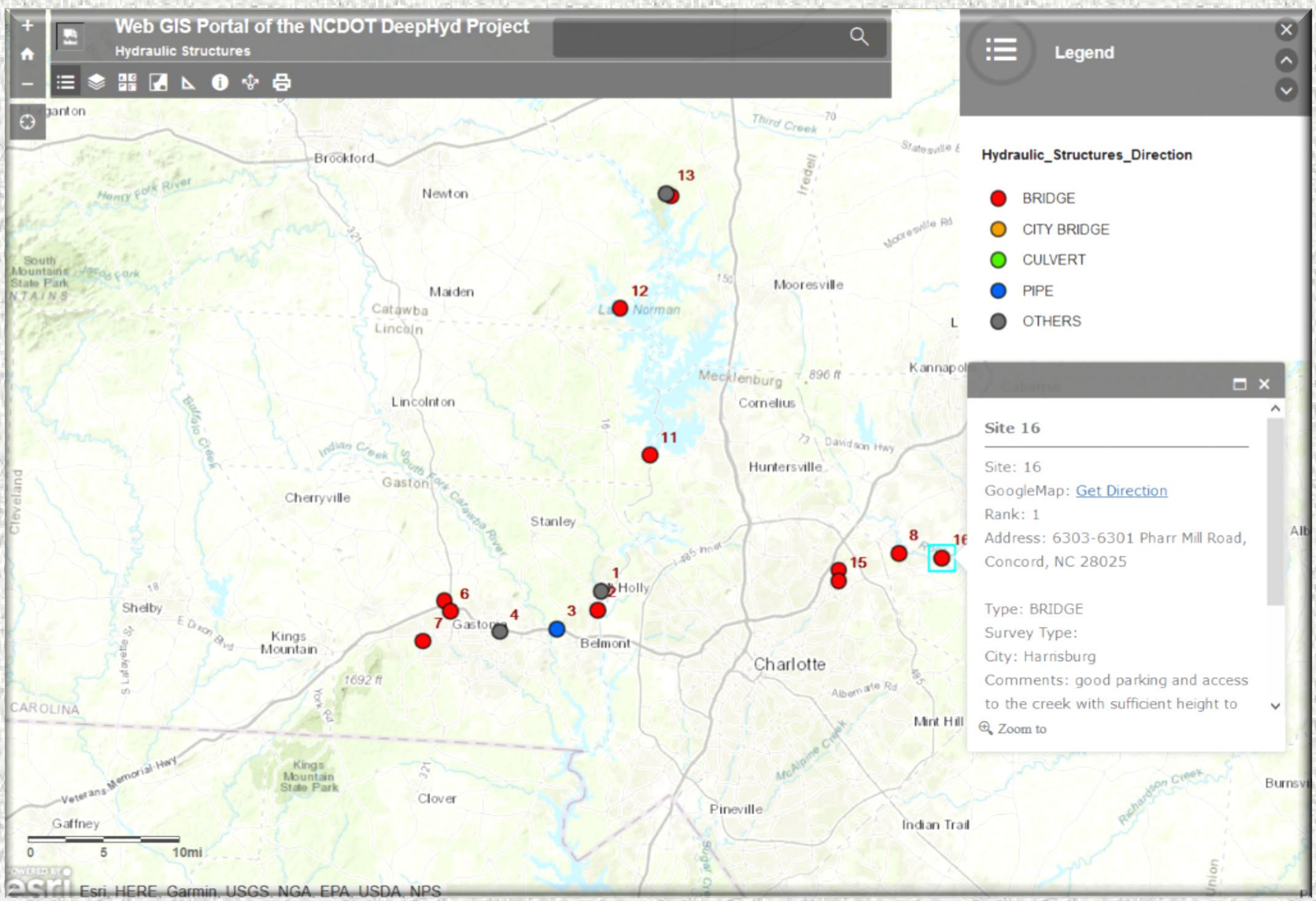
Framework

- We have been developing **DeepHyd**, a novel spatially explicit 3D modeling framework and software package that are based on **deep learning** as a cutting-edge artificial intelligence approach for <u>automated and reliable classification of hydraulic structures from point cloud data</u>.



Field Data Collection

- Web GIS-based interface that guides fieldwork design



- Web 2.0 design
- Wordpress web interface
- ESRI ArcGIS Online for geospatial data management and mapping

https://cybergis.uncc.edu/deephyd/

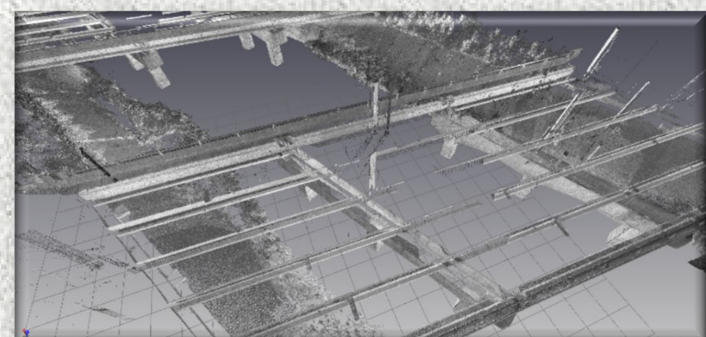
Field Data Collection

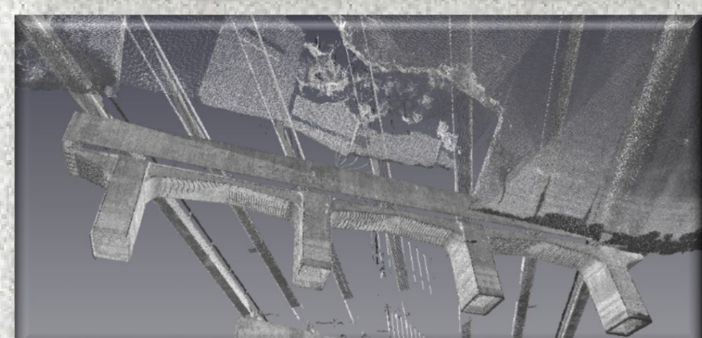
- **Terrestrial LiDAR data and intensity images** of hydraulic structures for sites (including bridges, culverts, and pipes)
  - FARO Focus S 350
- **Bathymetric sonar data** for at least one of those sites using an unmanned NC DOT bathymetric surveying boat
- Use **UAS (drone) technologies** to collect geotagged pictures and videos of the hydraulic structures
  - DJI Phantom 4 Pro V2.0
- Collect topographic info via **GPS and total station** to field truth the LiDAR and sonar results

Image and information source: https://www.dji.com/phantom-4-pro
https://www.kwipped.com/rentals/product/topcon-gts220-total-station/1535
https://www.faro.com/en-gb/products/construction-bim-cim/faro-focus/

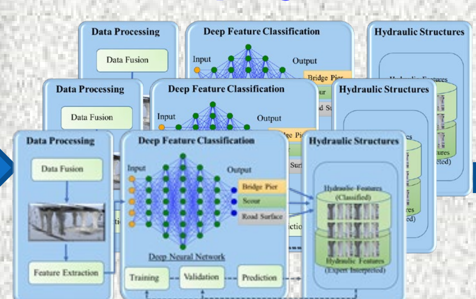
Deep Learning for 3D Point Cloud Classification

- A **deep learning-based artificial intelligence approach** for the classification of the extracted features into hydraulic structures of interest

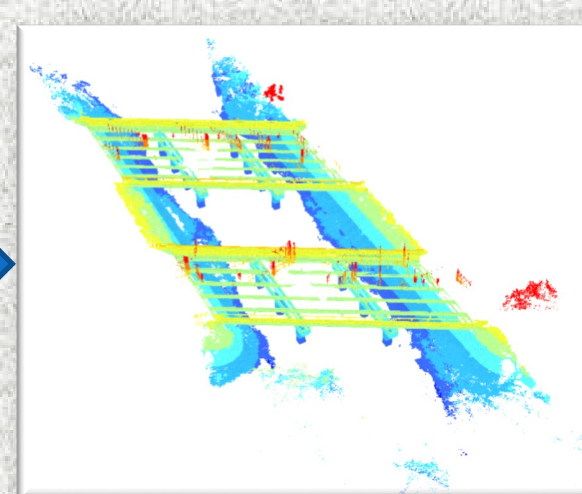




DeepHyd

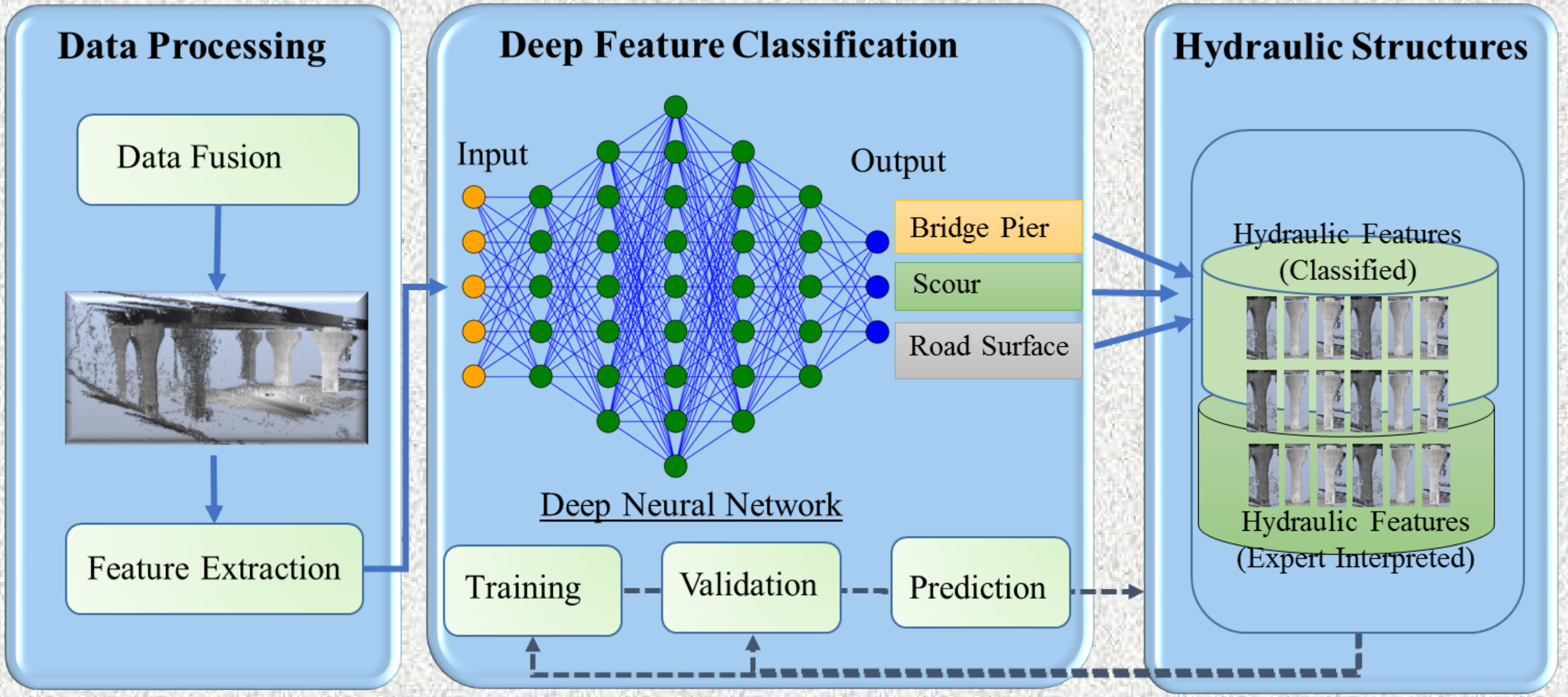


3D Object Detection
3D Object Classification



Deep Learning for 3D Point Cloud Classification

- Combine, and compare with, expert knowledge from fieldwork for training and testing of deep learning classifiers

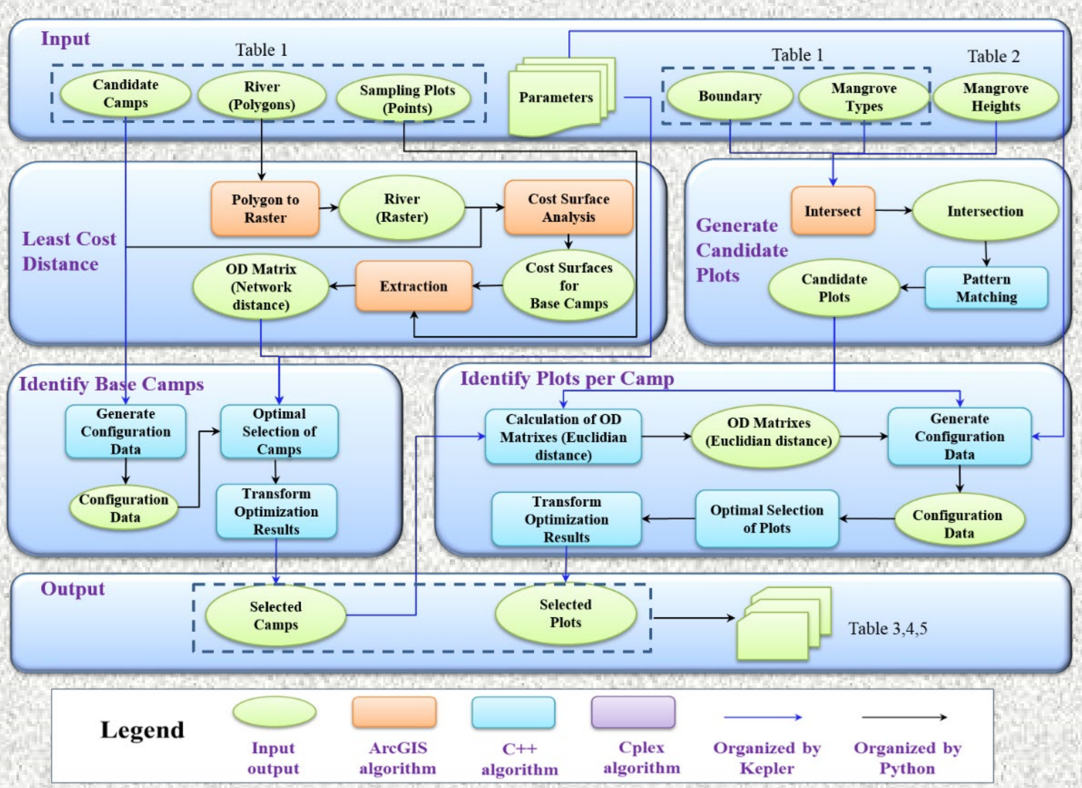


Model Automation-Integration-Acceleration

- Use the **GIS-based scientific workflows to automate** 1) the classification task, and 2) the management, pre/post-processing, and 3D visual analytics of point clouds and related data
  - Geospatial analysis and modeling steps often need to be **repeated** (for training and testing of the deep learning classifiers) and **reused** by different users
  - **A number of** analysis/modeling steps are often involved and need to be **coupled** in this project

Model Automation-Integration-Acceleration

- **GIS-based scientific workflows automate 1)** the classification task, and 2) the management, pre/post-processing, and 3D visual analytics of related data



(Figure Source: Tang et al. 2017)

- ***Model Automation!***
- ***Model Integration!***
- ***Model Acceleration!***

- Solutions:
  - Kepler workflow management system (https://kepler-project.org/)
  - Python
  - Jupyter Notebook
  - **Open-source!**

Model Acceleration

- Leveraging **high-performance computing (HPC) capabilities** to resolve the big data-driven computational challenge of geospatial analysis and modeling in this project
  - **Parallel geocomputational algorithms** that deploy the processing, analysis, or modeling steps to HPC resources at Center for Applied GIScience (CAGIS) at UNC Charlotte.
    - **Sapphire**: 288-CPU Windows cluster for advanced geocomputation!
    - Graphics Processing Units (GPUs)

Image source: https://i0.wp.com/hanusoftware.com/wp-content/uploads/event_218867862.png?w=360&ssl=1

Preliminary Results

Field Data Collection

- Use **UAS (drone) technologies** to collect geotagged pictures and videos of the hydraulic structures
    - Ongoing (testing and validation)

<u>Sample Snapshots</u>

Location: UNC Charlotte

Field Data Collection

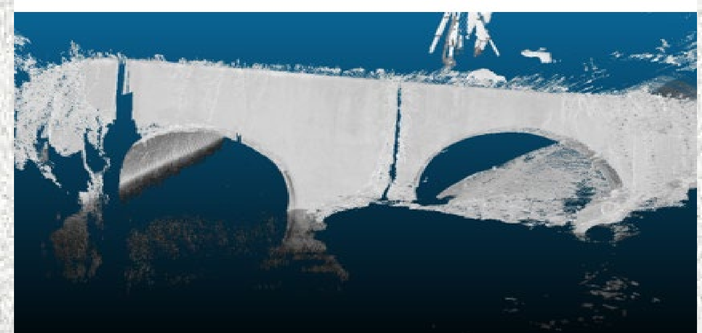
- **LiDAR Point Cloud**

2D Image | 3D Point Cloud

Site #8

Site #7

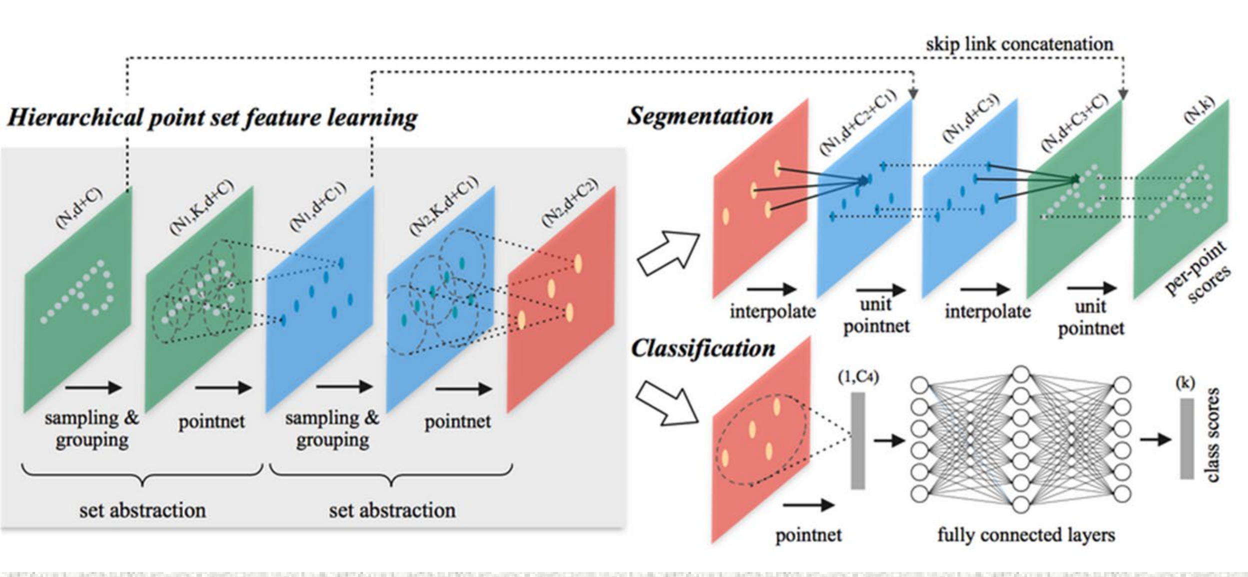
Site #3



https://cybergis.uncc.edu/deephyd/ for bridge number

Deep Learning for 3D Point Cloud Classification

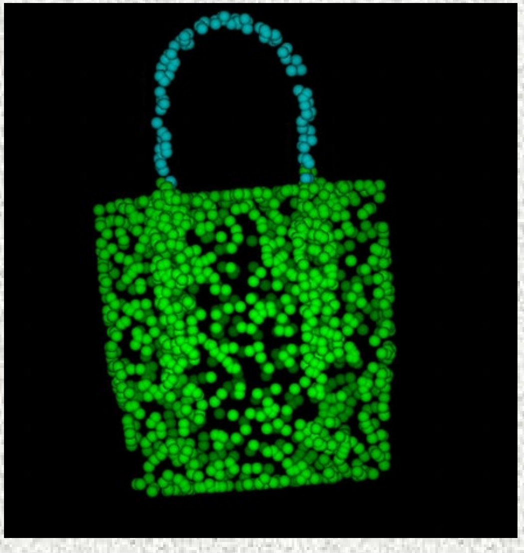
- **Hardware**
  - **CUDA-enabled GPU**
    - **Nvidia Tesla K40 (2,880 cores)**
- **Software**
  - **Point Net++**: A state of the art point cloud semantic segmentation method
  - **TensorFlow** for deep learning
  - **CUDA 9.0** enabling GPU computing
  - **Docker** (Container as services)

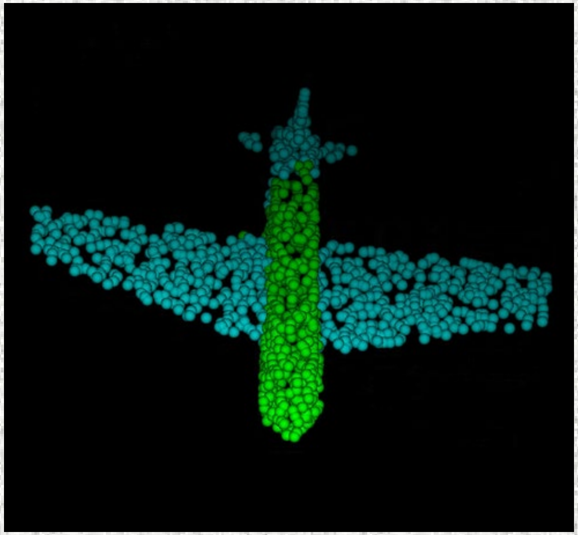


PointNet++ and image source: http://stanford.edu/~rqi/pointnet2/
TensorFlow: https://www.tensorflow.org/
CUDA 9.0: https://developer.nvidia.com/about-cuda
CUDA: Compute Unified Device Architecture
GPU: Graphics Processing Units

Deep Learning Classification of Point Cloud Data

- A test run has been completed on the Shapenet demo data
  - 16 category, more than 10 thousand models
  - 30 epochs in need of 3 hours on Tesla K40 GPU (2,880 cores)



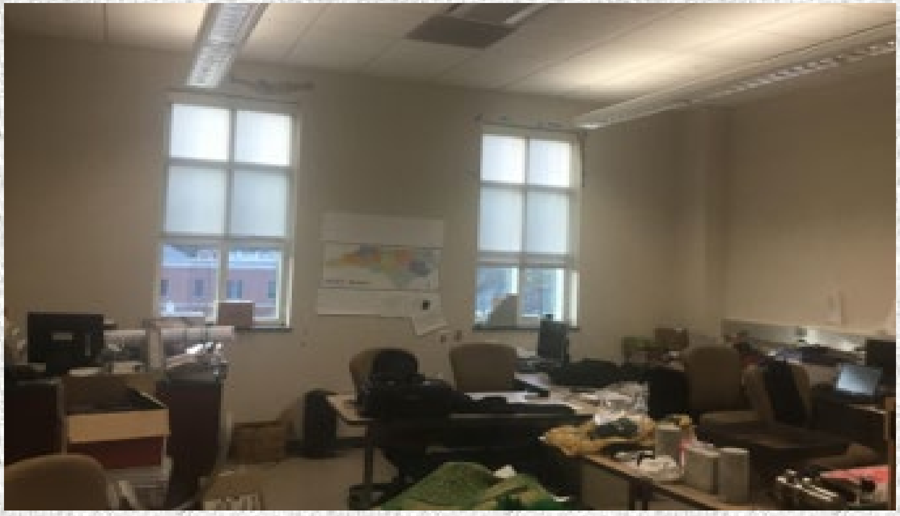


Examples of learned results by the deep learning algorithm

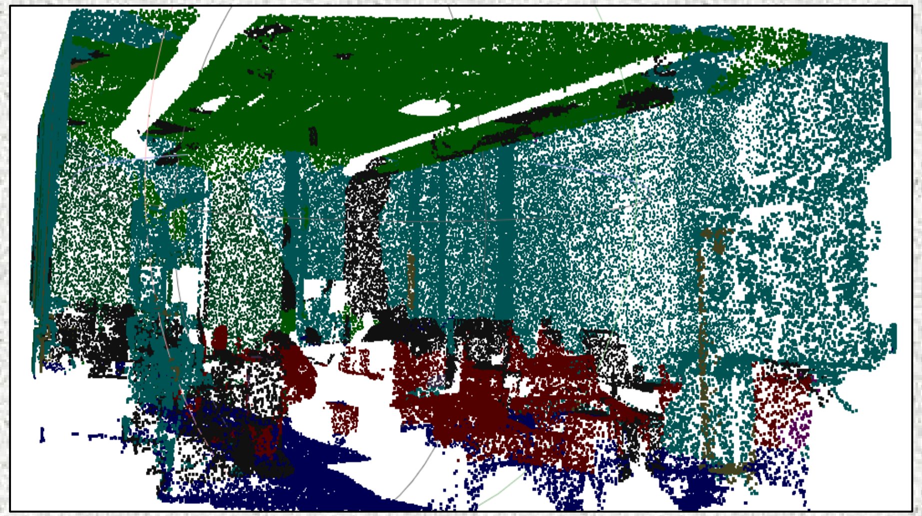
Shapenet: https://www.shapenet.org/

Deep Learning Classification of Point Cloud Data

- Test run:
  - 261 indoor scenes with 70 million points
  - 13 types of objects (chair, wall, and floor etc.)
  - 10 hours for 60 epochs



2D image of an office at UNC Charlotte

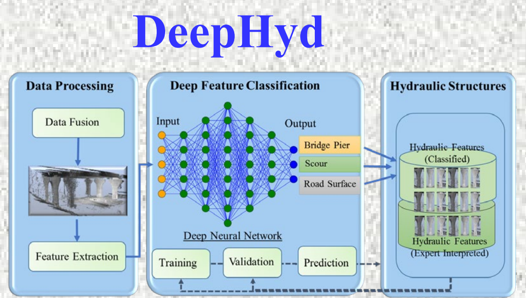


Classified LiDAR point cloud data using deep learning

- Specific bridge-related point cloud data need to be made (labelled) for training (ongoing)
- Further develop and fine tune the deep learning algorithm

Anticipated Research Products

- A **novel deep learning-based model, DeepHyd, for the automated and intelligent classification of hydraulic structures** from point cloud data collected by LiDAR and sonar technologies.
- An **open-source software package** that implements the proposed deep learning-based classification model.
- A **well-trained classifier** based on cutting-edge deep neural network technologies specifically engineered for the identification of hydraulic structures for NCDOT.
- **A database of hydraulic structures** identified by the deep learning model or domain experts for re-use.
- Tutorials and manuals of the proposed model and software tool for training users of interest.



Preliminary Conclusions

- The DeepHyd framework and associated software package, leveraging cutting-edge **deep learning** technologies, provides solid support for the **automated and efficient classification of 3D hydraulic structures** from point cloud data.
- The DeepHyd framework holds great promise in terms of **applicability of detecting other (3D) geospatial features**.
- This DeepHyd products will significantly aid the mission of the NCDOT Hydraulics Unit with respect to:
  - Development of **guidelines for data collection for roadway drainage studies**
  - **Waterway hydraulic calculations and design** based on NCDOT standards
- The established procedures and systems can **further enhance data sharing** between NCDOT and other stakeholders such as
  - USGS and the Department of Environmental Protection (DEP) to **prevent environmental degradation**,
  - Department of Public Safety for **the asset management and evaluation of hydraulic structures** (e.g. bridges, or road surfaces).

References

- **Chen, S.E.** (2012). Laser Scanning Technology for Bridge Monitoring, *Laser Scanner Technology*, InTech Pub., ISBN 979-953-307-265-3.
- Erhan, D., Bengio, Y., Courville, A., Manzagol, P.A., Vincent, P. and Bengio, S., 2010. Why does unsupervised pre-training help deep learning?. *Journal of Machine Learning Research*, *11*(Feb), 625-660.
- LeCun, Y., Bengio, Y. and Hinton, G., 2015. Deep learning. *Nature*, *521*(7553), 436-444.
- Prendergast, L.J. and Gavin, K., 2014. A review of bridge scour monitoring techniques. *Journal of Rock Mechanics and Geotechnical Engineering*, *6*(2), 138-149.
- **Tang, W.** and Feng, W., 2017. Parallel map projection of vector-based big spatial data: Coupling cloud computing with graphics processing units. *Computers, Environment and Urban Systems*, *61*, 187-197.
- **Tang, W.**, Feng, W., Jia, M., Shi, J., Zuo, H., Stringer, C.E. and Trettin, C.C., 2017. A cyber-enabled spatial decision support system to inventory Mangroves in Mozambique: coupling scientific workflows and cloud computing. *International Journal of Geographical Information Science*, *31*(5), pp.907-938.
- Watson, C., **Chen, S.E.**, Bian, H. and Hauser, E., 2011. LiDAR scan for blasting impact evaluation on a culvert structure. *Journal of Performance of Constructed Facilities*, *27*(4), 460-467.
- Yu, Y., Li, J., Guan, H., Jia, F. and Wang, C., 2015. Learning hierarchical features for automated extraction of road markings from 3-D mobile LiDAR point clouds. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *8*(2), 709-726.
- Zheng, M., **Tang, W.**, and Zhao, X., 2019, Hyperparameter optimization of neuralnet work-driven spatial models accelerated using cyber-enabled high-performance computing, *International Journal of Geographical Information Science*. 33(2): 314-345

Thank you!
Questions?

https://gis.uncc.edu