NORTH CAROLINA
Department of Transportation

Research & Innovation Summit - 2020

Characterizing changing extreme rainfall for a more resilient transportation system within North Carolina

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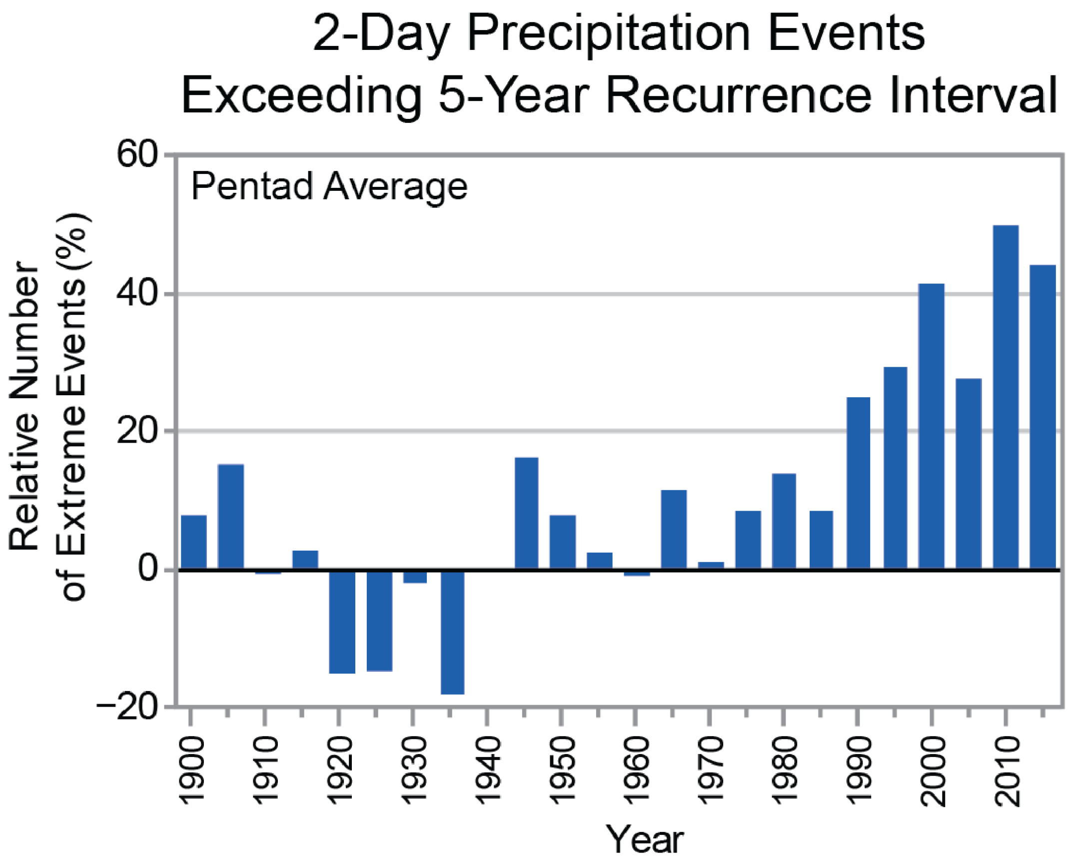
October 13, 2020

Historical Trends in Extreme Precipitation



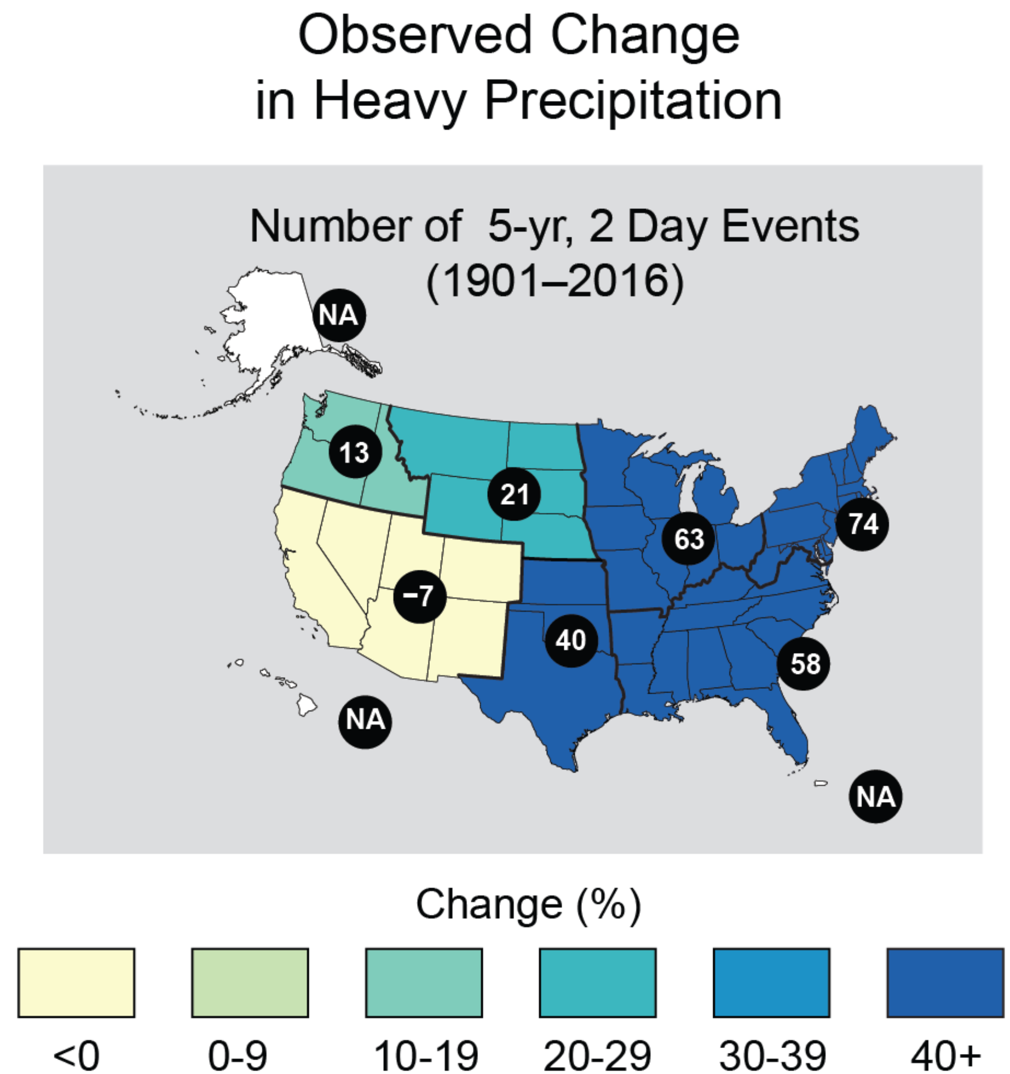
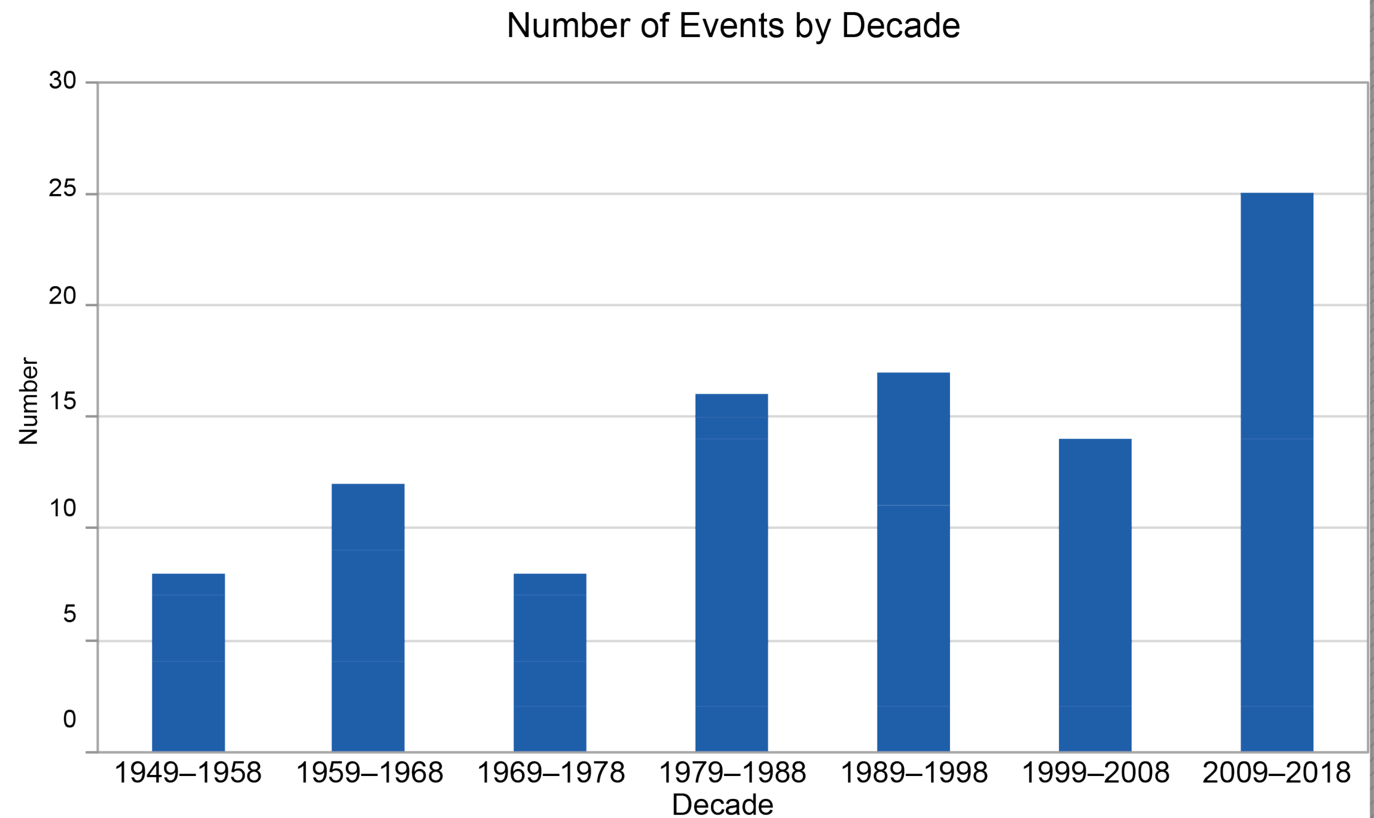


Figure source: adapted from Figures 7.3 & 7.4 in *Climate Science Special Report, Fourth National Climate Assessment Volume 1*, USGCRP 2017.

Top 100 Events with 4-5 day rainfall totals averaged over 20,000 km^2 (1949-2018)



Kunkel and Champion 2019, An assessment of rainfall from Hurricanes Harvey and Florence relative to other extremely wet storms in the United States, *Geophysical Research Letters*, **46** (22).

Global Warming->Saturation Water Vapor Increases

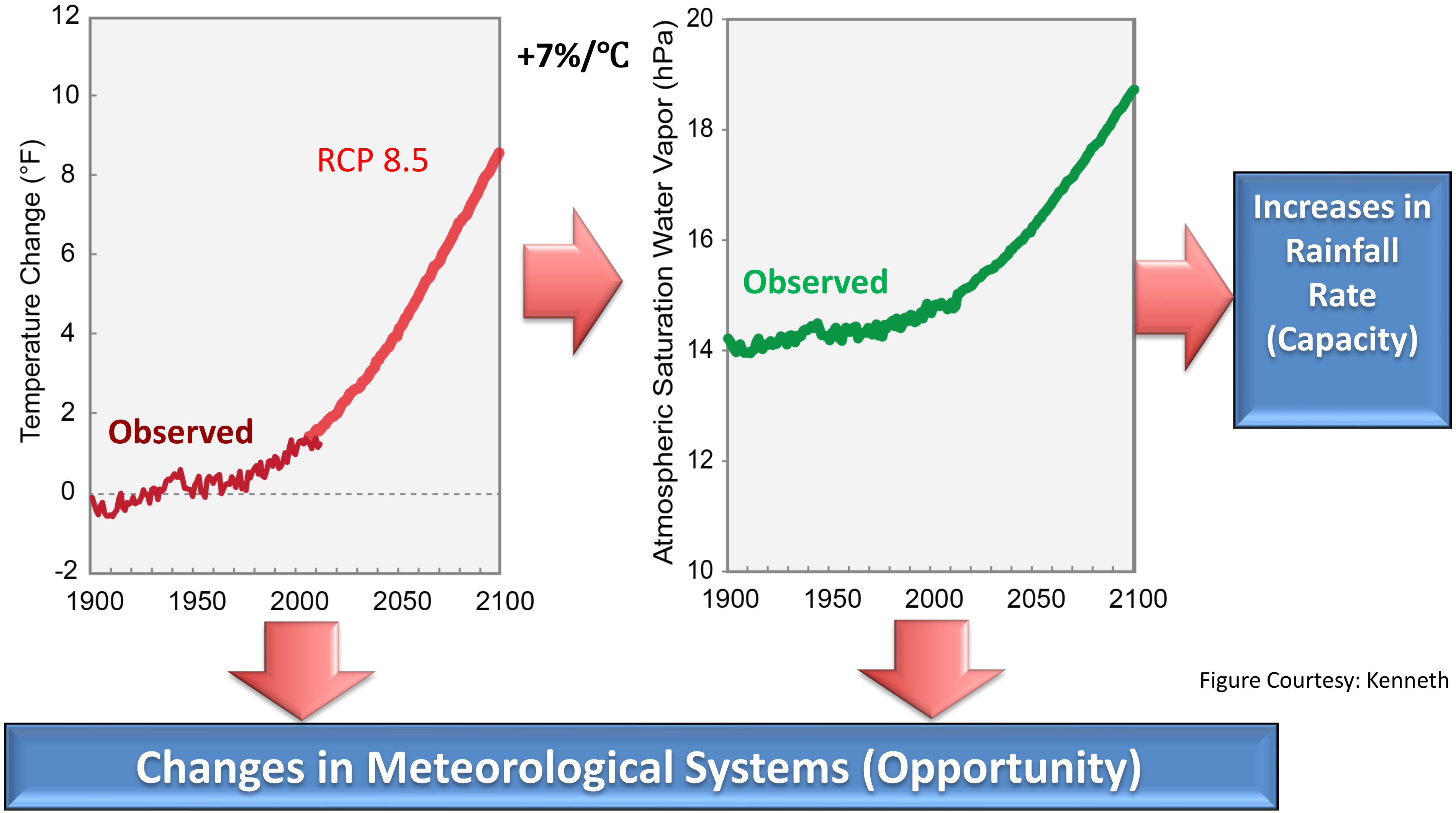
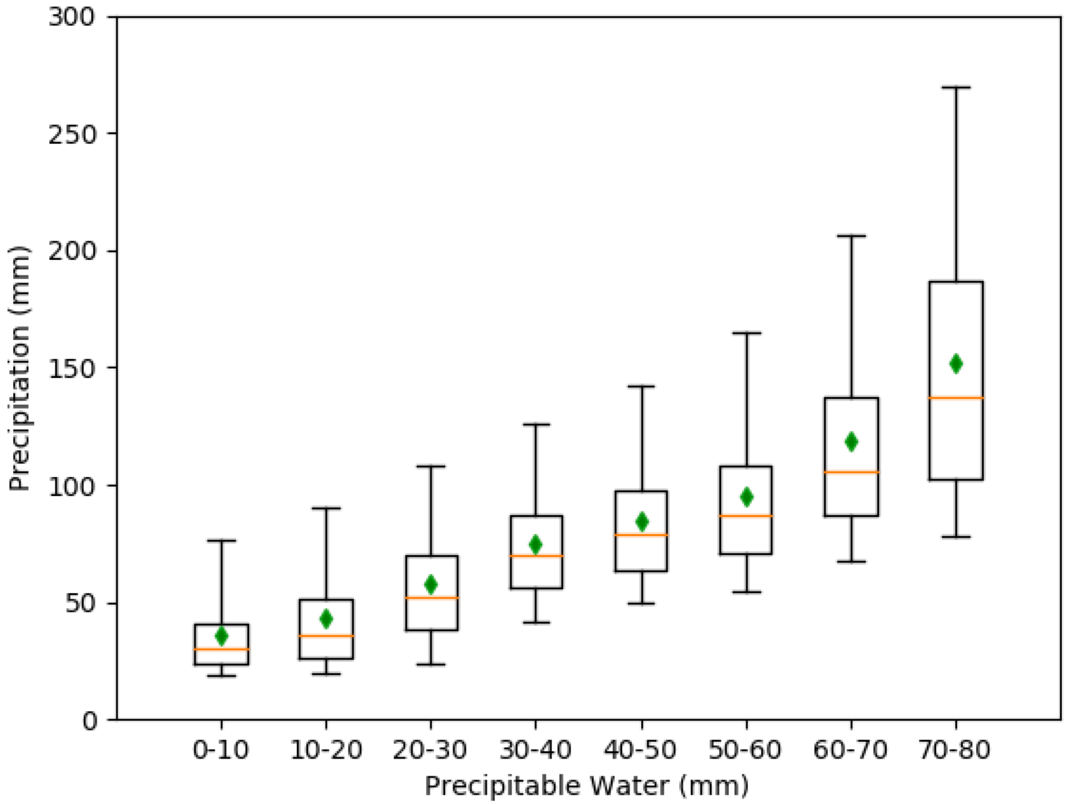


Figure Courtesy: Kenneth Kunkel (NCICS)

Extreme Precipitation Amounts vs Water Vapor

For ~3000 U.S. stations
Examined the Annual Maximum Series
with local precipitable water (total column water vapor)
on the day of each station extreme event



The amount of precipitation in historical extreme precipitation events increases (on average) monotonically with the amount of atmospheric water vapor

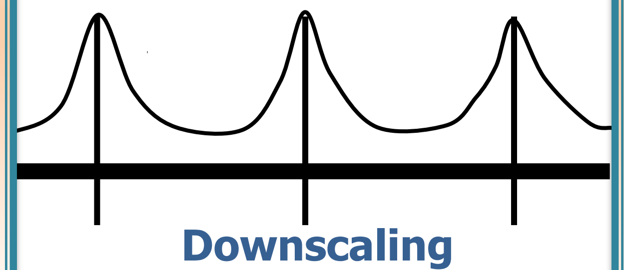
Figure Courtesy: Kenneth Kunkel (NCICS)

How can we characterize plausible changes in changes in rainfall extremes as the climate warms at regional to local scales needed for design?

Downscaling

Global Climate Models (GCMS)

- Comprehensive science
- Emissions scenarios
- Multi-century data
- Coarse resolution



Regional / Local Impacts of Climate Change

- This study: frequency and intensity of extreme rainfall

Large, well-established coordinated programs (30+ GCMs)

Known Problem with GCMs: Simulating Rainfall Extremes

Multiple sources available that improve the representation of extreme rainfall

Problems:
not well-coordinated
multiple methods
limited comparisons between methods

Improve Confidence When Multiple Methods Give Similar Outcomes

Statistical Downscaling

Recommended method from Federal Highways for investigating future precipitation extremes

Establish relationship between what GCMs can simulate over the historical period (large-scale weather patterns) with observed local response (precipitation).

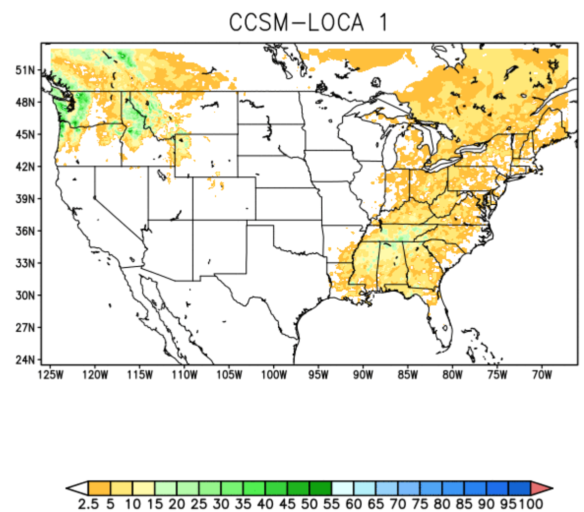
Use the established relationship to derive local precipitation in the future.

Some Pros:
Computationally efficient - downscale many different GCMs & future scenarios
Bias correction

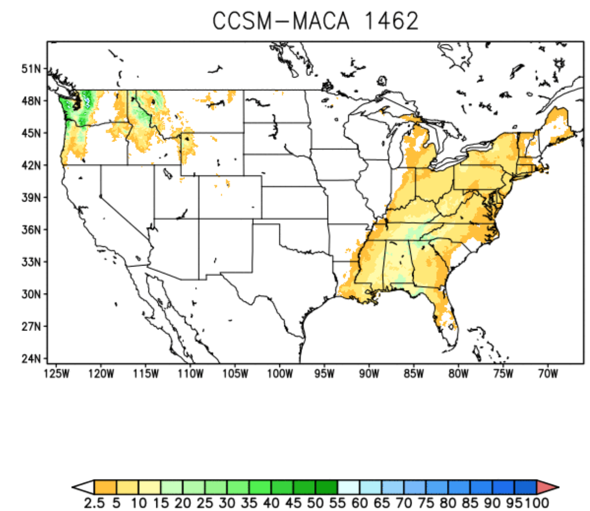
Some Issues:
Different Statistical Methods Used
Different Historical Obs. Datasets Used
Assumes stationarity

Simulated Daily Precipitation from two statistical methods same GCM realization

LOCA Federal Highway Recommendation



MACA



Improve Confidence When Multiple Methods Give Similar Outcomes

Dynamical Downscaling (Regional Climate Modeling)

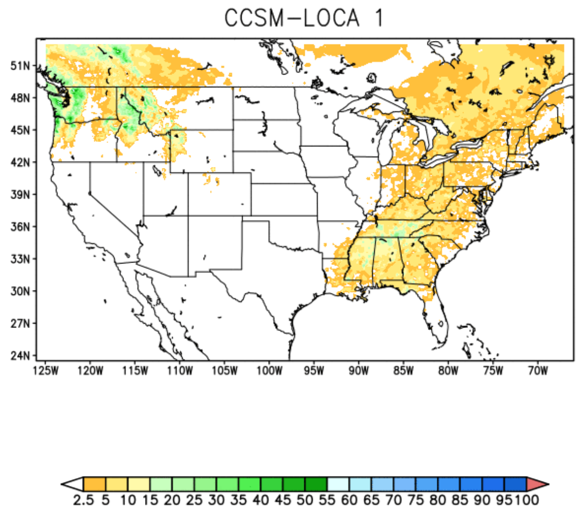
Use the GCM as input to a numerical weather model to simulate regional climate for a. scenario and period of interest

Some Pros:
Model physics developed and tested for higher resolution
Resolve important land surface features (topography/land cover)

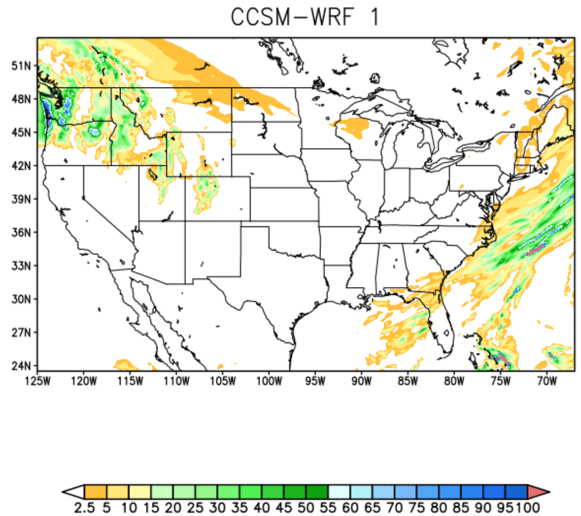
Some Issues:
Computationally Expensive – only downscale certain GCMs and scenarios for select time slices
Inherit GCM Bias
Single model configuration

Simulated Daily Precipitation from statistical and dynamical downscaling same GCM realization

LOCA Federal Highway Recommendation



Dynamical



Improve Confidence When Multiple Methods Give Similar Outcomes

Can we determine how a specific weather event would differ in an altered climate?

1.) Simulate the event using a numerical weather model, replicate its main features

2.) Apply projections of large-scale environmental change to the model input, and re-run the simulation: **"Pseudo Global Warming" method**

Advantages:

- Compare "same" event in different environments
- Run at high resolution to capture extreme conditions

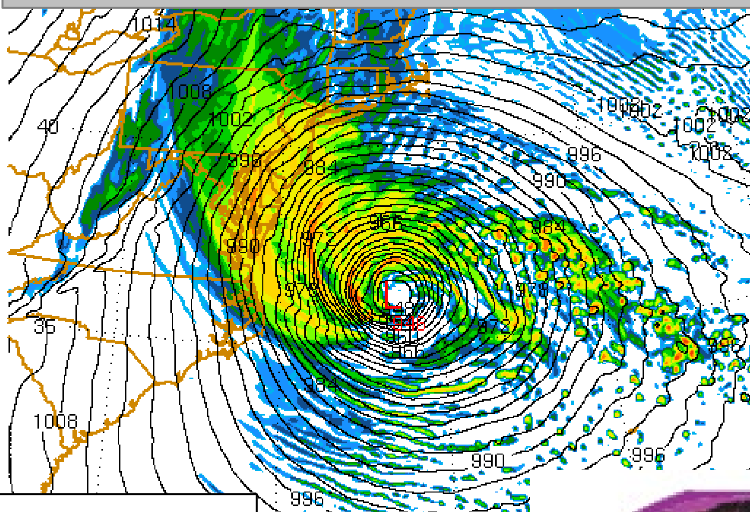
Disadvantages:

- Assume that a similar pattern would repeat in future – unlikely
- Difficult to study changes in the likelihood of event

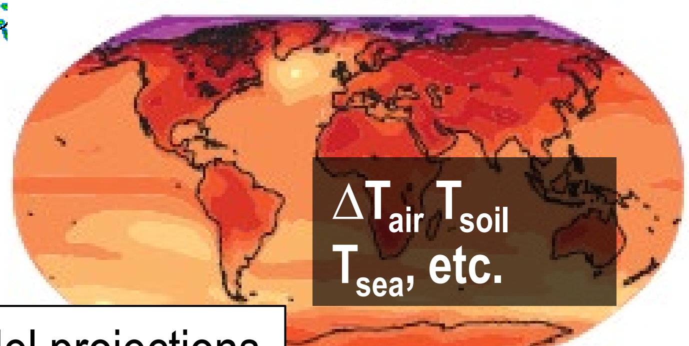
Pseudo Global Warming (PGW) Method

- Simulate weather event with observational input
- Apply climate model projected changes to input, re-run “future” or “past” version of event
- Can run for events or seasons, with “future or past environments”

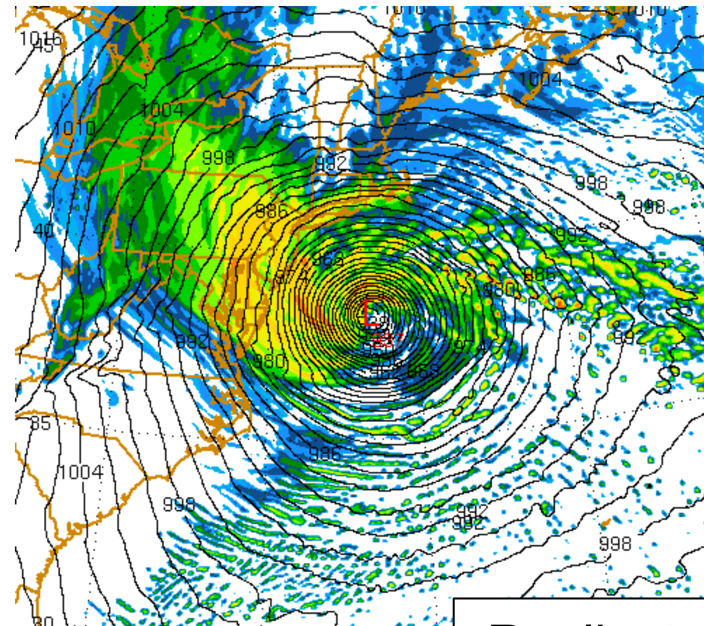
Simulate weather event using observational analyses for input



Set of hi-res model simulations

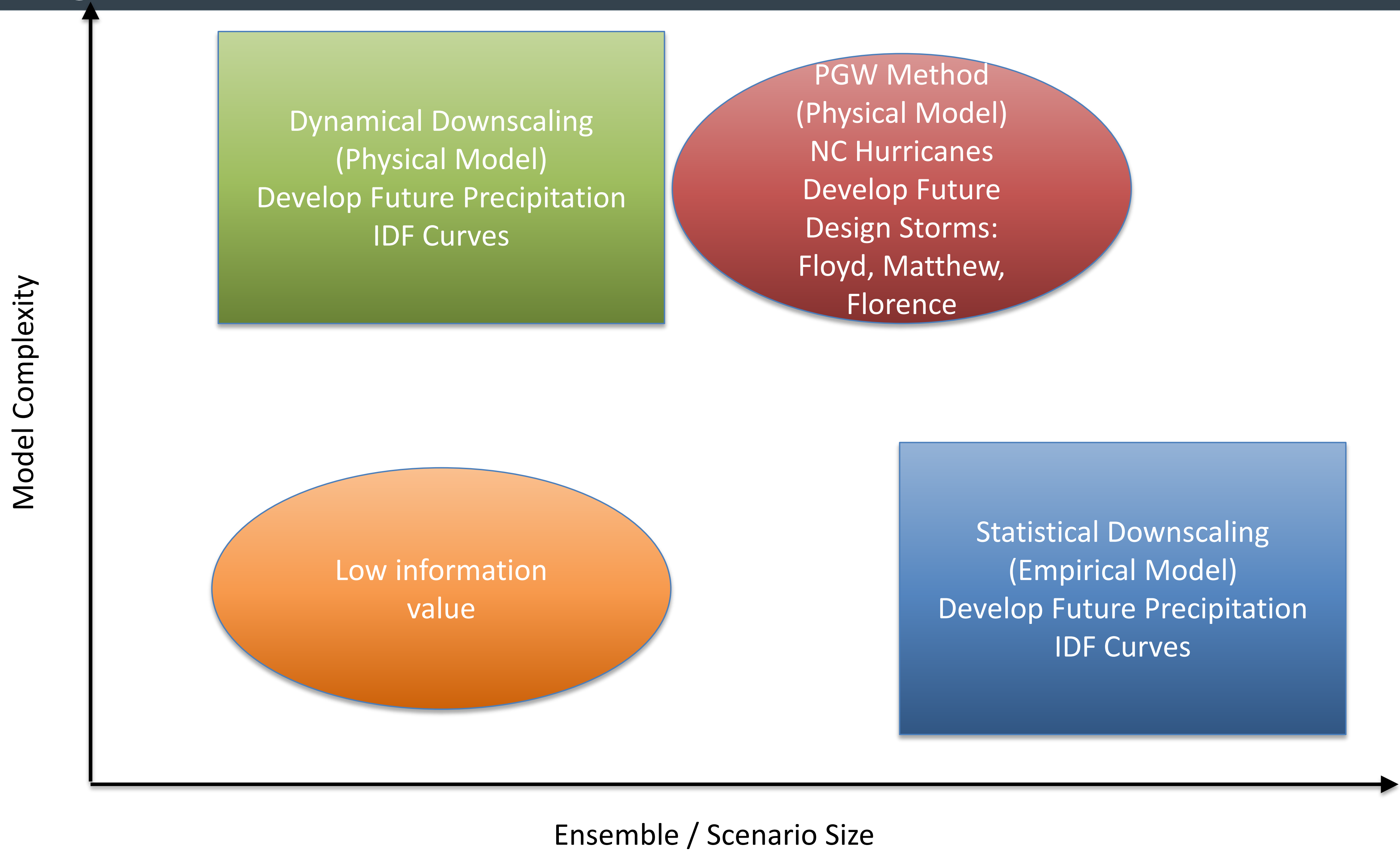


Climate model projections



Replicate set of hi-res simulations

Figure Courtesy: Gary Lackmann (NCSU MEAS)


Dynamical Downscaling
(Physical Model)
Develop Future Precipitation
IDF Curves
PGW Method
(Physical Model)
NC Hurricanes
Develop Future
Design Storms:
Floyd, Matthew,
Florence
Model Complexity
Low information
value
Statistical Downscaling
(Empirical Model)
Develop Future Precipitation
IDF Curves
Ensemble / Scenario Size

Project Goals:

1) Work with NC DOT and stakeholders to help inform analysis (durations, basins, return periods), experimental design (storms to be modeled w/ PGW), and products (downstream data needs such as format and visualization tools)
2) Use Federal Highway Guidance to derive future IDF Curves using multiple sources of downscaled climate data
3) PGW Experiments (focus right now is on recent Hurricanes)
4) Compare different methods/data to help build a more resilient transportation system

THANK YOU

Like to know more about this project:
Contact
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The automation and acceleration of deep learning-based detection of 3D hydraulic structures from point cloud data: A cyberinfrastructure-enabled approach

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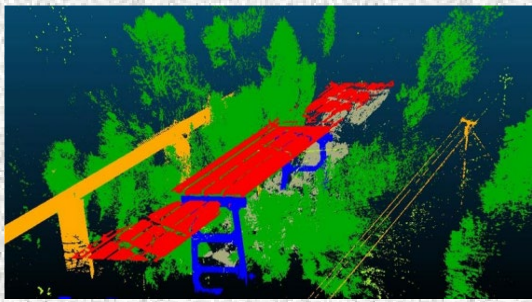
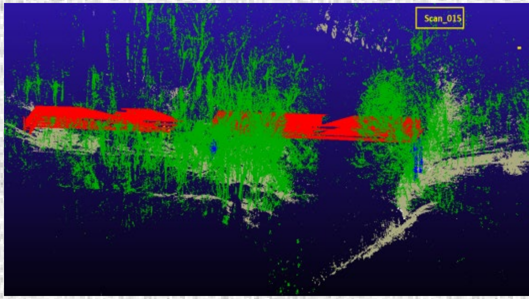
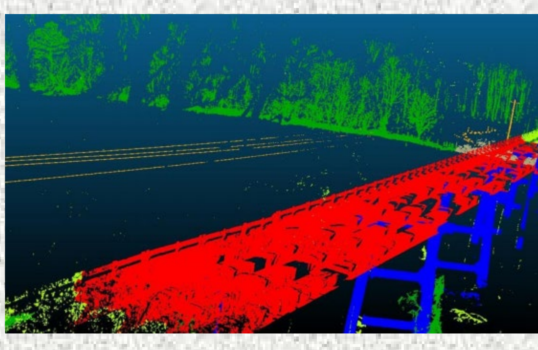
  - PIs: Drs. Wenwu Tang, Shenen Chen, John Diemer, Craig Allan from the University of North Carolina at Charlotte
  - Graduate Assistants: Tianyang Chen, Tarini Shukla, Zachery Slocum, Navanit Sri Shanmugam, Vidya Subhash Chavan
- Matthew Macon, Rodney Hough, Donald Early, Photogrammetry Unit, NCDOT

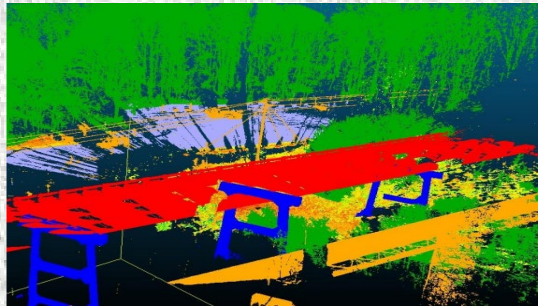
Introduction

- 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).
- However, **the efficient processing and classification** of point cloud data to generate 3D hydraulic features of interest represent a grand **big data-driven computational challenge**.



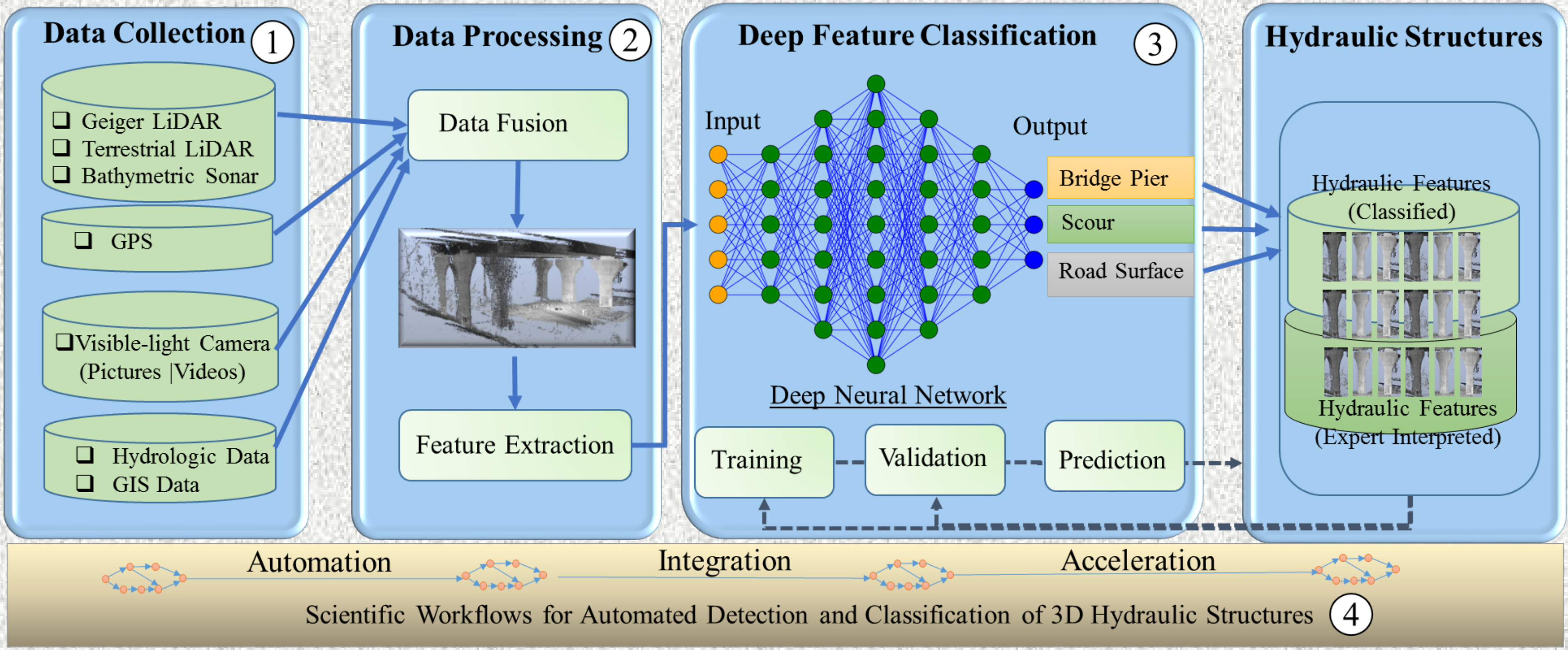






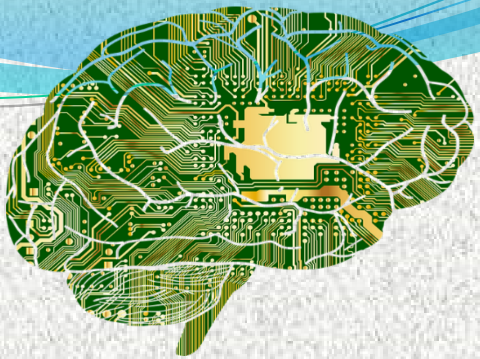
Framework

- 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>.



Background

Artificial Intelligence



- Deep learning for 3D object detection
  - 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)

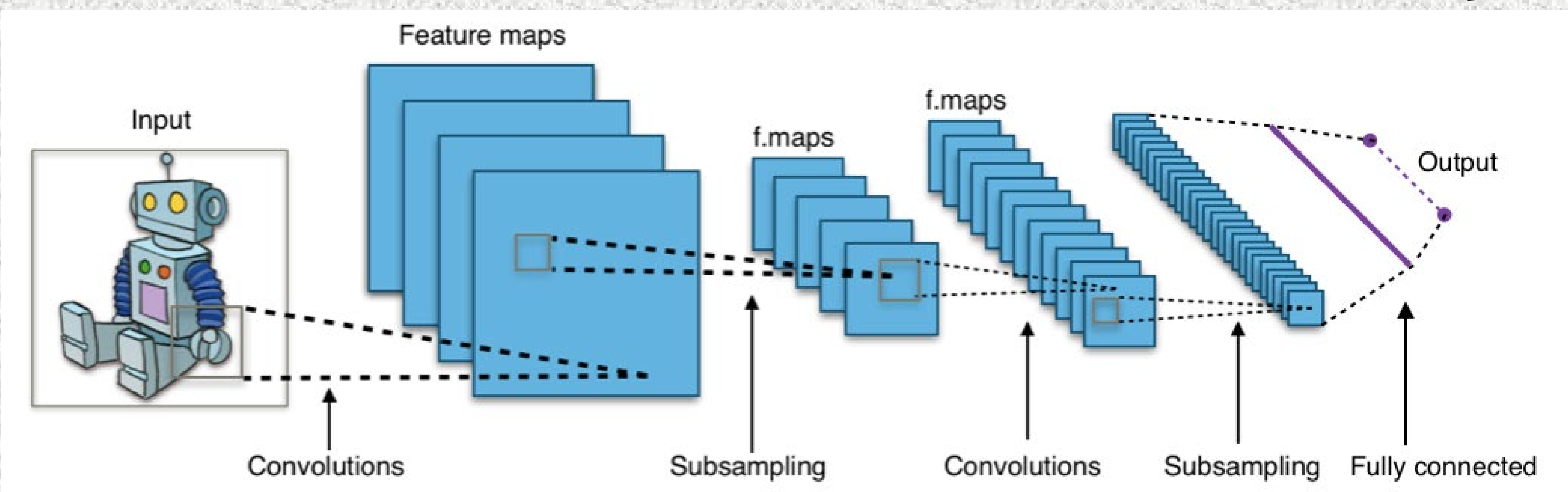
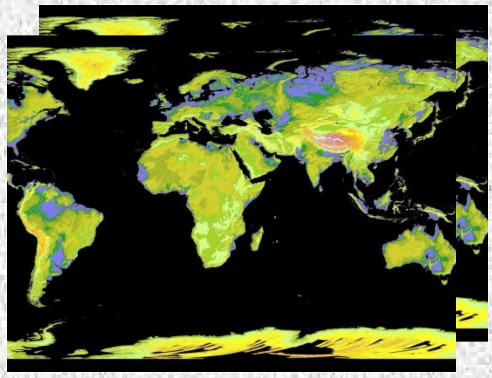
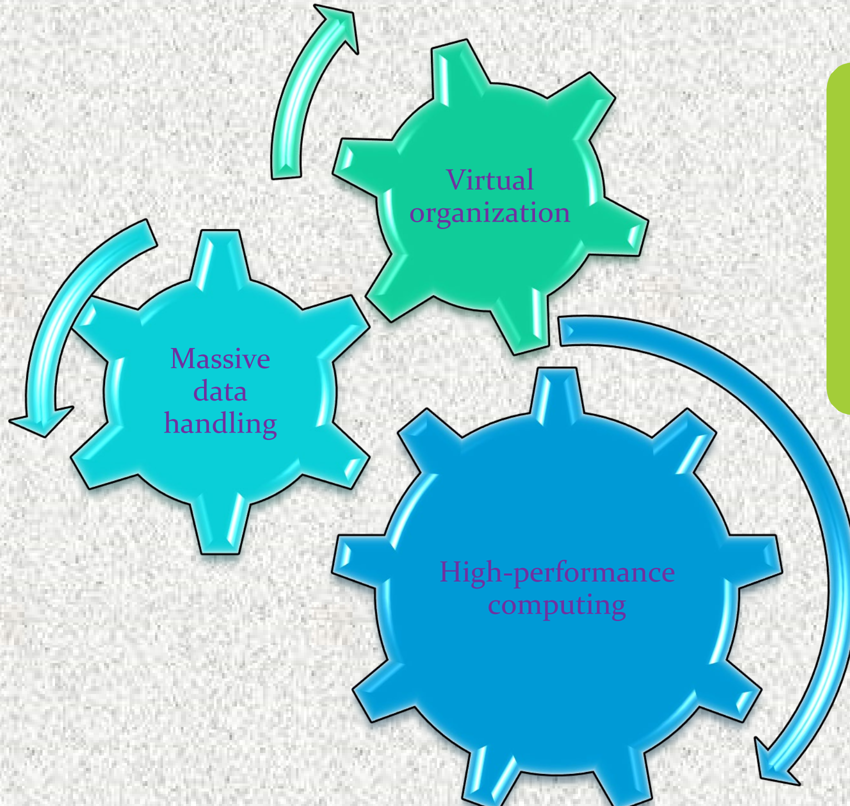
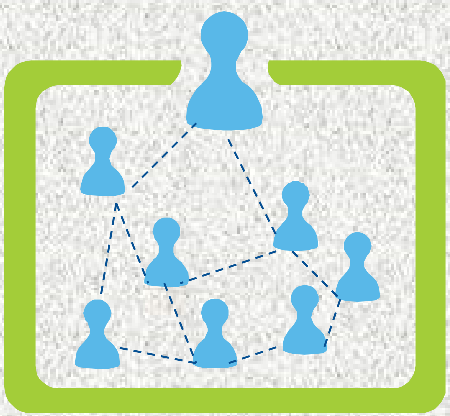


Image source: https://upload.wikimedia.org/wikipedia/commons/8/81/Deep_learning.png
https://en.wikipedia.org/wiki/File:Typical_cnn.png

Cyberinfrastructure







http://www.tacc.utexas.edu/fileadmin/templates/SubtacctemplateStaticDropdown/images/ranger.jpg
http://www.nasa.gov/multimedia/imagegallery/image_feature_1545.html

Ranger at TACC (62,976 cores)

Supercomputing Resources

www.teragrid.org
www.xsede.org

Ranger @ TACC
(#CPUs: 62,976; Disk: 1.7 PB)

XSEDE: Extreme Science and Engineering Digital Environment

Graphics Processing Units (GPU)

- Many-core computing architecture
- Data parallelism

Nvidia Tesla K40 Processor
2,880 processing cores
12G memory
1.43 Tflops (peak performance)

Several order of magnitude of acceleration

Image source: http://www.nvidia.com/object/tesla-servers.html

Data Collection

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
  - GPS (rented): Trimble R10 GNSS receiver
  - Performance of Network RTK
    - Horizontal: 8mm+0.5ppm
    - Vertical: 15mm+0.5ppm
  - Virtual Reference Station(VRS) network:
    - North Carolina VRS network by NC Geodetic Survey
- Sonar system:
  - Lowrance HDS Live 7 (version 8.3)



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/
https://www.lowrance.com/globalassets/inriver/resources/000-14416-001_09.jpg?w=1000&h=500&scale=both&mode=max&quality=70
http://trl.trimble.com/docushare/dsweb/Get/Document-889531/TrimbleR10_Model-2_GNSSReceiver_UserGuide.pdf

Survey Sites in NC

Site #2

Site #6

Site #14

Site #11

Site #3

Site #7

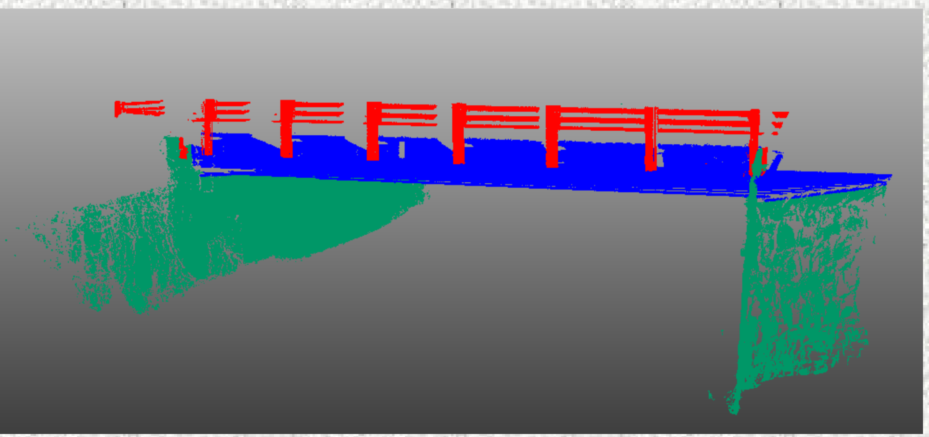
Site #16

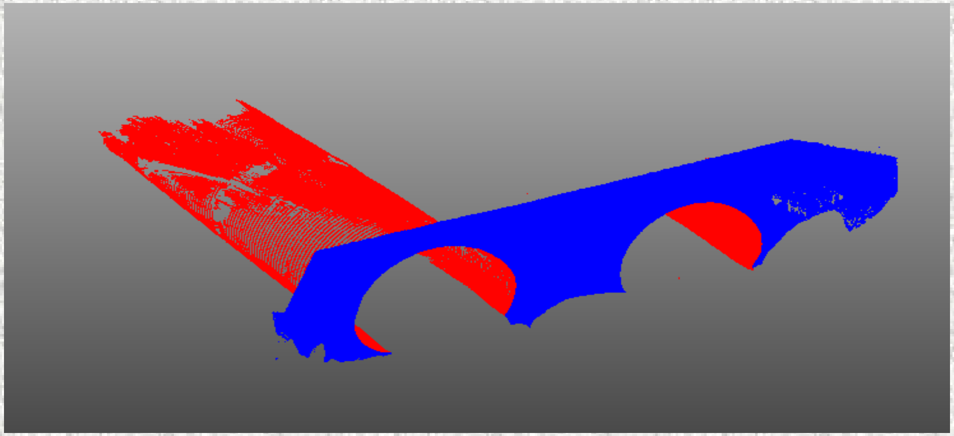
Site #5

Site #8

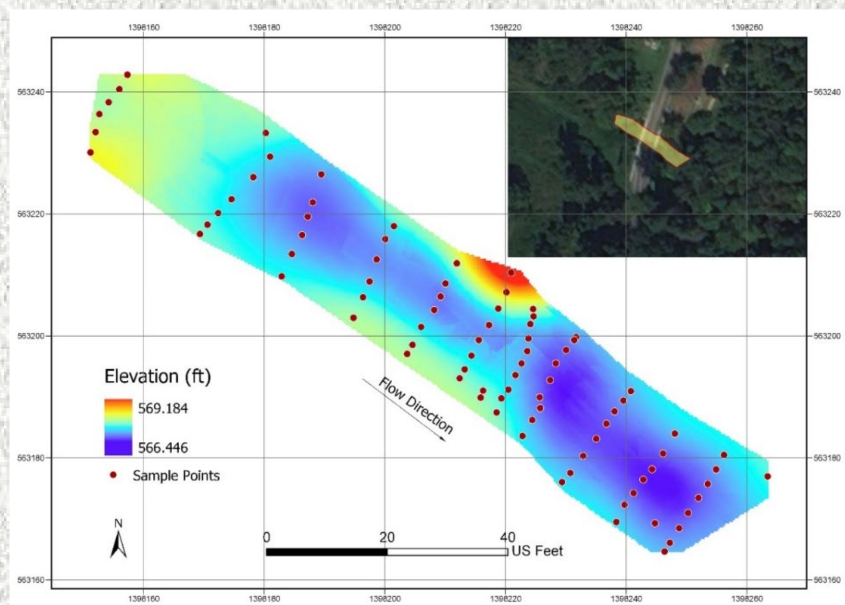
Site #	# LiDAR Scanning	# Sonar Points	# total station points	# Drone images	# camera images
Site 2	1		86		308
Site 3	2		98		157
Site 5	1		241		220
Site 6	2		101		363
Site 7	1		95		251
Site 8	3		168		398
Site 11	5	824			
Site 14	1		205		420
Site 15	1			181	213
Site 16	4	1095	127	109	
Site 17	4	3,180			

Point Cloud Data

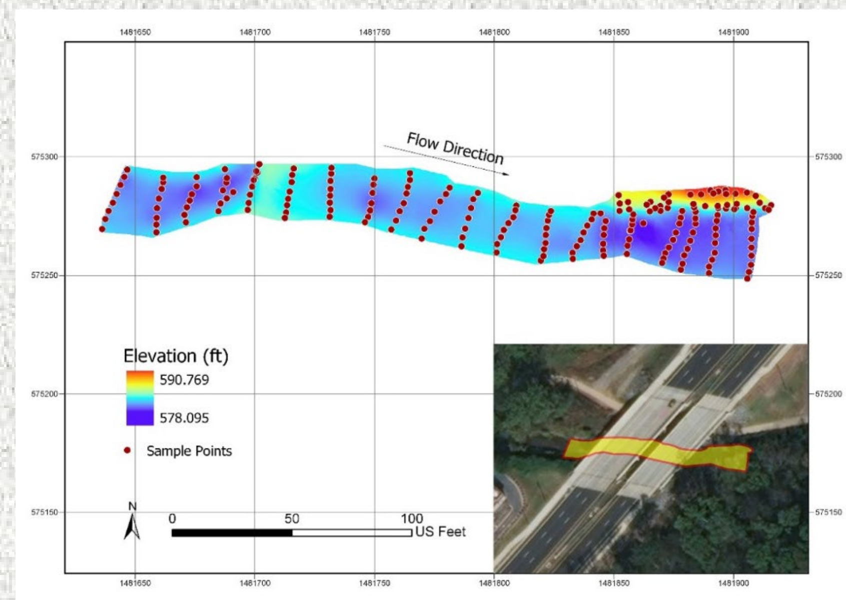




Bathymetric Data



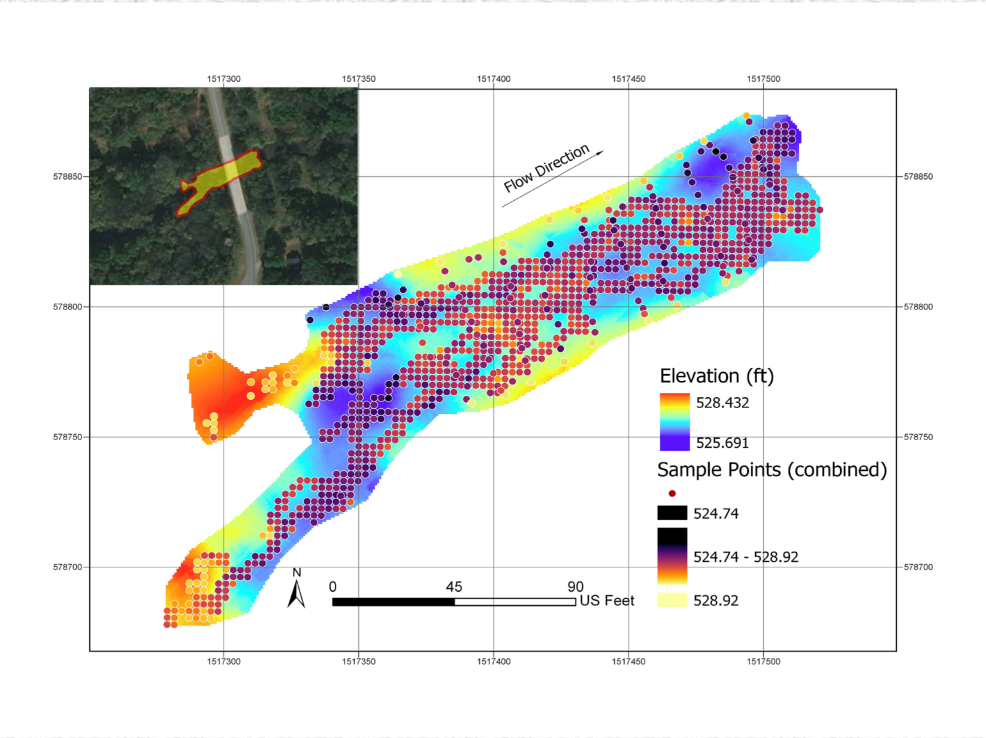
Site#2



Site#14

- Data collected using Virtual Reference System and total station outside the bridge and under the bridge, respectively.

Sonar data collection



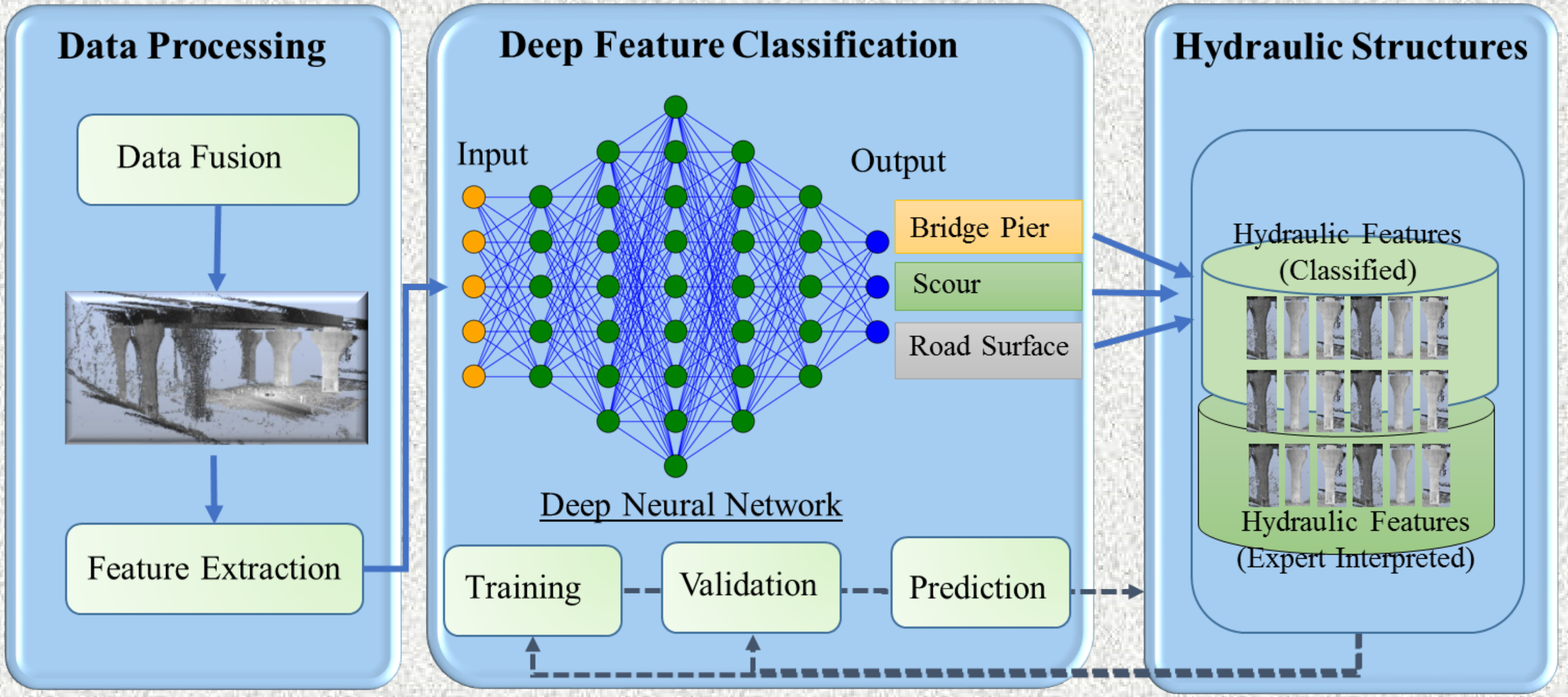
Site #16

- Data were collected using VRS, total station and sonar (single beam echosounder)
- Accuracy of sonar data estimated by calculating residual (elevation from VRS – elevation of stream bottom)

Deep Learning Framework: DeepHyd

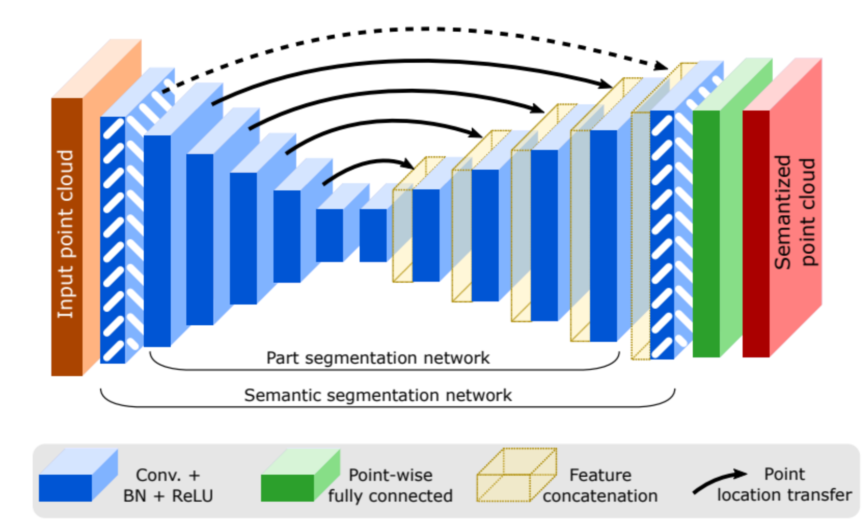
Deep Learning for 3D Point Cloud Classification

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

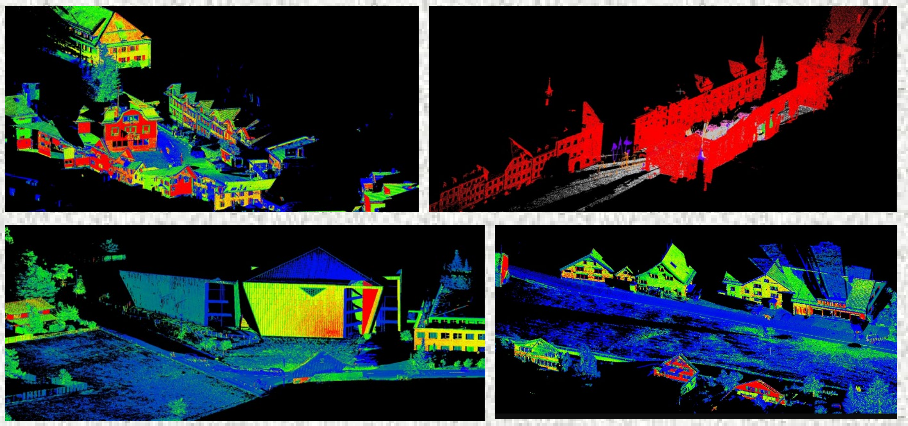


Convpoint: Continuous Convolutions For Point Cloud Processing

- Boulch (2020) proposed a new deep learning-based framework for 3D semantic segmentation, named ConvPoint, which hits the rank #1 performance on the large-scale 3D benchmark (http://www.semantic3d.net/).



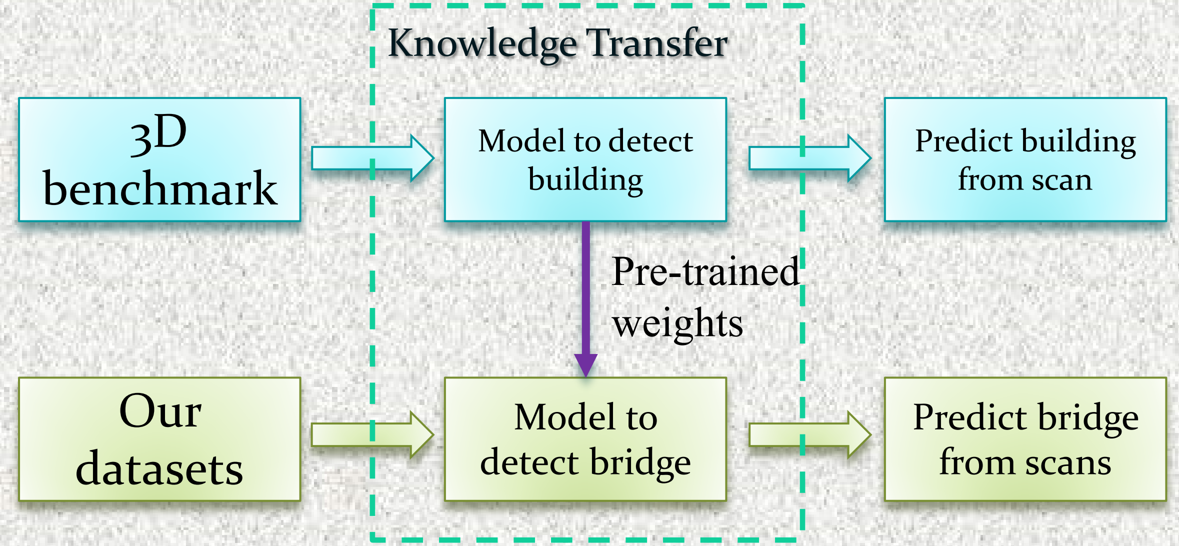
Segmentation networks proposed by Boulch (2020)



Demonstration of the 3D benchmark

Transfer Learning

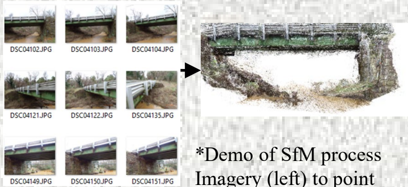
- Transfer learning is the improvement of deep learning in a new task through the transfer of knowledge from a related task that has already been learned (Olivas, 2009). Transfer learning can provide better initial weights than random ones, which can help prevent the model overfitting on the training data and accelerate the training process to better convergence. It is especially helpful when the training data is not sufficient as it is in our case.



Model Automation-Integration-Acceleration

- Use the **GIS-based scientific workflows (Tang et al. 2017) 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

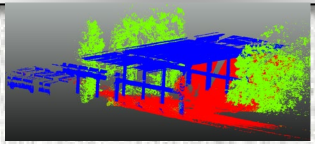
Framework of Scientific Workflow for Automation



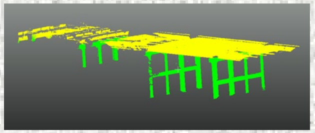
*Demo of SfM process
Imagery (left) to point cloud (right)

Structure from Motion (SfM) to construct 3D point cloud from imagery

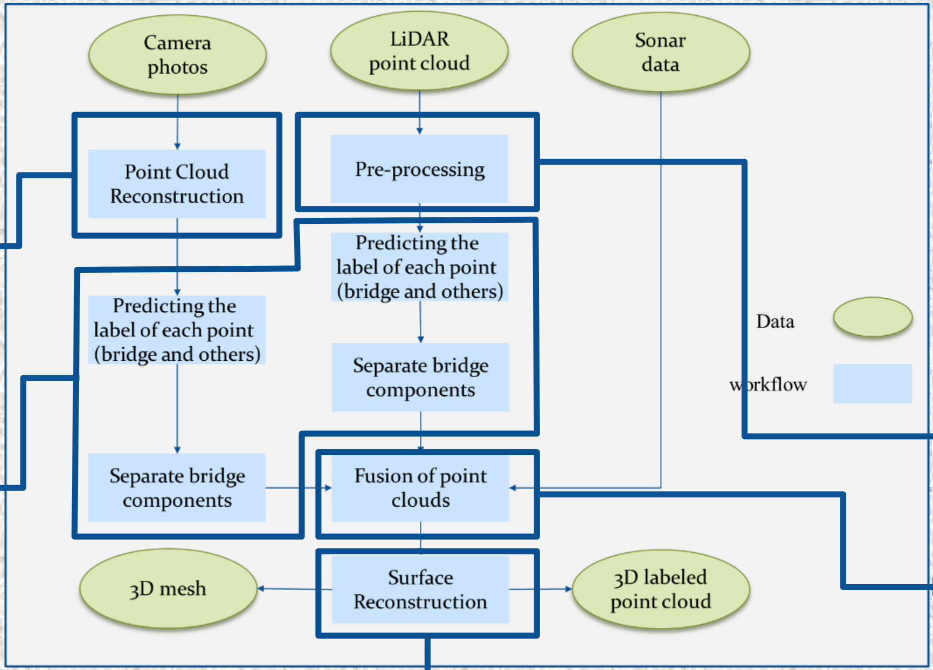
Use the two trained models to predict the labels of each point:
1. Detect bridge from the point c loud
2. Detect different bridge components from point cloud of the detected bridge



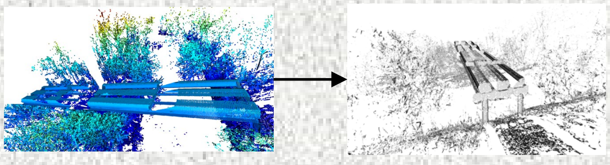
*Prediction results of detected bridge from the scene



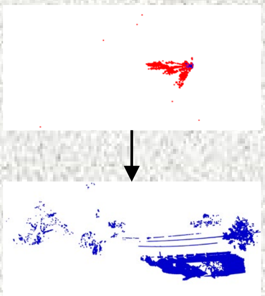
*Prediction results of bridge components



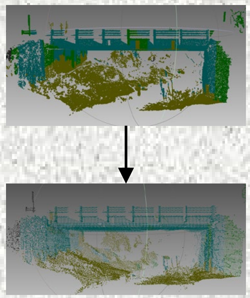
Adopt surface reconstruction methods to convert point cloud to polygon mesh or other types of 3D model (based on NCDOT requirement).



*Demo of the result of the surface reconstruction
From point cloud (left) to polygon mesh (right)



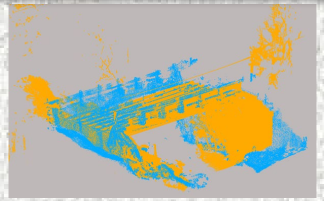
*Demo of outlier removal
Red are removed automatically



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

1. Outlier removal tool by Open3D, an open-source python lib, to remove noise
2. Spatial sampling to 1cm

Adopt Iterative Closest Point from CloudCompare, an open source software, to register the point clouds



*Demo of fusion of point clouds
Blue and yellow are two point clouds. They are registered after this process

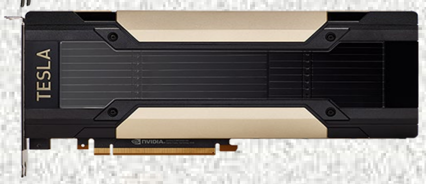
Acceleration of Deep Learning

- Cyberinfrastructure-enabled **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) and URC (University Research Computing) at UNC Charlotte.
    - **Sapphire**: 288-CPU Windows cluster for advanced geocomputation!
    - Graphics Processing Units (GPUs) cluster at URC (24 advanced GPUs)

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

GPUs for Supercomputing-level Acceleration

- 5 new GPU nodes with 24 latest GPUs (urc.uncc.edu)



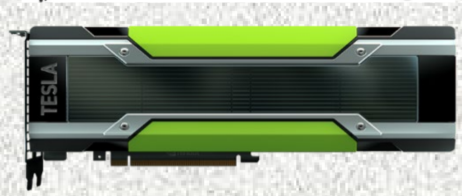
1 GPU Compute Node:
- Dual Intel Xeon Silver 4215R CPU @ 3.20GHz (16 cores total)
- 192GB RAM (~ 12GB/core)
- 8 x Titan V GPUs (12GB HBM2 RAM per GPU; #CUDA cores: 5,120)

2 GPU Compute Nodes, each having:
- Dual Intel Xeon Silver 4215R CPU @ 3.20GHz (16 cores total)
- 192GB RAM (~ 12GB/core)
- 4 x Titan RTX GPUs (24GB GDDR6 RAM per GPU; #CUDA cores: 4,608)

2 GPU Compute Nodes, each having:
- Dual Intel Xeon Silver 4215R CPU @ 3.20GHz (16 cores total)
- 192GB RAM (~ 12GB/core)
- 4 x Tesla V100s GPUs (32GB HBM2 RAM per GPU; #CUDA cores: 5,120)

--------------previous computing resource-----------------

2 GPU Compute Node, each having
- 192GB RAM (~ 12GB/core)
- 8 x GTX 1080 Ti GPUs (11GB RAM per GPU; #cores: 3,584)



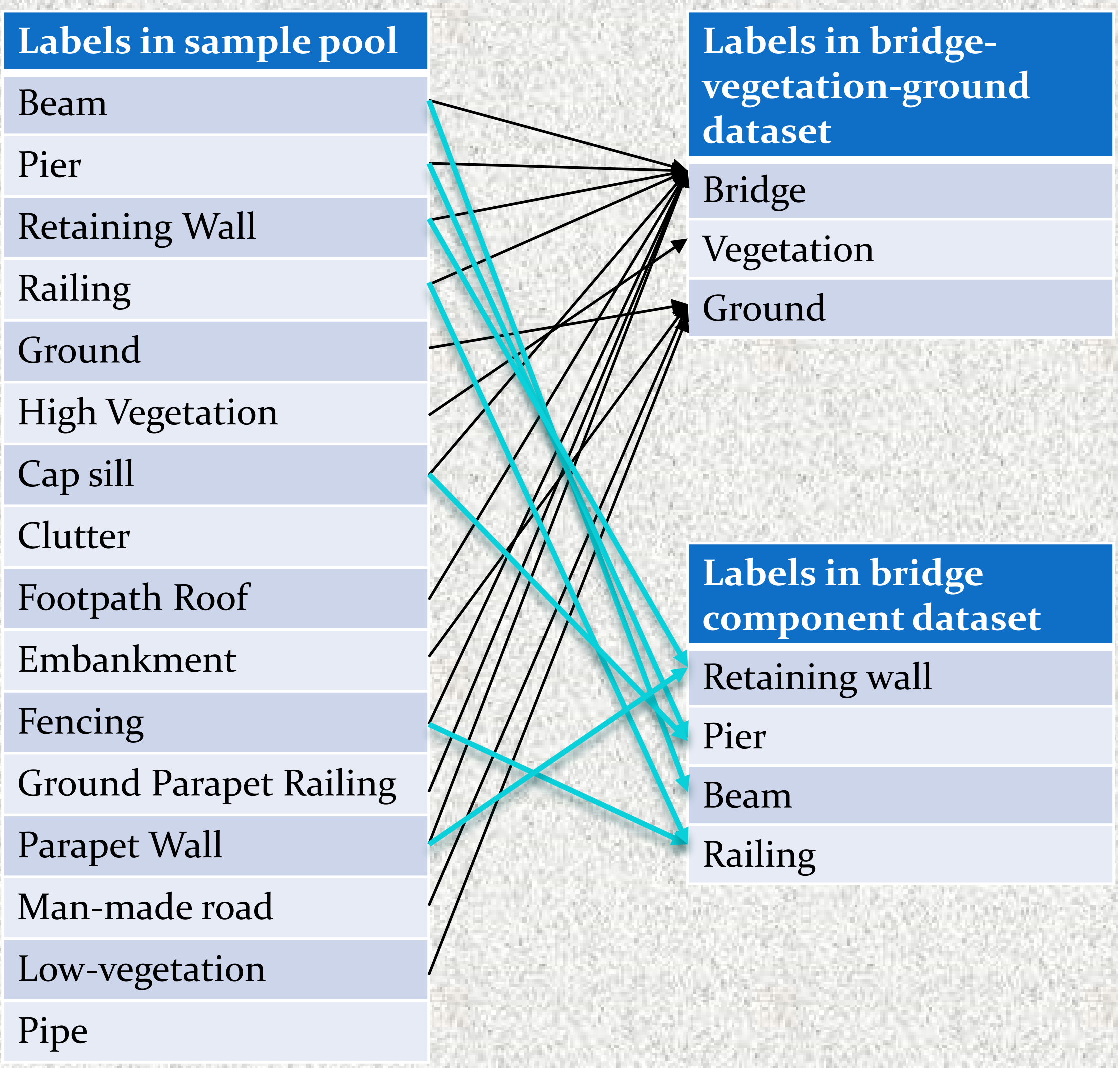
4 GPU Compute Nodes, each having
- 192GB RAM (~ 12GB/core)
- 2 x Tesla K80 GPUs (24GB RAM per GPU; #cores: 4,992)

This slide is adapted from a powerpoint from urc.uncc.edu

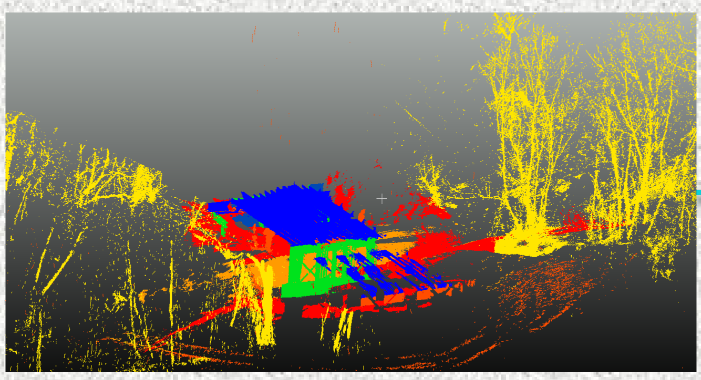
Results

Annotation of Samples

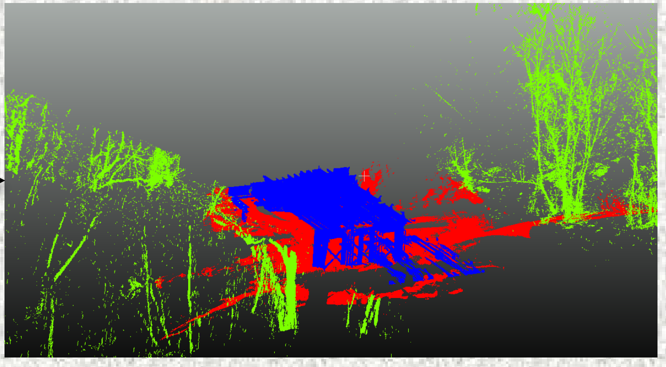
- Size of annotated sample pool:
  - Total # annotated scans: 41 (11 from study sites and 30 from previous scanning)
  - #classes: 16
- Two sample sets were generated from the annotated sample pool:
  - 1. Bridge-vegetation-ground dataset with 3-categories: bridge, vegetation, and ground
  - 2. Bridge component dataset with 4-categories: wall, pier, beam, railing



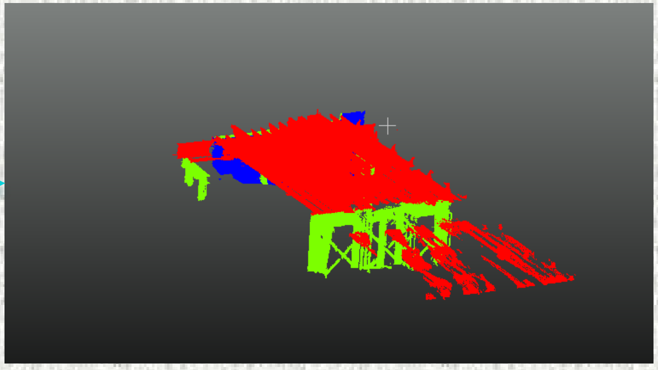
Demonstration of Annotated Samples



Data in annotated sample pool



Data in bridge-vegetation-ground dataset



Data in bridge component dataset

The annotated sample pool is aggregated to generate the two pools of datasets for training the two models.

*Colors represent different labels.

Statistics of the Two Pools of Labeled Datasets

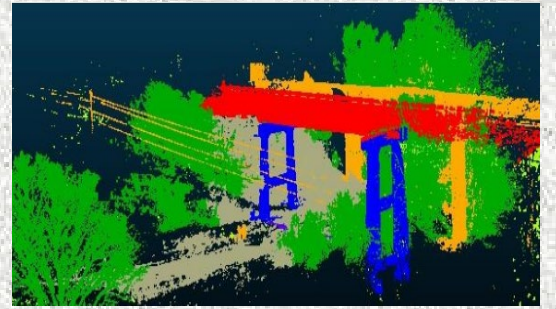
Bridge-vegetation-ground

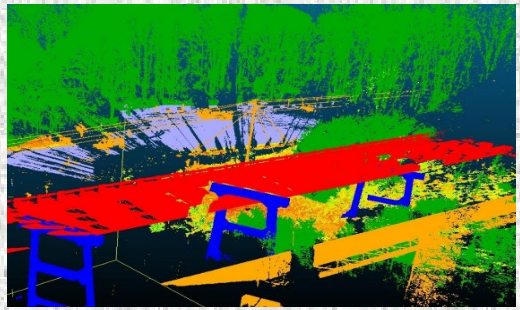
Statistics/Labels	Bridge	Vegetation	Ground	Total
Total	109,354,102	35,122,404	62,993,247	207,469,753
Percentage	**52.71%**	**16.93%**	**30.36%**	100.00%

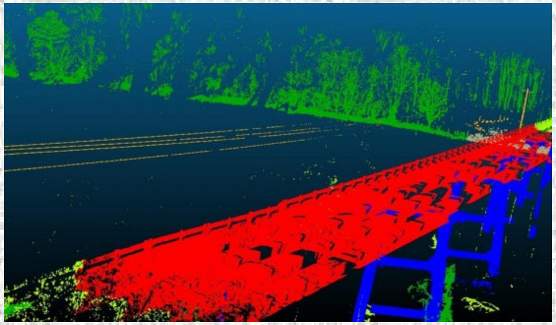
Bridge-component dataset

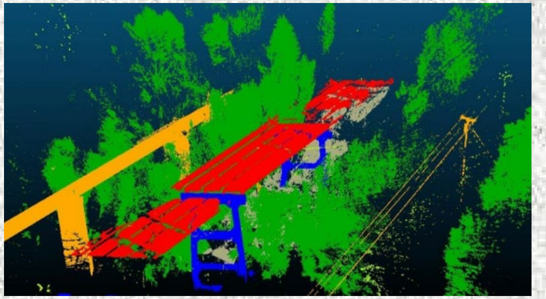
Statistics/Labels	Wall	Pier	Beam	Railing	Total
Total	6,949,996	17,673,431	76,778,145	4,818,671	106,220,243
Percentage	**6.54%**	**16.64%**	**72.28%**	**4.54%**	100.00%

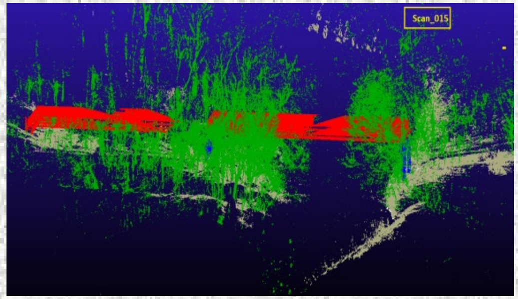
Annotated Training Samples

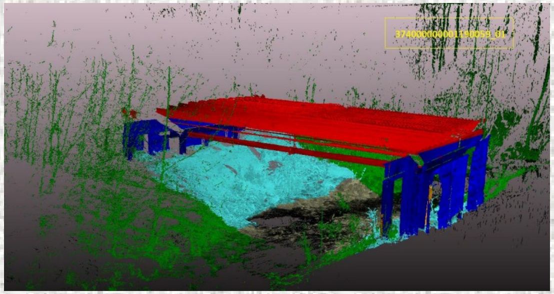


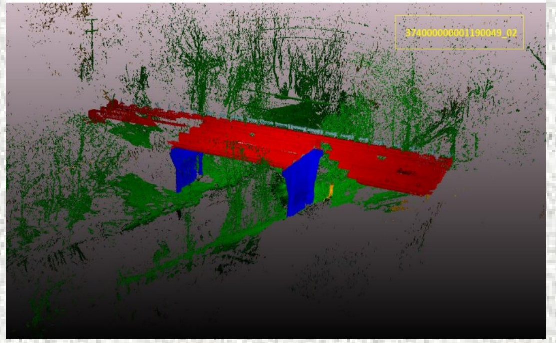


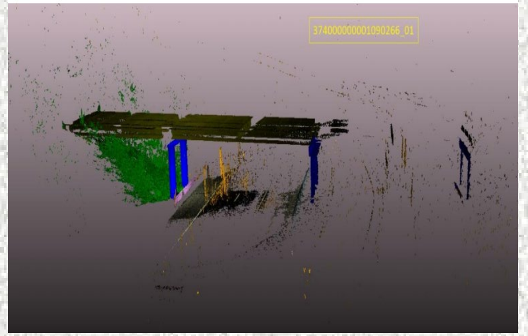


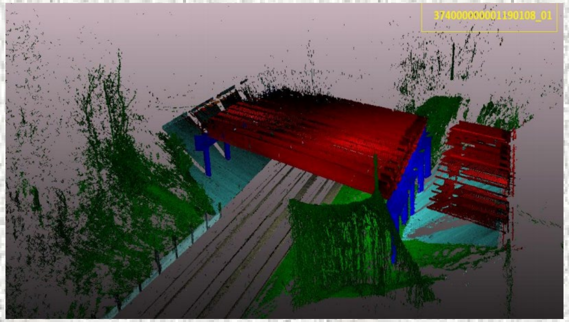












Parameter Tuning

Total Sequential Computing Time for Parameter Tuning on The Two Models: **2,746 hours (114 days)**

Model to detect bridge from the LiDAR scan

Model to detect bridge components from a bridge

Parameter tuning on model hyper-parameters (total 1,362 hours)

*treatment with learning rate scheduler

Treatment #	Learning Rate	# iteration	GPU	#GPU	Computing Time (hours)
Treatment 1	1.00E-02	500	1080Ti	1	42
Treatment 2	1.00E-02	1,000	1080Ti	1	52
Treatment 3	1.00E-02	1,500	K80	1	70
Treatment 4	1.00E-03	500	1080Ti	1	42
Treatment 5	1.00E-03	1,000	K80	1	53
Treatment 6	1.00E-03	1,500	K80	1	70
Treatment 7	1.00E-04	500	1080Ti	1	42
Treatment 8	1.00E-04	1,000	1080Ti	1	51
Treatment 9	1.00E-04	1,500	K80	1	69
Treatment 10	1.00E-05	1,000	1080Ti	1	51
Treatment 11	1.00E-05	1,500	1080Ti	1	68
Treatment 12*	1.00E-02	1,500	Titan RTX	1	67
Treatment 13*	1.00E-03	1,500	Titan V	1	68
Treatment 14*	1.00E-04	1,500	Titan V	1	68
				Total	813

Treatment #	Learning Rate	# iteration	GPU	#GPU	Computing Time (hours)
Treatment 1	1.00E-02	500	1080Ti	1	31
Treatment 2	1.00E-02	1,000	1080Ti	1	41
Treatment 3	1.00E-02	1,500	1080Ti	1	47
Treatment 4	1.00E-03	500	1080Ti	1	29
Treatment 5	1.00E-03	1,000	1080Ti	1	41
Treatment 6	1.00E-03	1,500	1080Ti	1	47
Treatment 7	1.00E-04	500	1080Ti	1	31
Treatment 8	1.00E-04	1,000	1080Ti	1	41
Treatment 9	1.00E-04	1,500	K80	1	43
Treatment 10	1.00E-05	1,000	K80	1	32
Treatment 11	1.00E-05	1,500	K80	1	43
Treatment 12*	1.00E-04	1,500	Titan V	1	41
Treatment 13*	1.00E-05	1,500	Titan V	1	41
Treatment 14*	1.00E-06	1,500	Titan V	1	41
				Total	549

Parameter tuning on data generation parameters (total 1,384 hours)

Treatment #	block size	# point per block	GPU	#GPU	Computing Time (hours)
Treatment 1	5	16,384	Tesla V100	1	80
Treatment 2	5	12,288	Tesla V100	1	80
Treatment 3	5	2,048	Titan RTX	1	80
Treatment 4	5	4,096	Titan RTX	1	80
Treatment 5	5	8,192	Titan V	1	80
Treatment 6	10	2,048	Titan V	1	80
Treatment 7	10	4,096	Titan V	1	80
Treatment 8	10	8,192	Titan V	1	80
Treatment 9	1	2,048	Titan V	1	80
Treatment 10	1	4,096	Titan V	1	80
Treatment 11	1	8,192	Titan V	1	80
				Total	**880**

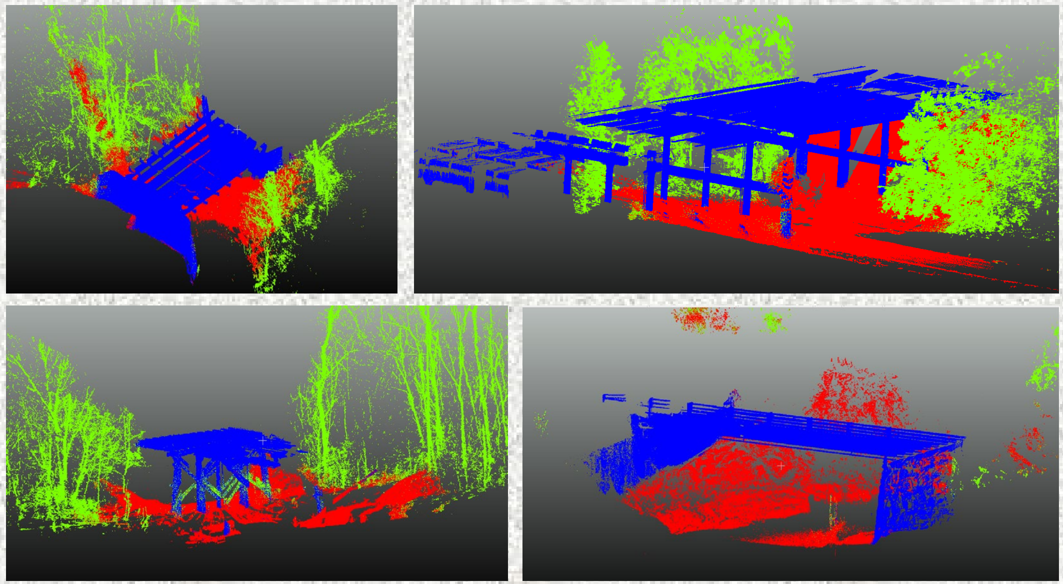
Treatment #	block size	# point per block	GPU	#GPU	Computing Time (hours)
Treatment 1	1	4,096	Titan V	1	35
Treatment 2	1	8,192	Titan V	1	45
Treatment 3	5	4,096	Titan RTX	1	36
Treatment 4	5	8,192	Titan V	1	46
Treatment 5	10	4,096	Titan V	1	35
Treatment 6	10	8,192	Titan RTX	1	46
Treatment 7	10	16,384	Titan RTX	1	71
Treatment 8	20	4,096	Titan V	1	41
Treatment 9	20	8,192	Titan V	1	49
Treatment 10	50	4,096	Titan V	1	47
Treatment 11	50	8,192	Titan V	1	54
				Total	505

Parameter Tuning Acceleration

- Total Sequential Computing Time for Parameter Tuning on The Two Models:
  - **2,746 hours (114 days)**
- Total Parallel Computing time using GPU cluster:
  - **268 hours (11 days)**
- Acceleration Factor (sequential time/parallel time):
  - **10.25**

Prediction Results on Validation Datasets

Bridge-vegetation-ground Model



Label	Color
Bridge	Blue
Vegetation	Green
Ground	Red

Confusion matrix in percentage

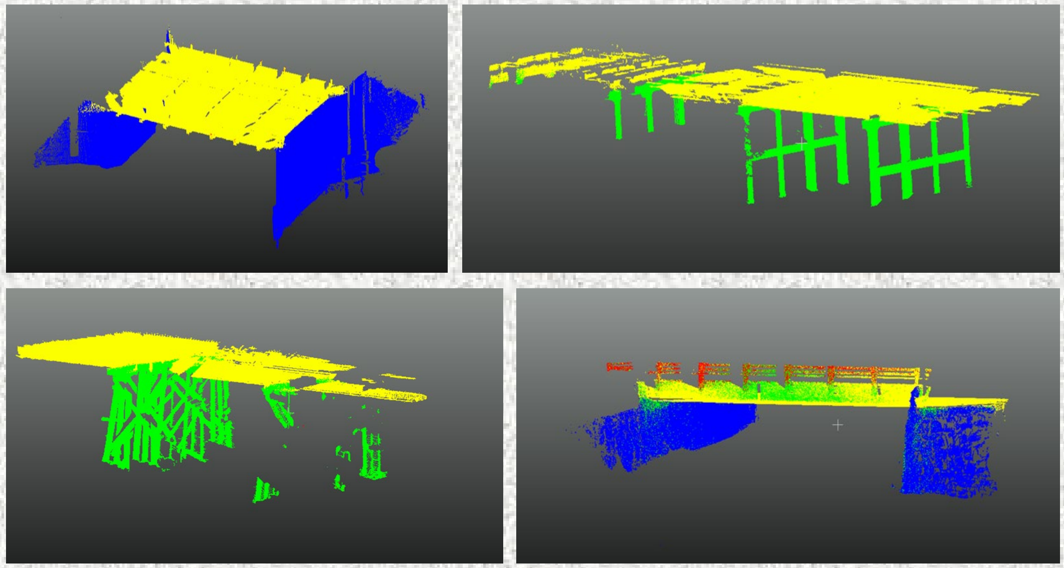
Origin/Pred	Bridge	Vegetation	Ground	Total
Bridge	**58.51%**	0.32%	0.24%	59.07%
Vegetation	0.02%	**9.91%**	0.29%	10.23%
Ground	0.30%	0.58%	**29.82%**	30.71%
Total	58.83%	10.82%	30.36%	100.00%

Performance metrics

Measure	Value
Overall Accuracy	98.38%
Average Accuracy	97.65%
Intersection Over Union (IOU)	94.67%
IOU_bridge	98.62%
IOU_vegetation	89.41%
IOU_ground	96.00%

Prediction Results on Validation Dataset

Detection of bridge components



Confusion matrix in percentage

Origin/Pred	Retaining wall	Pier	Beam	Railing	Total
Retaining wall	**6.36%**	0.16%	0.07%	0.00%	6.58%
Pier	0.09%	**14.80%**	0.21%	1.57%	16.67%
Beam	0.08%	0.38%	**75.79%**	0.02%	76.27%
Railing	0.00%	0.13%	0.17%	**0.19%**	0.48%
Total	6.52%	15.46%	76.23%	1.78%	100.00%

Performance metrics

Measure	**Value**
Overall Accuracy	97.13%
Average Accuracy	80.90%
Intersection Over Union (IOU)	71.85%
IOU_wall	94.18%
IOU_pier	85.37%
IOU_beam	98.81%
IOU_railing	1.89%

Label	Color
Retaining wall	**Blue**
Pier	**Green**
Beam	**Yellow**
Railing	**Red**

Conclusions

- The cyberinfrastructure-enabled approach **enables and empowers** the automation and acceleration of 3D point cloud classification using deep learning techniques that are **computationally demanding**.
- The DeepHyd framework and associated software package, driven by cutting-edge **deep learning** technologies, are well tailored to the **classification of 3D hydraulic structures** from point cloud data.
- This DeepHyd framework will provide substantial support for the mission of the NCDOT Hydraulics Unit, e.g.,
  - 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 Department of Public Safety for the asset management and evaluation of hydraulic structures (e.g. bridges, or road surfaces).

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Thank you!
Questions?

https://gis.uncc.edu

NORTH CAROLINA
Department of Transportation

Research & Innovation Summit - 2020

Tillage and Compost Effects on Roadside Runoff

Josh Heitman, NCSU Crop & Soil Sciences

October 13, 2020

Necessary actions at construction sites lead to soil conditions that are challenging for grass establishment and stormwater management.

Can tillage (possibly with soil amendment) improve conditions for grass establishment and ultimately stormwater infiltration?

Simulated post-construction site conditions:

Site	Texture	Tillage (cm)	Amendments	Sub-treatment
Sandhills	Sand	0, 15, 30	compost (5 cm), lime (0, 1.5, 3[1] Mg ha^{-1})	--
Mountain	Sandy clay loam	0, 15, 30	compost (5 cm), xPAM[2] (0.32 Mg ha^{-1})	traffic (90 kPa)
Piedmont 1	Sandy clay	0, 15, 30	lime (0, 1.25, 2.5[1] Mg ha^{-1})	traffic (177 kPa)
Piedmont 2	Sandy clay	0, 30	compost (5 cm)	traffic (177 kPa)
Piedmont 3	Clay loam (fill)	0, 30	compost (5 cm), xPAM[2] (0.672 Mg ha^{-1}), gypsum (11.2 Mg ha^{-1})	--

Measured infiltration and bulk density at 6 month intervals for up to 30 months.

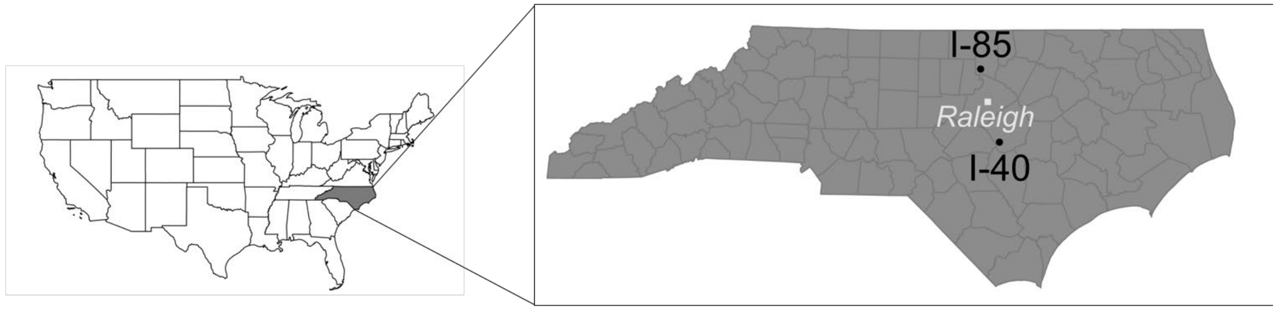
Key takeaways from *simulated post-construction sites*:

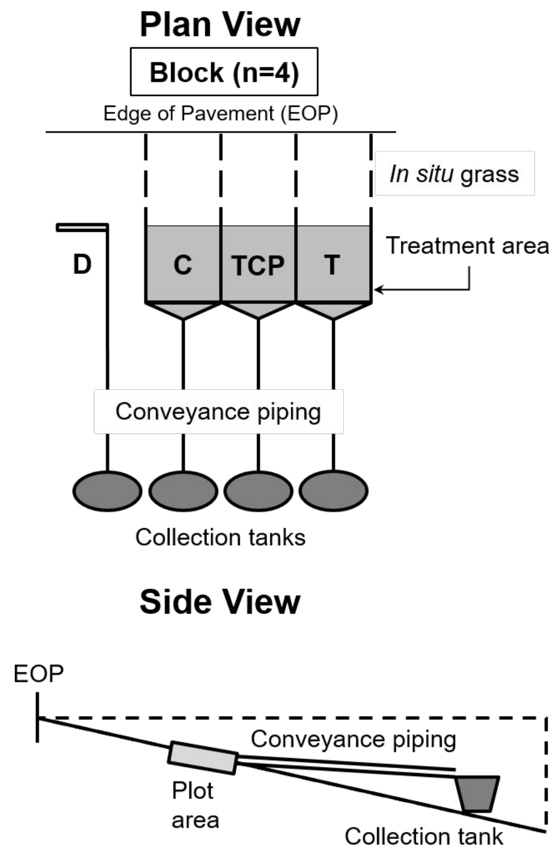
- Soil bulk density increased over time, but remained below pre-tillage levels >24 months.
- Amendments (compost, gypsum, xPAM) generally had little impact on infiltration compared to tillage alone, except where trafficked.
- Tillage increased infiltration (≥3X) at all sites (compared to compacted controls), and improvements were maintained for >24 months.

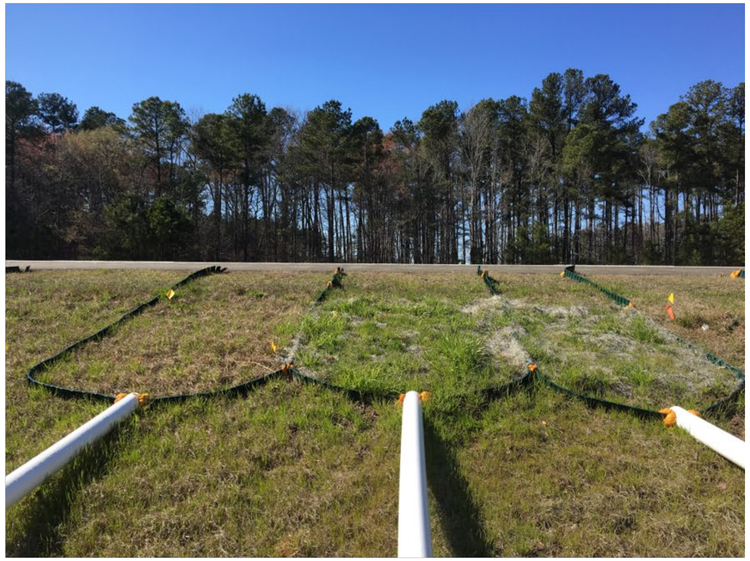
Is tillage (possibly with soil amendment) an effective ‘retrofit’ stormwater management practice?

Objective: *Test effects of <u>tillage</u> and <u>tillage with compost amendment</u> compared to existing roadside conditions on active roadways.*

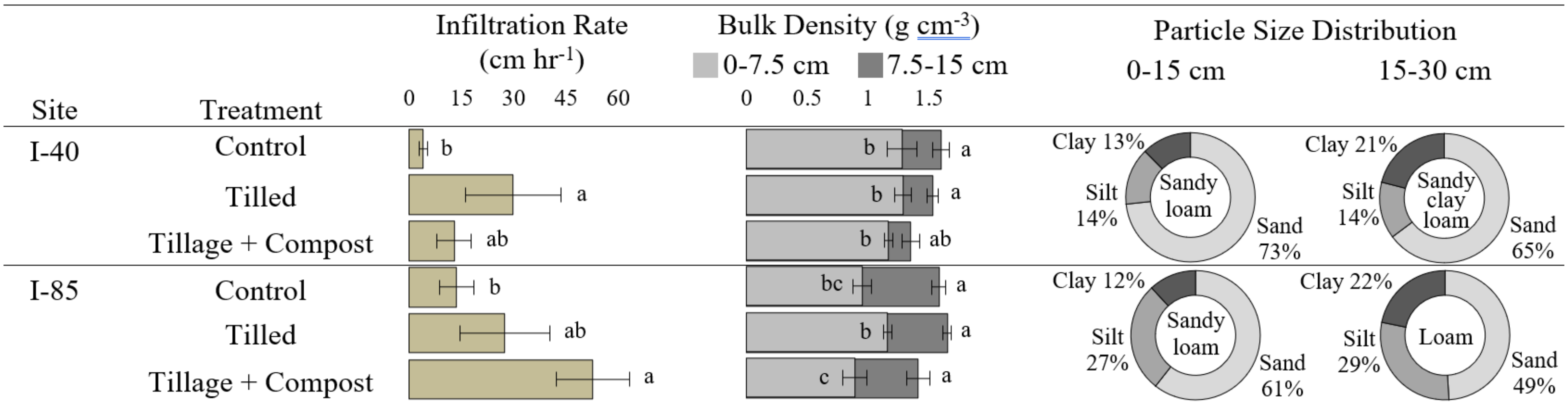
- Compost added as 2 inch depth.
- Tilled to 8 inch depth.
- Control was existing grass stand.
- Measurements collected for approximately 12 months for runoff volume and periodic water quality sampling.
- Infiltration rates measured after 12 months.





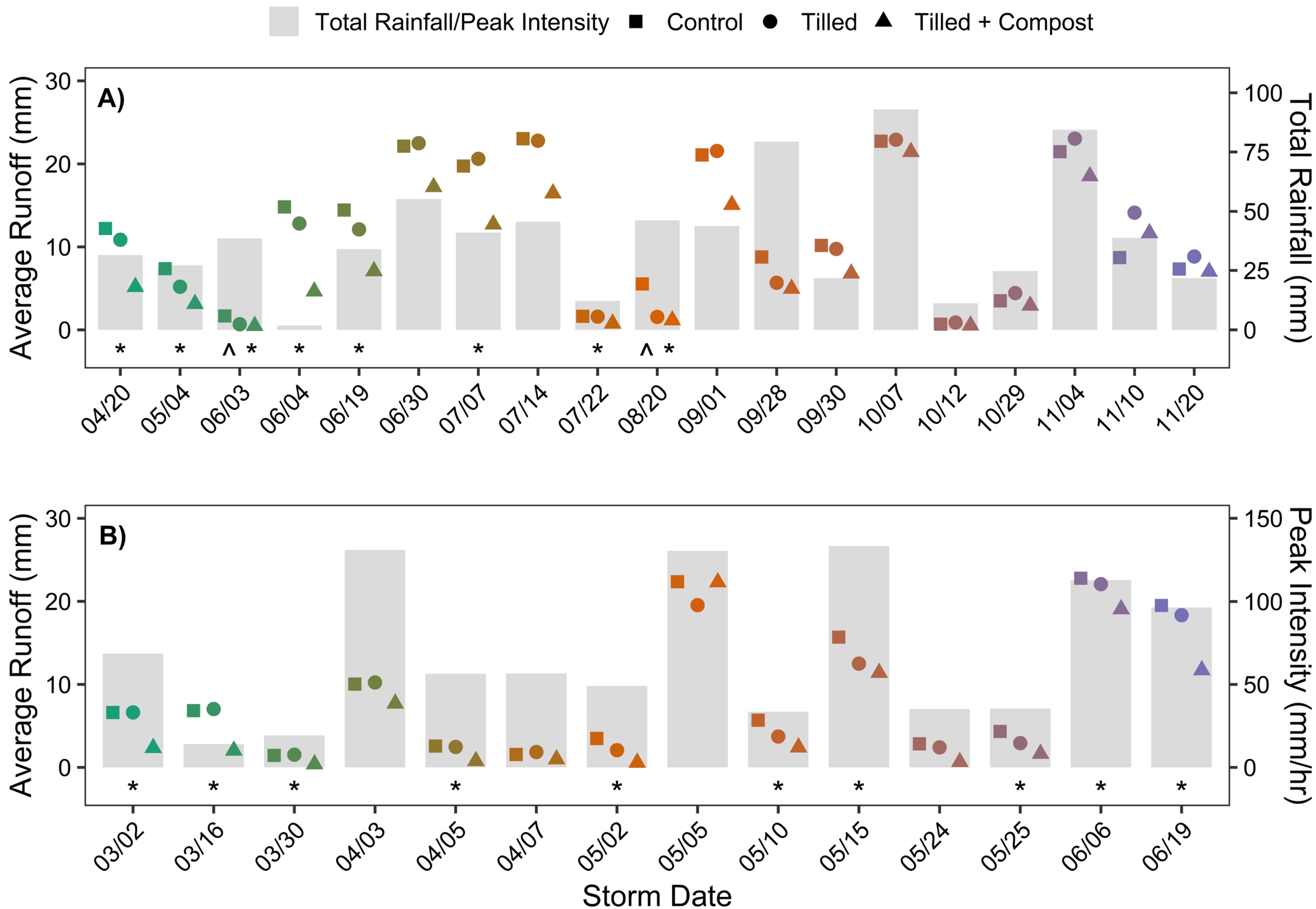


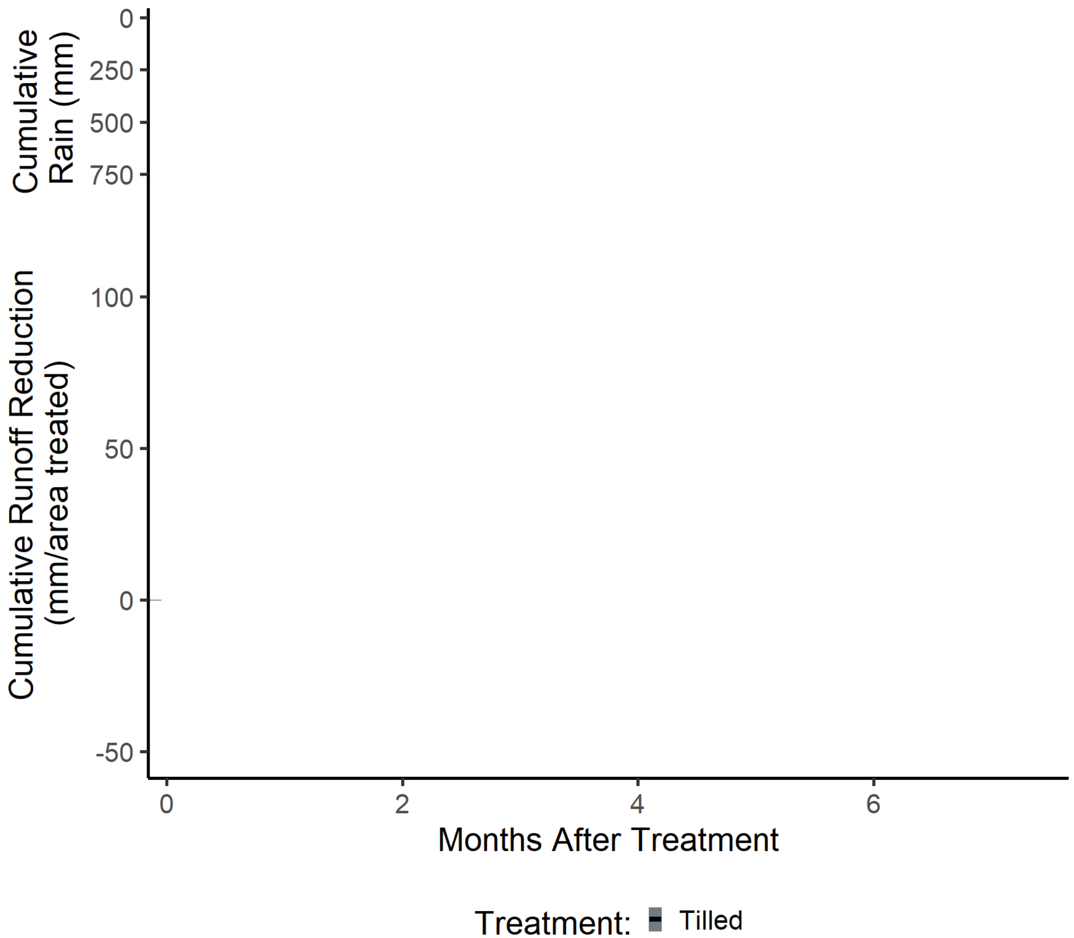
Infiltration rate improvements differed by site:



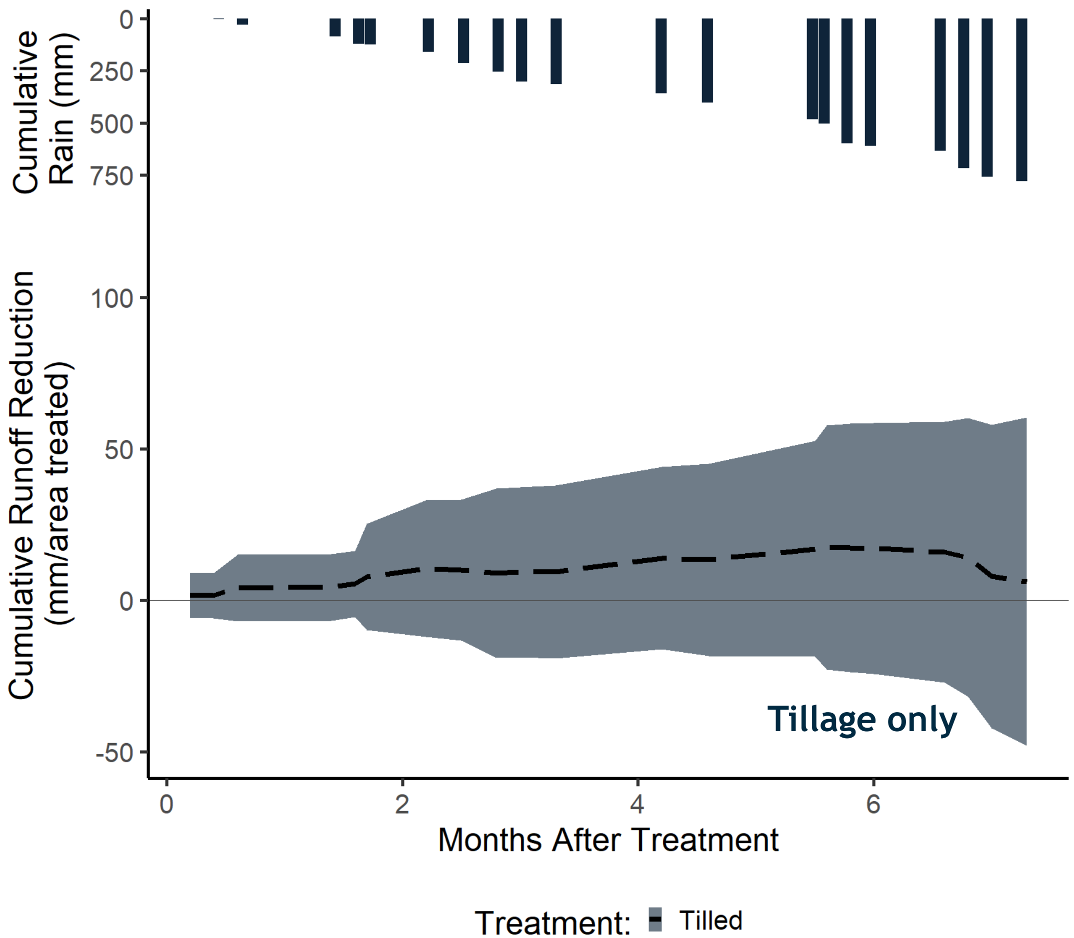
I-40

I-85

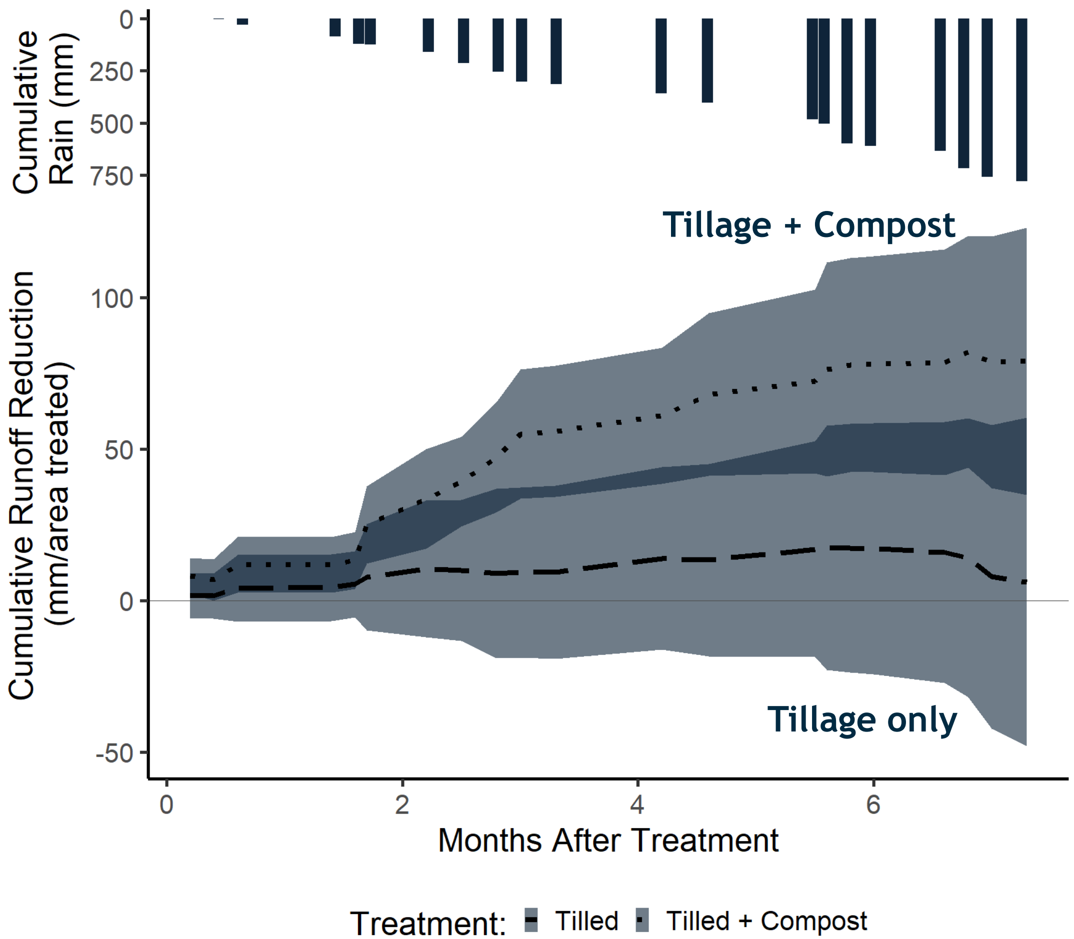

Total Rainfall/Peak Intensity
Control
Tilled
Tilled + Compost
A)
Average Runoff (mm)
Total Rainfall (mm)
04/20
05/04
06/03
06/04
06/19
06/30
07/07
07/14
07/22
08/20
09/01
09/28
09/30
10/07
10/12
10/29
11/04
11/10
11/20
B)
Average Runoff (mm)
Peak Intensity (mm/hr)
03/02
03/16
03/30
04/03
04/05
04/07
05/02
05/05
05/10
05/15
05/24
05/25
06/06
06/19
Storm Date


Cumulative
Rain (mm)
0
250
500
750
Cumulative Runoff Reduction
(mm/area treated)
100
50
0
-50
0
2
4
6
Months After Treatment
Treatment:
Tilled

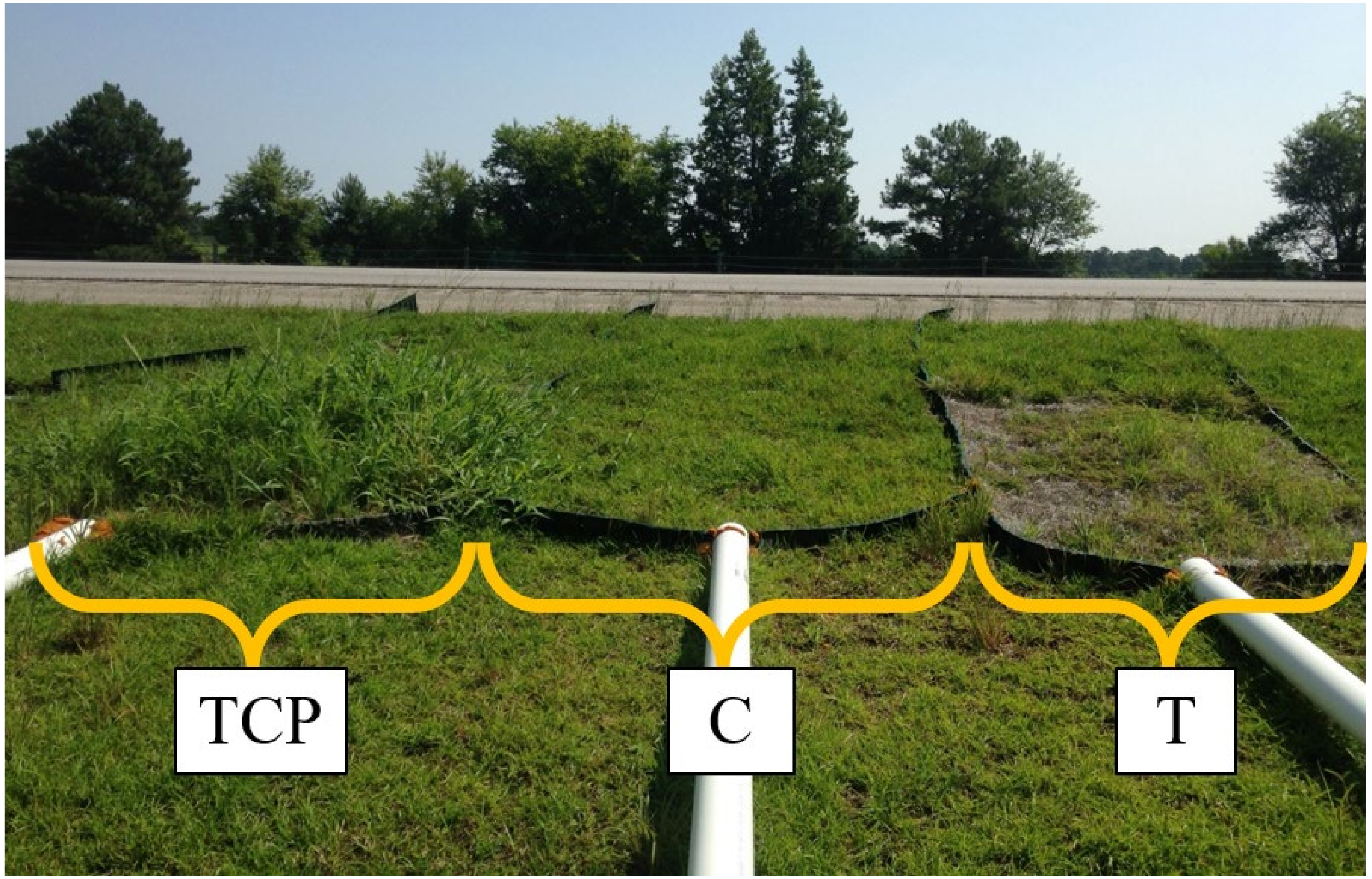
I-40


Cumulative
Rain (mm)
0
250
500
750
Cumulative Runoff Reduction
(mm/area treated)
100
50
0
-50
Tillage only
0
2
4
6
Months After Treatment
Treatment:
Tilled

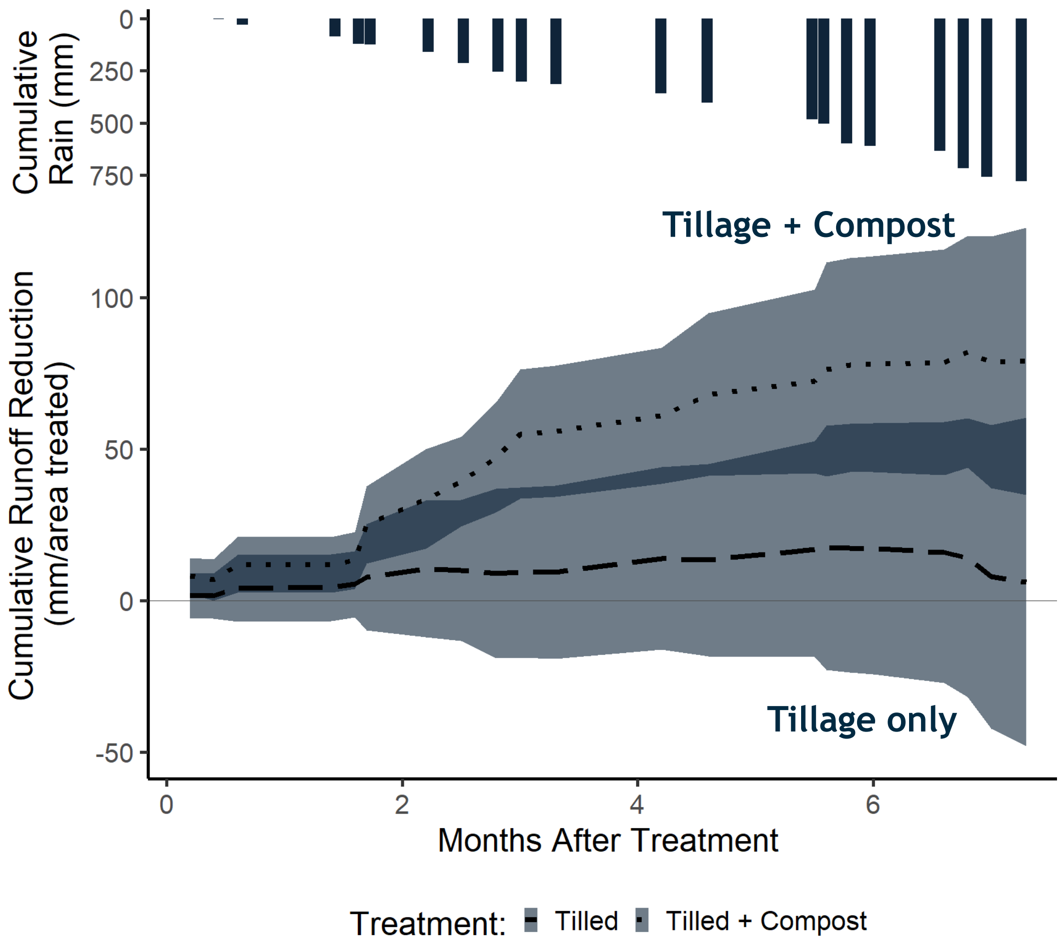
I-40


Cumulative Rain (mm)
0
250
500
750
Cumulative Runoff Reduction (mm/area treated)
100
50
0
-50
Tillage + Compost
Tillage only
0
2
4
6
Months After Treatment
Treatment: Tilled Tilled + Compost

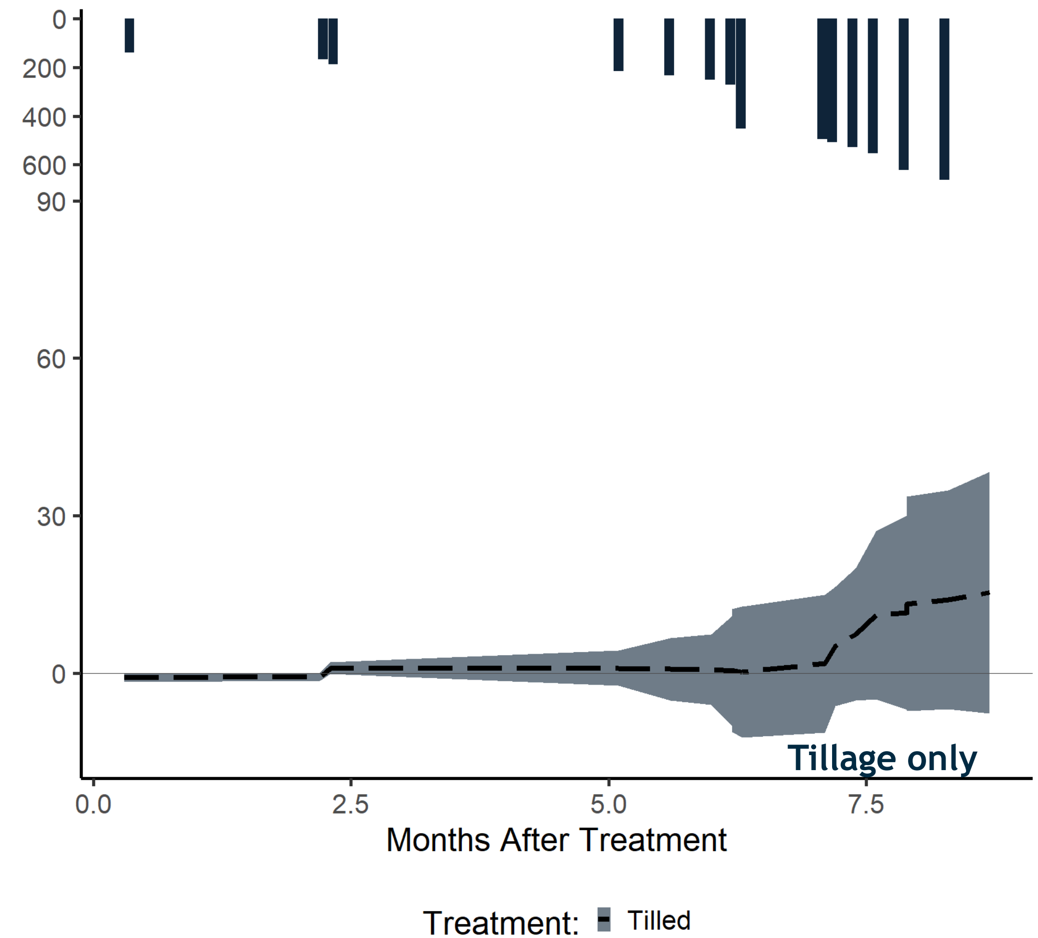
I-40

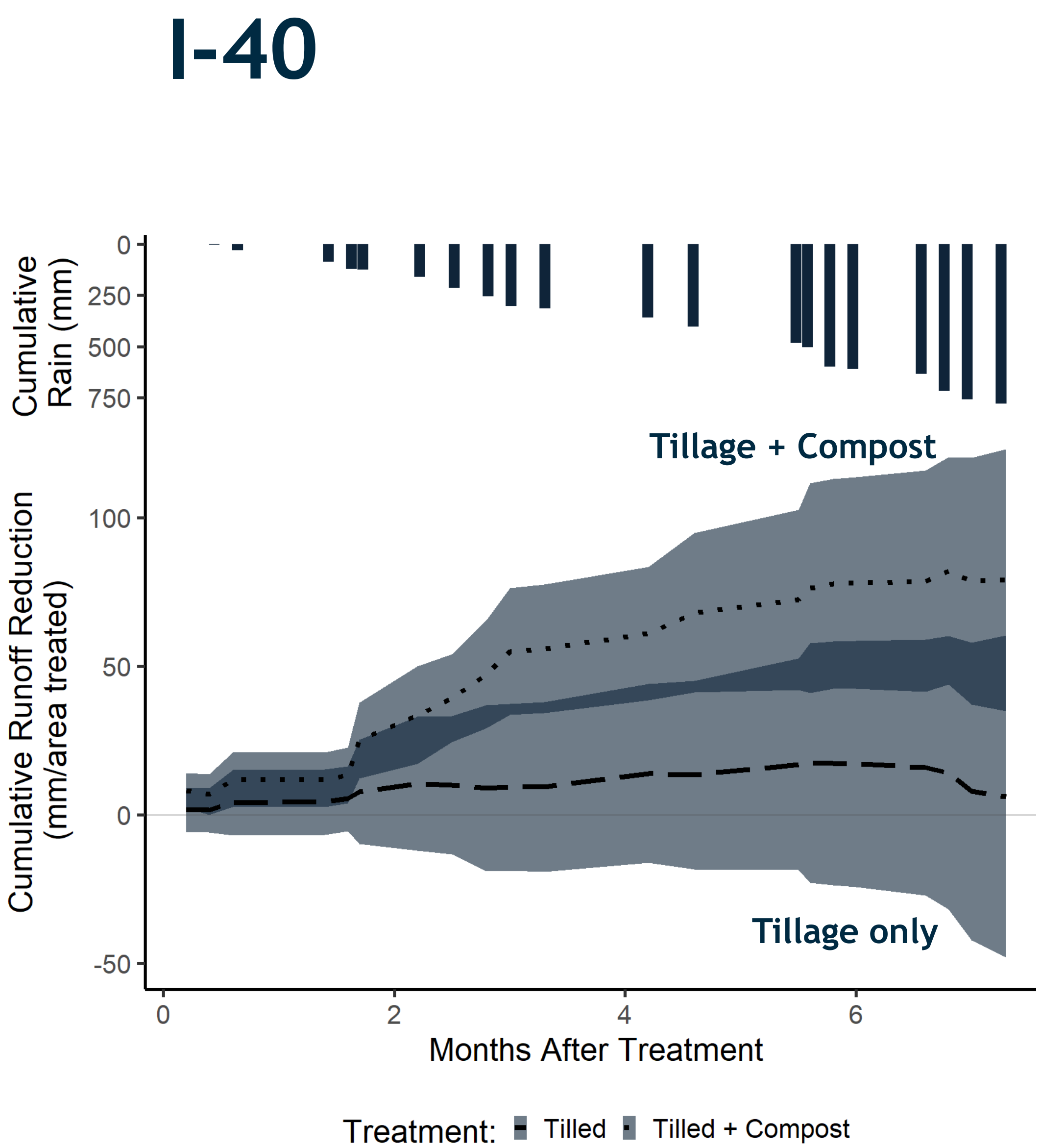


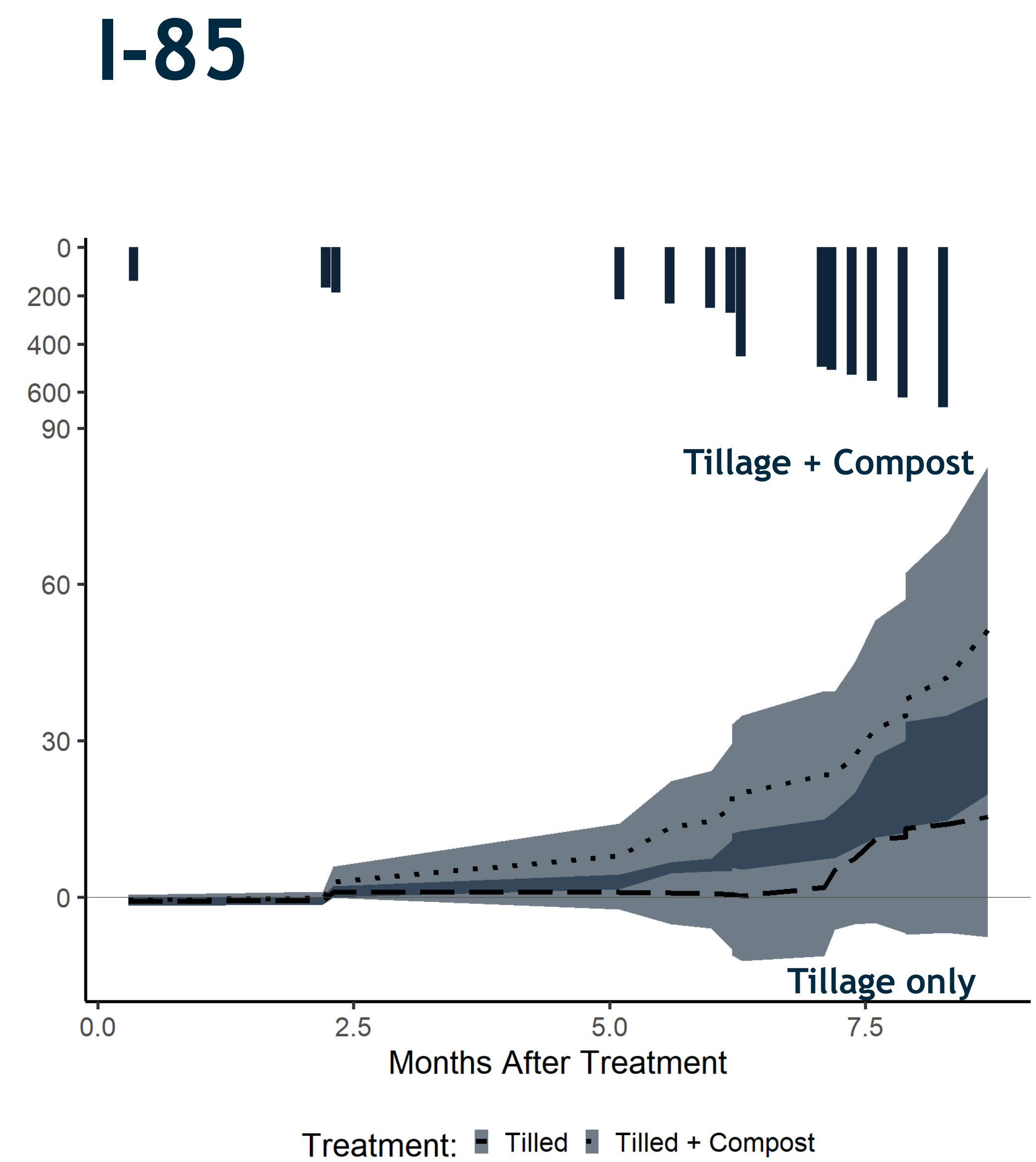
I-40


Cumulative Rain (mm)
0
250
500
750
Tillage + Compost
Cumulative Runoff Reduction (mm/area treated)
100
50
0
-50
Tillage only
0
2
4
6
Months After Treatment
Treatment: Tilled Tilled + Compost

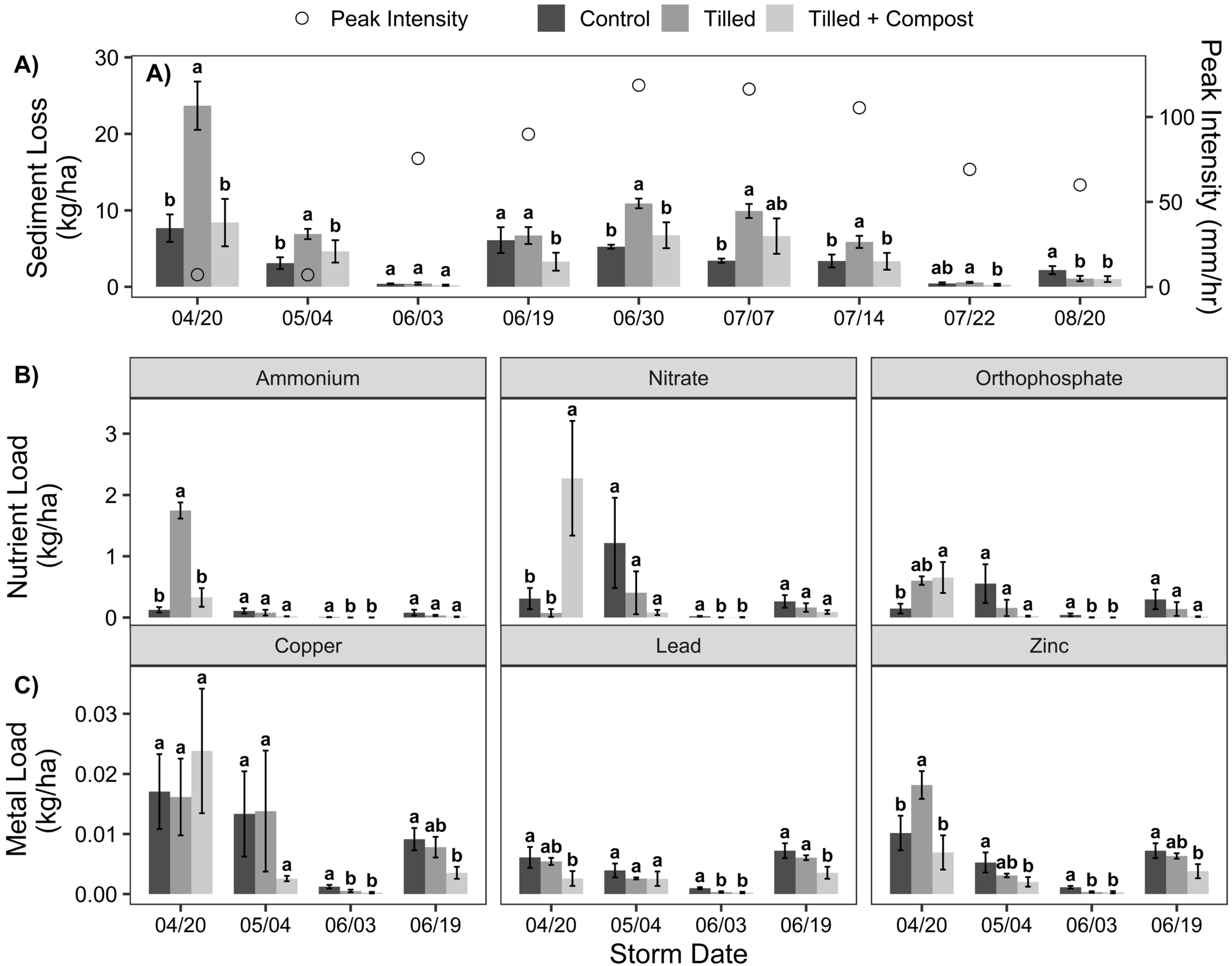
I-85


0
200
400
600
90
60
30
0
Tillage only
0.0
2.5
5.0
7.5
Months After Treatment
Treatment: Tilled

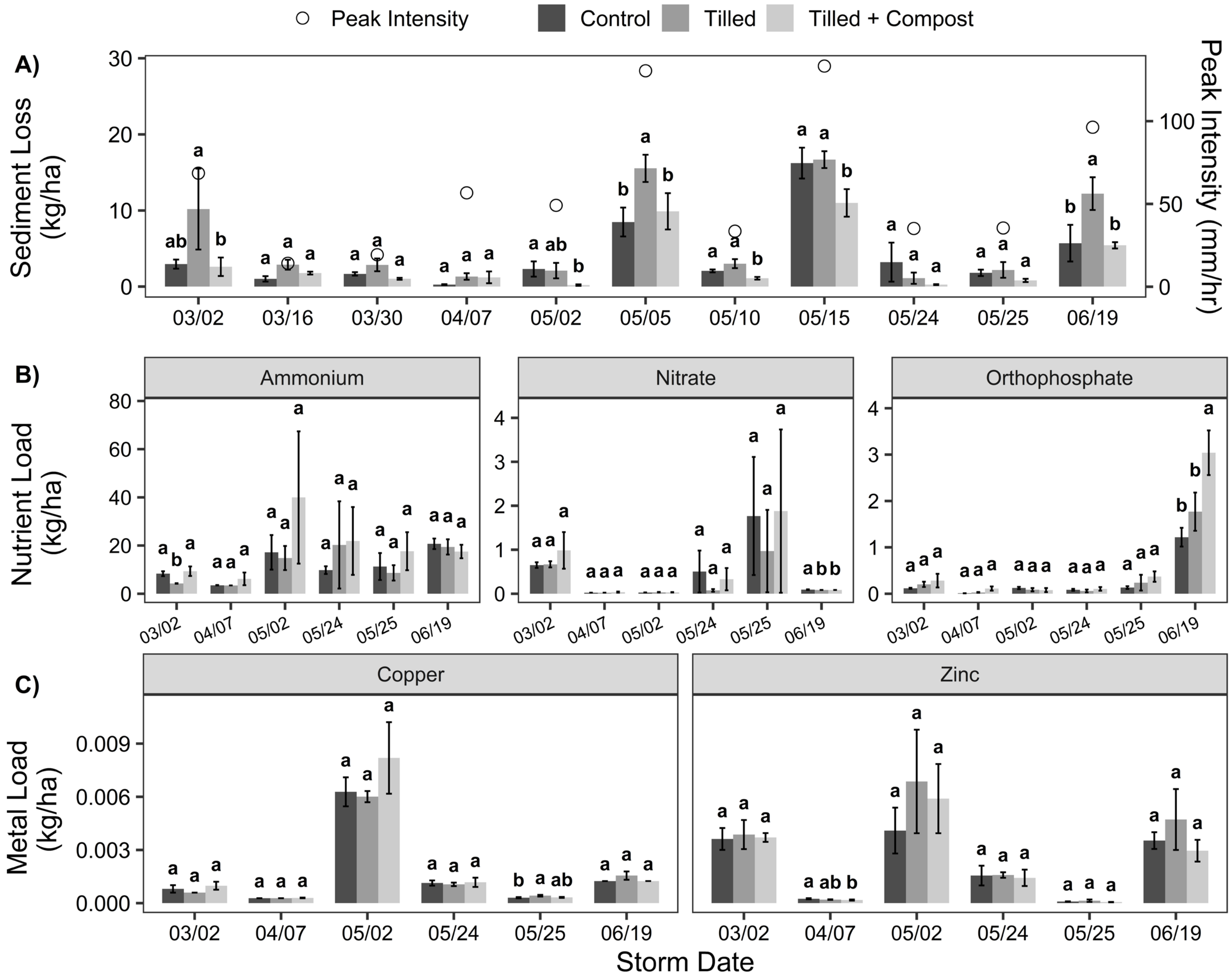

I-40
Cumulative Rain (mm)
0
250
500
750
Cumulative Runoff Reduction (mm/area treated)
100
50
0
-50
Tillage + Compost
Tillage only
0
2
4
6
Months After Treatment
Treatment: Tilled Tilled + Compost


I-85
0
200
400
600
90
60
30
0
Tillage + Compost
Tillage only
0.0
2.5
5.0
7.5
Months After Treatment
Treatment: Tilled Tilled + Compost

I-40


Peak Intensity
Control
Tilled
Tilled + Compost
A)
Sediment Loss (kg/ha)
Peak Intensity (mm/hr)
04/20
05/04
06/03
06/19
06/30
07/07
07/14
07/22
08/20
B)
Ammonium
Nitrate
Orthophosphate
Nutrient Load (kg/ha)
C)
Copper
Lead
Zinc
Metal Load (kg/ha)
Storm Date

I-85


Peak Intensity
Control
Tilled
Tilled + Compost
A)
Sediment Loss (kg/ha)
Peak Intensity (mm/hr)
03/02
03/16
03/30
04/07
05/02
05/05
05/10
05/15
05/24
05/25
06/19
B)
Nutrient Load (kg/ha)
Ammonium
Nitrate
Orthophosphate
C)
Metal Load (kg/ha)
Copper
Zinc
Storm Date

Conclusions

- Tillage with compost amendment reduced runoff losses along roadside sites; tillage alone was insufficient compared to existing roadside conditions.
- Compost directly improved infiltration rates for the finer-textured soils at I-85.
- Compost did not directly improve infiltrate rates at the sandier site (I-40) but did improve the vigor of the grass stand, which ultimately appeared to reduce runoff.
- Water quality was maintained or improved following tillage.