Geotechnical and Geophysics Is There a Connection?

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Problem Statement – Difficult Access Areas With Geotechnical Drill Rig

Research Flow

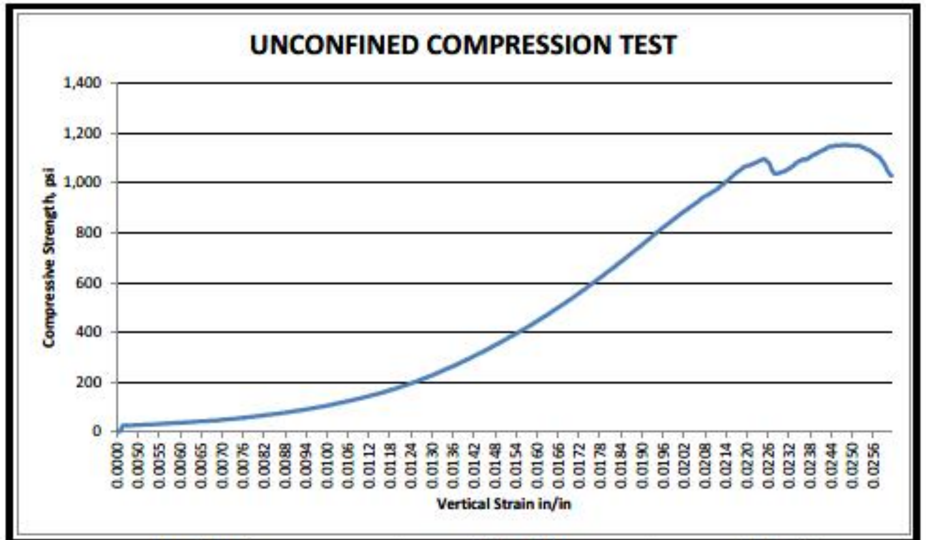
- **Geophysical Inputs**
  - SRT-Vp
  - MASW-Vs
  - ERT-Resistivity
  - IP-Chargeability
- **Geotechnical Outputs**
  - Lithology Classification
  - Moist Unit Weight-pcf

Research Methodology

- **Drill geotechnical boreholes for consulting clients.**

Research Methodology

- **Perform Laboratory Testing on Soil and Rock samples.**
  - Unconfined Compressive Strength
  - Moist Unit Weight
  - Unified Soil Classifications
    - Atterberg Limits
    - Gradation (sieve analysis)



Type of Break
Axial Splitting and Deformation

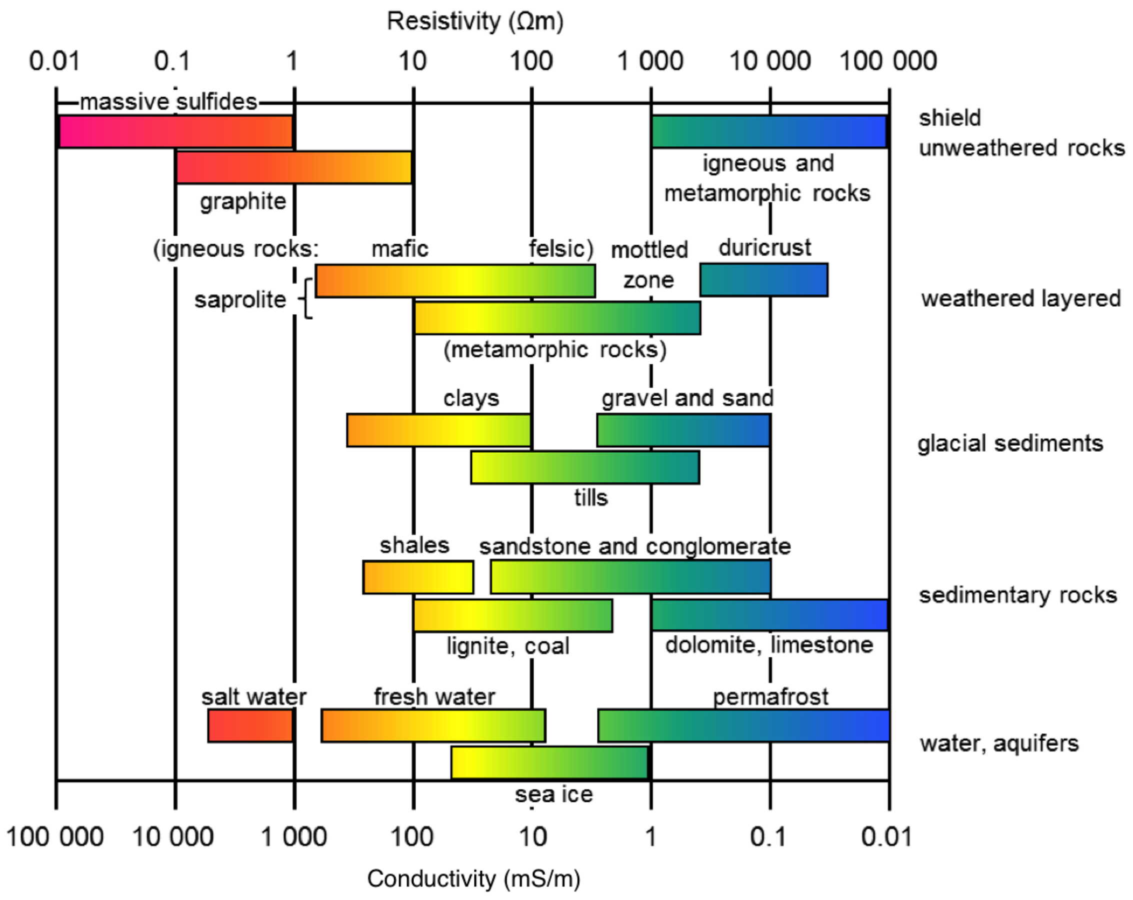
Visual Rock Classification
Sandy Mudstone
Fall River Formation

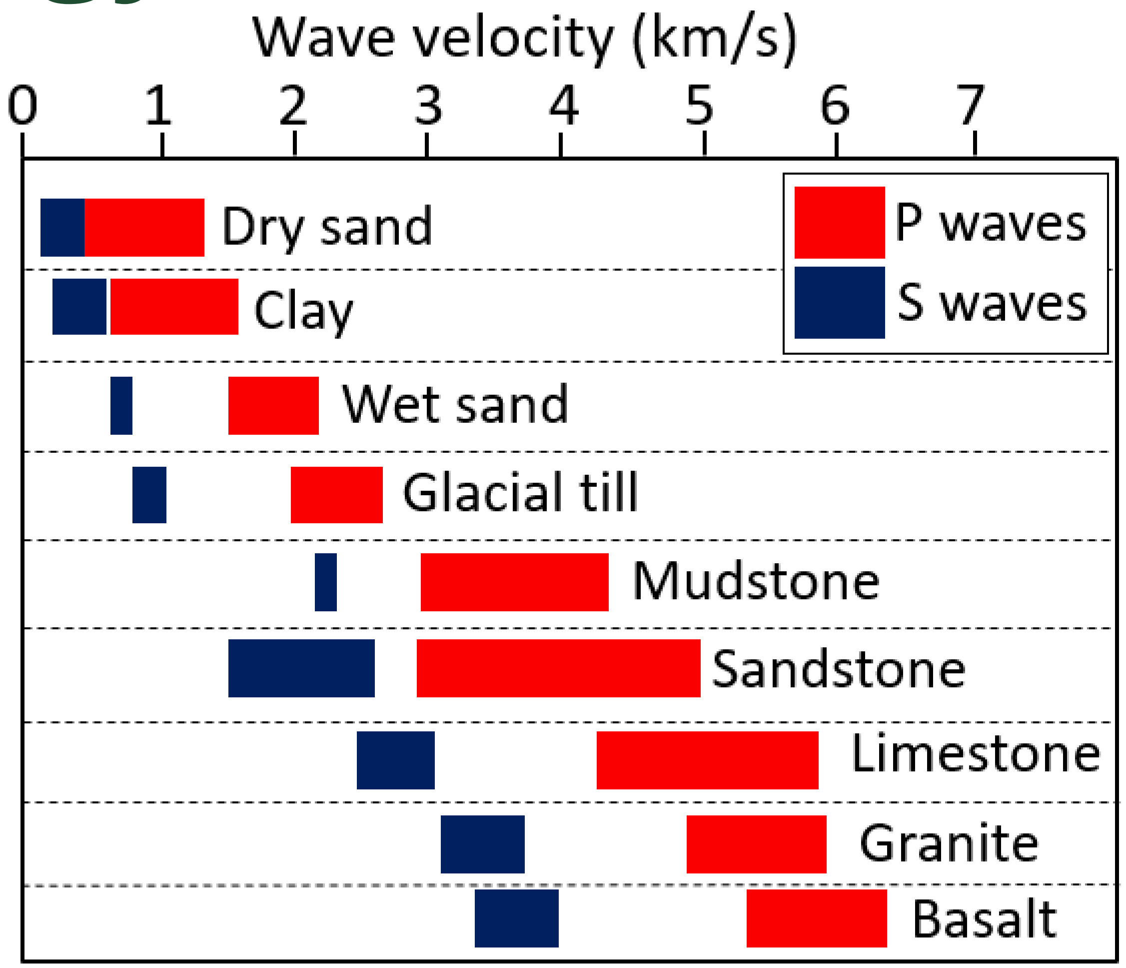
Rock Parameters		
Unit Weight	147.1	pcf
U.C. Strength	1,154.2	psi
Deformation Modulus	105,492	psi
ε_{50}	0.0124	in/in
Strain at Max	2.4828	%
Water Content	4.56	%

Photo Before

Photo After

Research Methodology

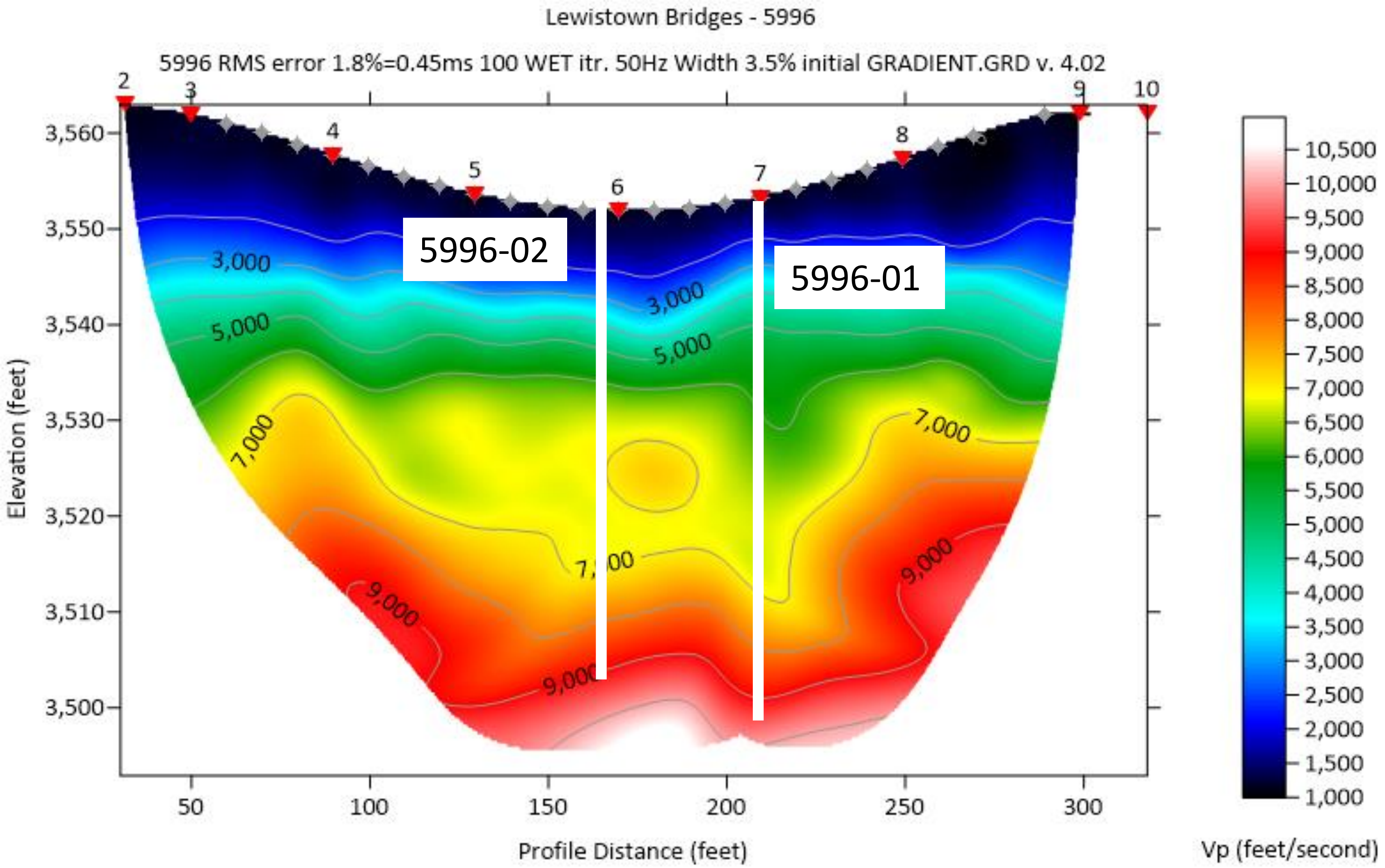




Research Methodology

- **Perform near-surface geophysics and match the 2D geophysical profiles to the station of the boreholes and depth of in-situ and laboratory samples.**

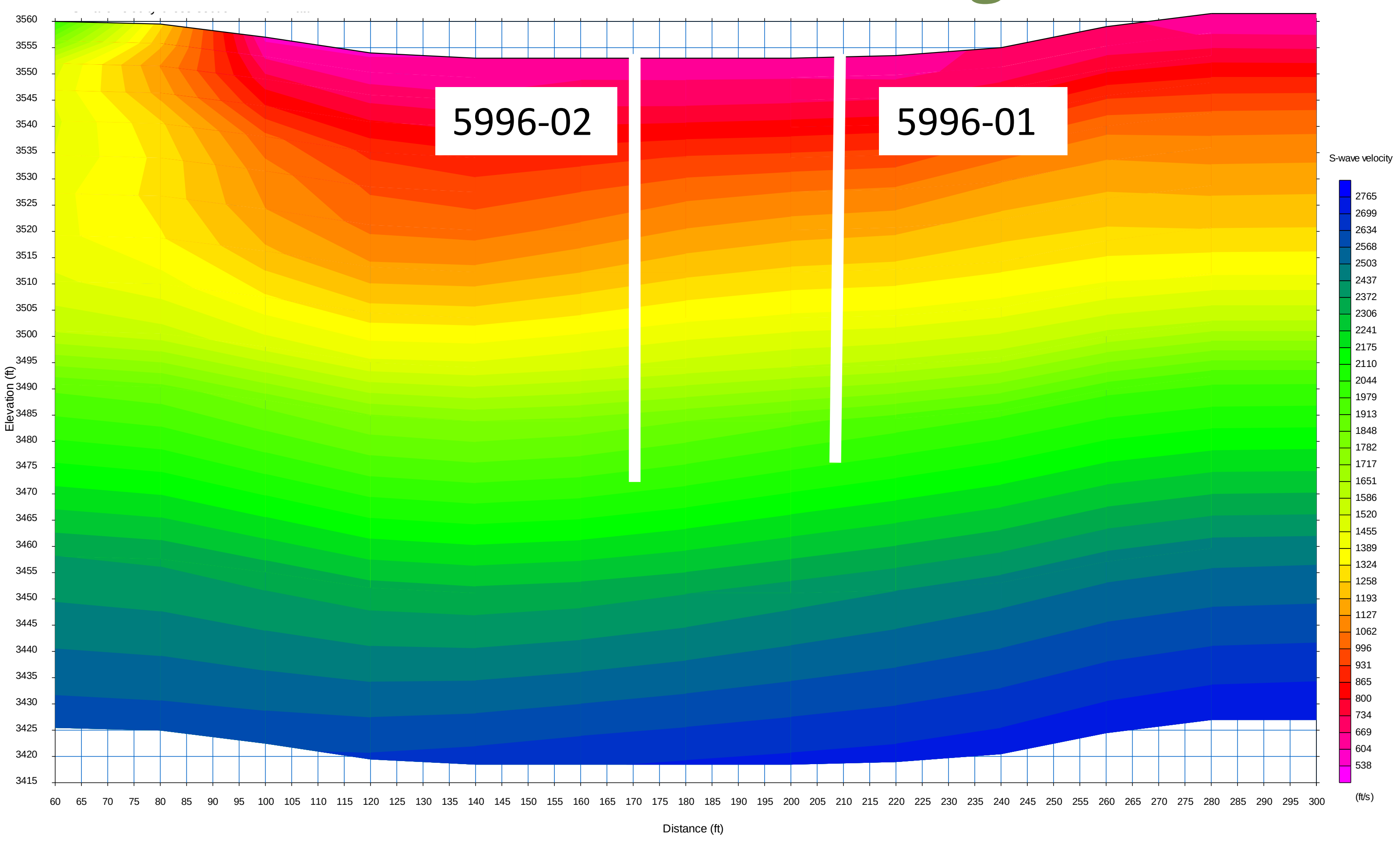
Research Methodology



Seismic Refraction Tomography – Rayfract®

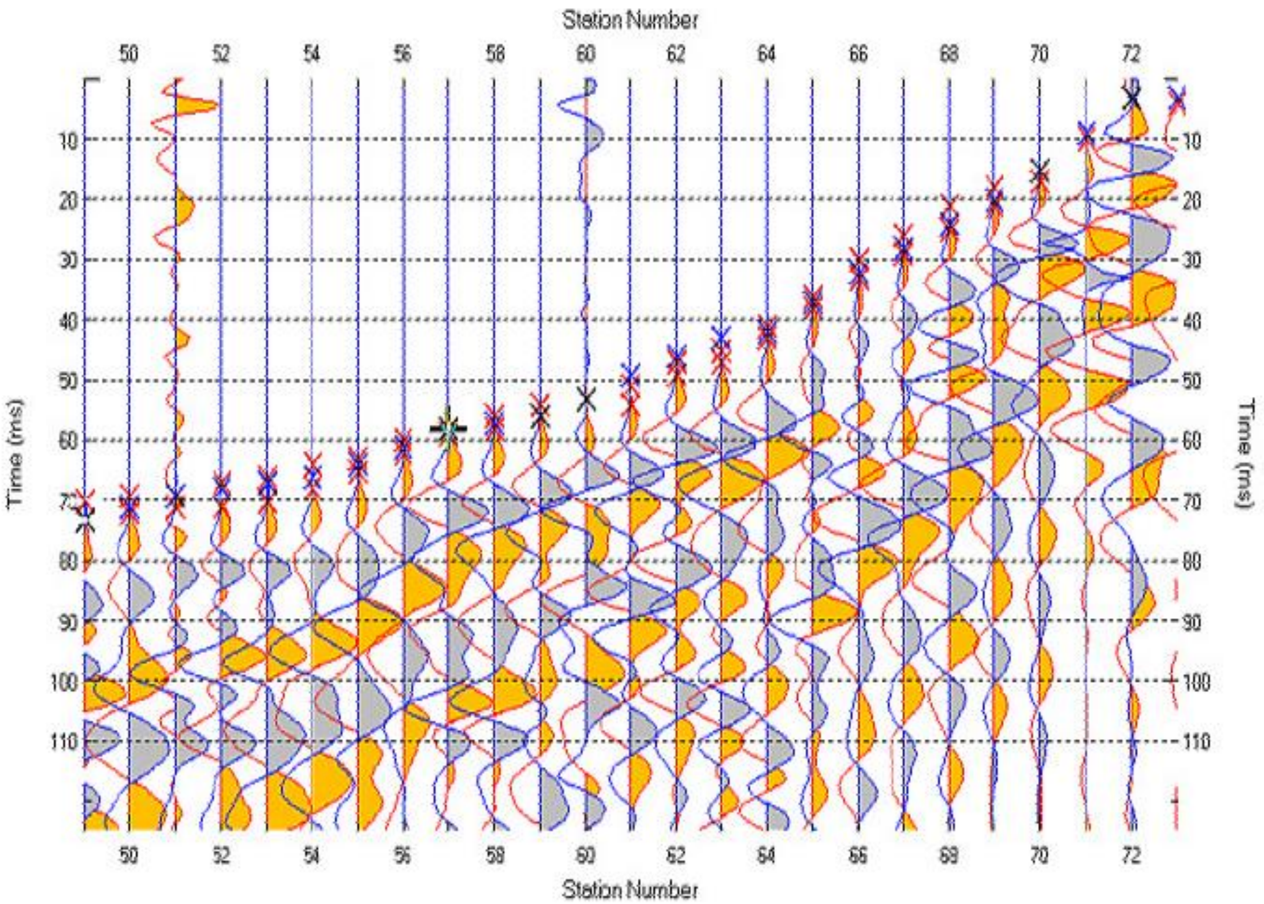
Research Methodology

Multi-Channel Analysis of Surface Waves – Seisimager®/GeoPlot®



Research Methodology

Shear Wave Refraction – Shallow Bedrock and non-dispersive soils.



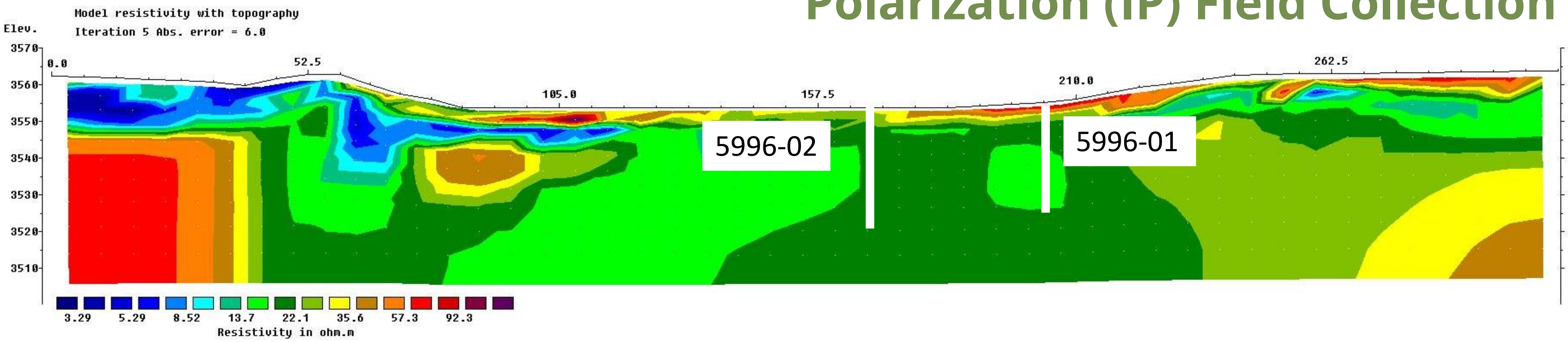
Research Methodology

Electrical Resistivity and Induced Polarization (IP) Field Collection

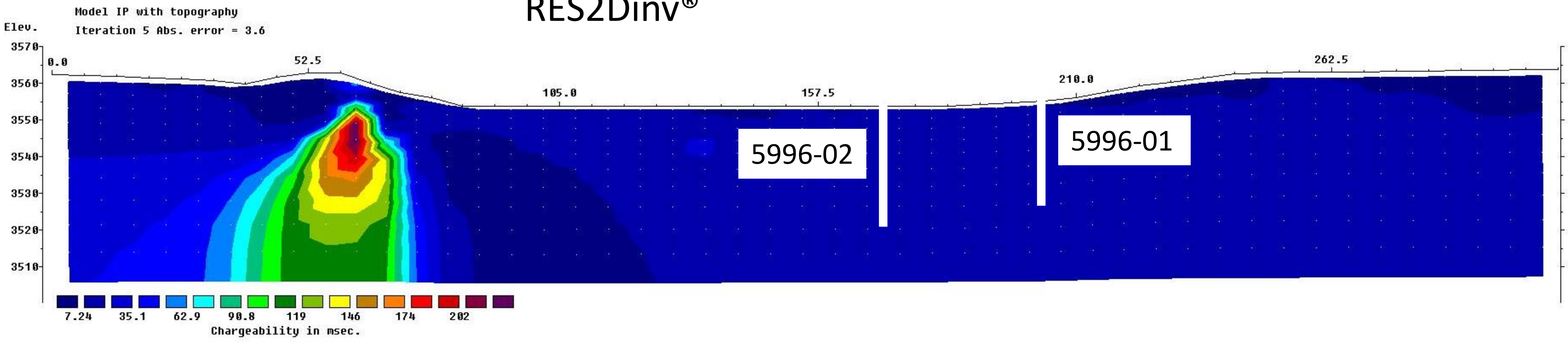
- ABEM Terrameter LS2 for Electrical Resistivity and IP

Research Methodology

Resistivity and Induced Polarization (IP) Field Collection



RES2Dinv®



Research Methodology

- Build a data set matching compression and shear seismic velocities, electrical resistivity, and induced polarization chargeability values to geotechnical parameters.

Bridge	Borehole	Sample Depth (feet)	Sample Type	Water Content (%)	Moist Unit Weight (pcf)	Static Modulus (psi)	UCS (psi)	Vp (ft/s)	Vs (ft/s)	ERT(ohm -m)	IP (msec)
5991	5991-01	14.25	HQ	4.6	147.1	105,494	1,154.2	6,508	2,162	50.3	11.0
		15.75	HQ	7.4	146.0	4,487	132.7	7,054	2,064	52.3	10.9
		25.25	HQ	6.4	150.4	52,802	725.2	9,044	2,246	66.2	12.0
	5991-02	10.75	HQ	8.3	144.0	9,610	199.1	4,958	1,719	43.4	13.5
		16.25	HQ	7.3	147.4	6,055	178.7	7,160	1,879	46.4	13.9
		19.25	HQ	6.4	148.8	87,454	1,190.7	7,557	1,879	51.1	14.2
5992	5992-01	8.50	Shelby	24.9	123.5	237	6.2	2,536	1,656	29.3	7.9
		18.20	HQ	7.0	148.2	25,233	449.7	6,219	1,995	60.7	9.4
		22.20	HQ	5.5	151.2	80,985	1,118.9	7,262	1,995	61.0	10.6
		27.25	HQ	6.4	150.0	115,402	1,080.7	7,867	2,624	60.6	12.0
	5992-02	21.15	HQ	7.3	147.6	16,302	331.9	5,813	1,352	60.3	14.4
		26.75	HQ	5.9	149.4	18,408	381.8	7,614	1,893	60.5	14.3
		30.60	HQ	6.3	150.1	55,133	676.3	8,455	2,210	60.3	14.3

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Western United States

Six American States

Montana

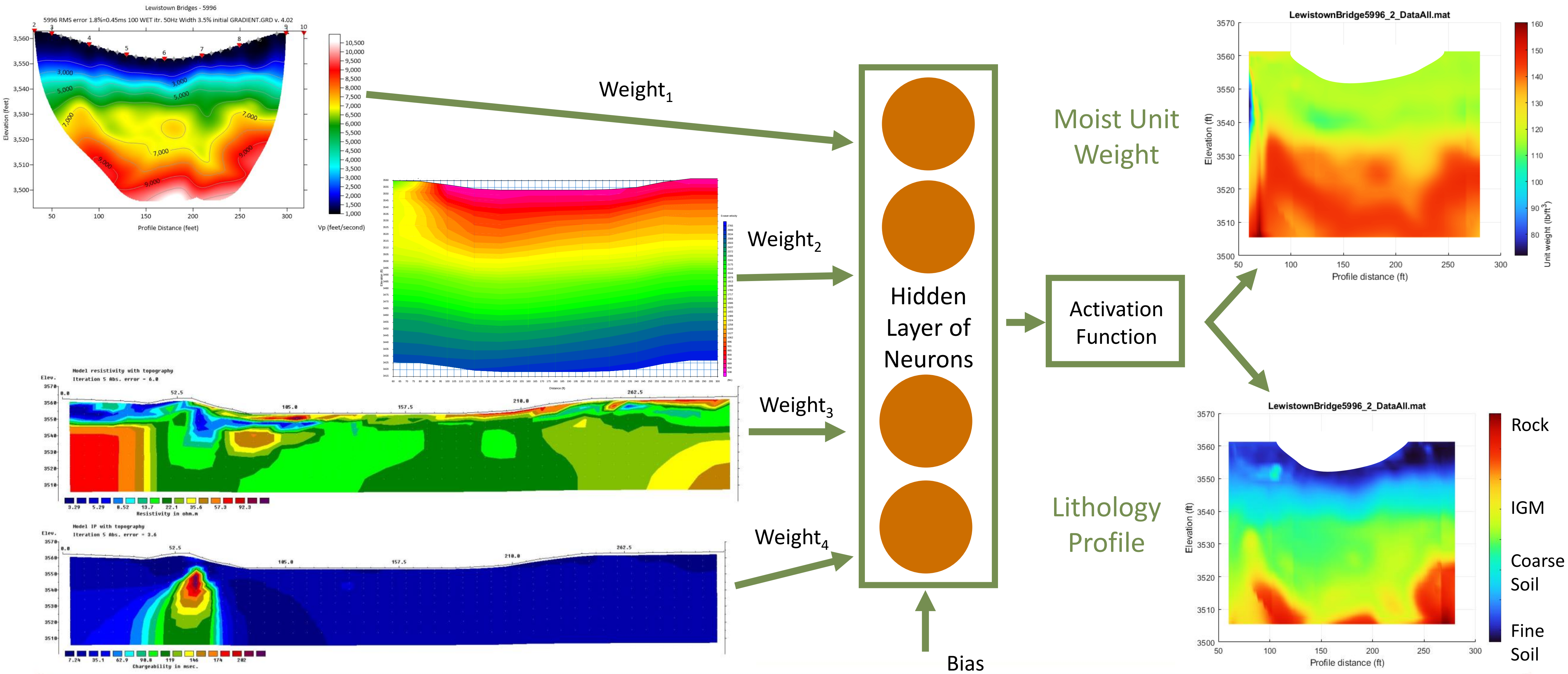
20 Locations

126 Geotechnical Boreholes To Date – From 2021 to Present

Correlate the Data Using Artificial Neural Networks – Supervised Learning

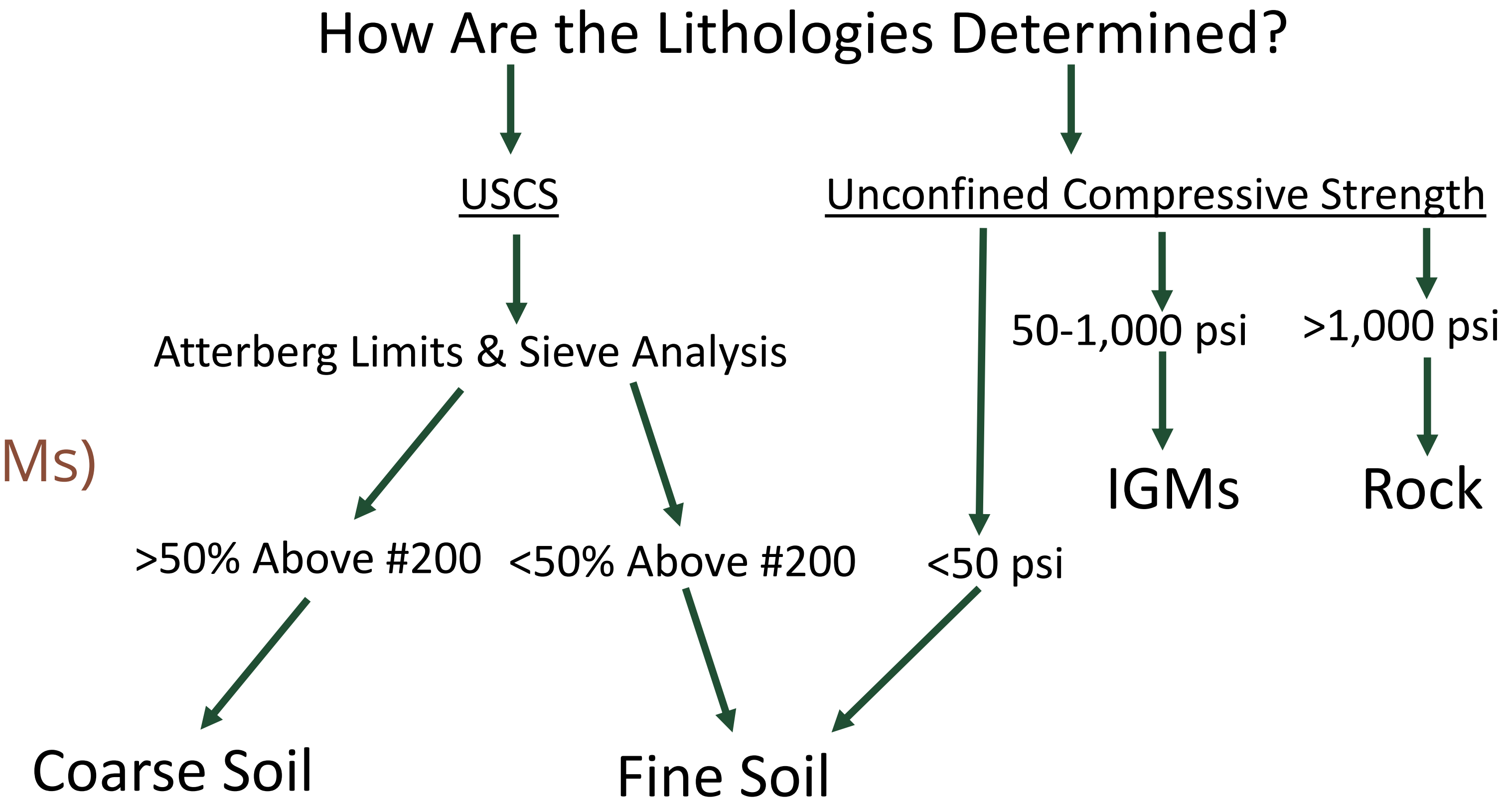
ANN Geophysical Inputs

Geotechnical Outputs



Lithology Prediction

- **Four Lithology Types:**
  - Fine Soil
    - Silts and Clays
  - Coarse Soil
    - Sands and Gravels
  - Intermediate Geomaterials (IGMs)
  - Rock



Lithology Prediction

All Data – 359 Classifications - 70% for Training and 30% for Testing

Training Confusion Matrix (Accuracy:77.38%)

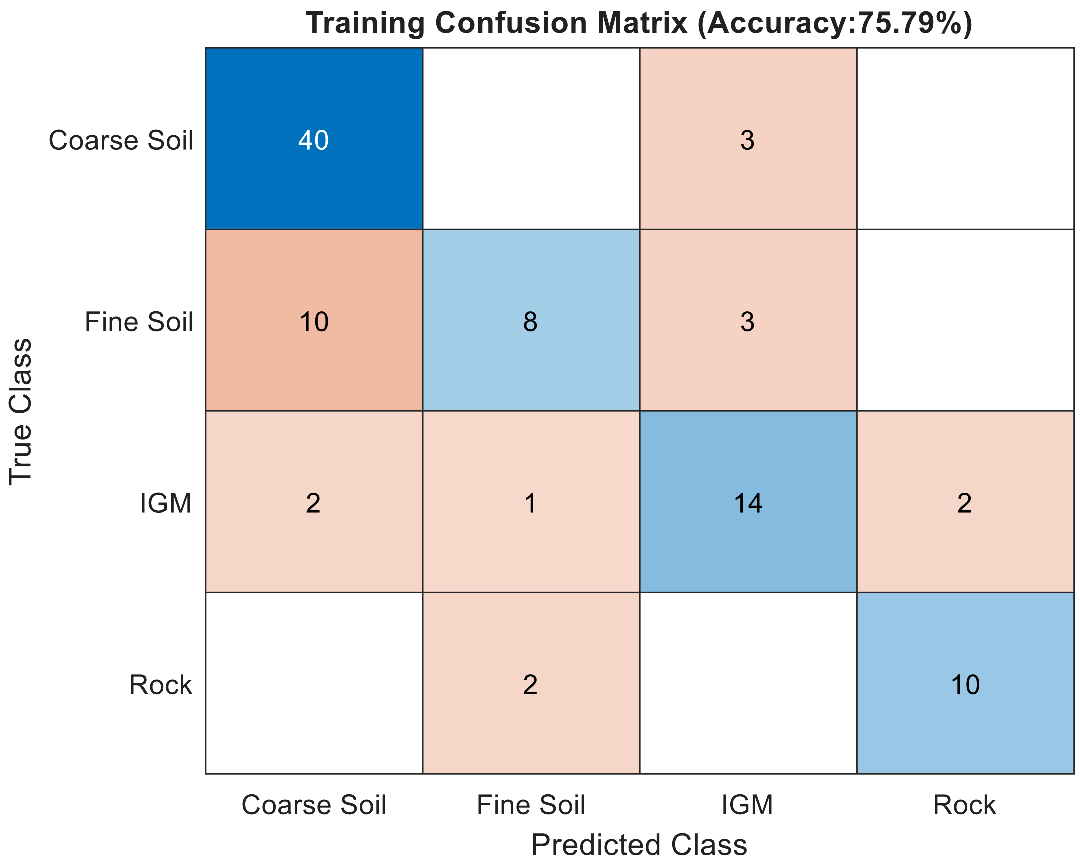
True Class \ Predicted Class	Coarse Soil	Fine Soil	IGM	Rock
Coarse Soil	71	17	5	2
Fine Soil	8	65	6	4
IGM	1	2	26	7
Rock	1		4	33

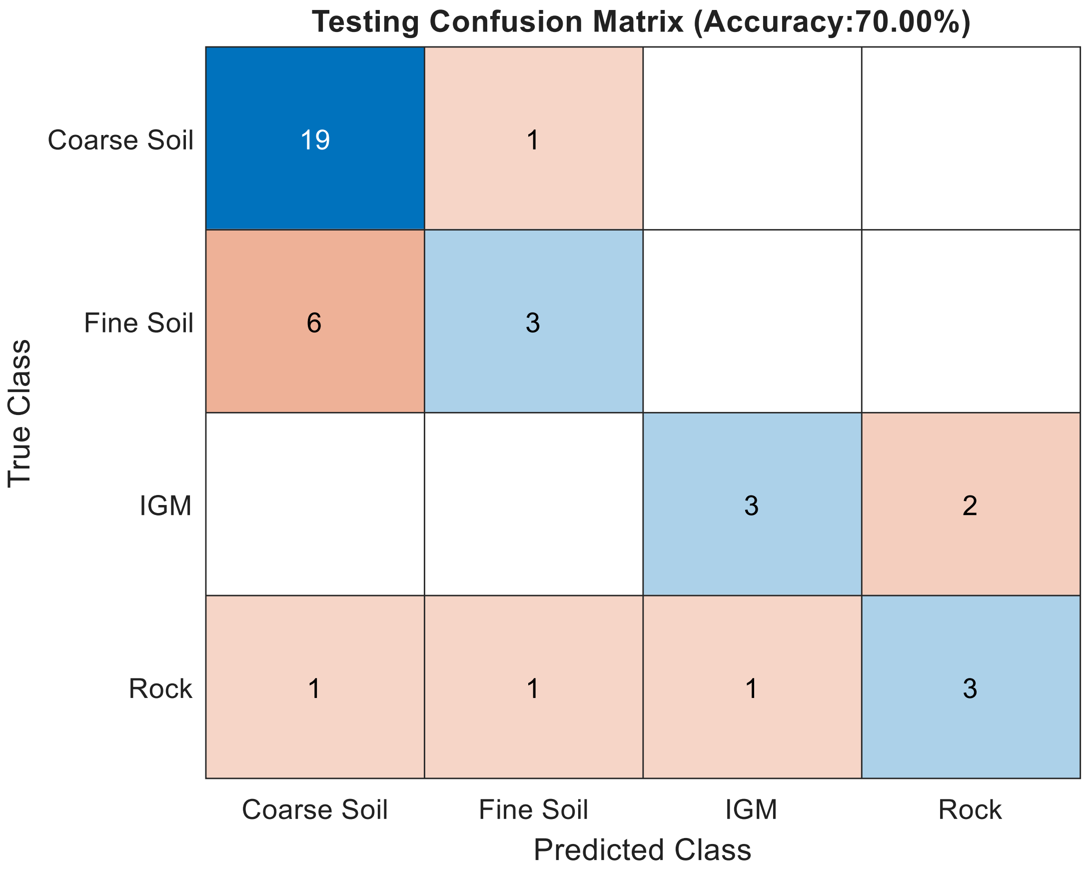
Testing Confusion Matrix (Accuracy:74.77%)

True Class \ Predicted Class	Coarse Soil	Fine Soil	IGM	Rock
Coarse Soil	36	7		
Fine Soil	8	26	3	1
IGM	2	1	6	2
Rock			3	12

Lithology Prediction

Below Groundwater Table – 135 Classifications - 70% for Training and 30% for Testing





Lithology Prediction

Above Groundwater Table – 224 Classifications - 70% for Training and 30% for Testing

Training Confusion Matrix (Accuracy:82.17%)

True Class \ Predicted Class	Coarse Soil	Fine Soil	IGM	Rock
Coarse Soil	42	13	2	
Fine Soil	7	56		
IGM	2	2	12	1
Rock			1	19

Testing Confusion Matrix (Accuracy:82.09%)

True Class \ Predicted Class	Coarse Soil	Fine Soil	IGM	Rock
Coarse Soil	15	3		
Fine Soil	2	23	3	
IGM			5	1
Rock	1		2	12

Lithology Prediction

All Data– 359 Classifications

“Dirty” Sand and Gravel – More than 12% Fines Reduces Predictability

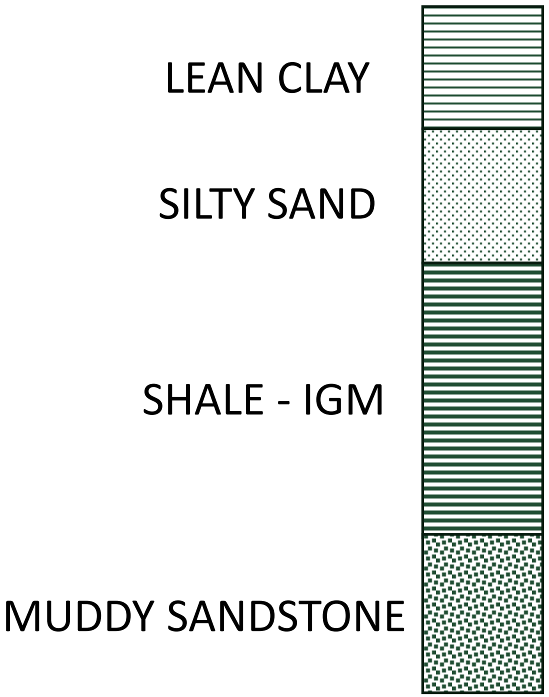
Training Confusion Matrix (Accuracy:77.38%)

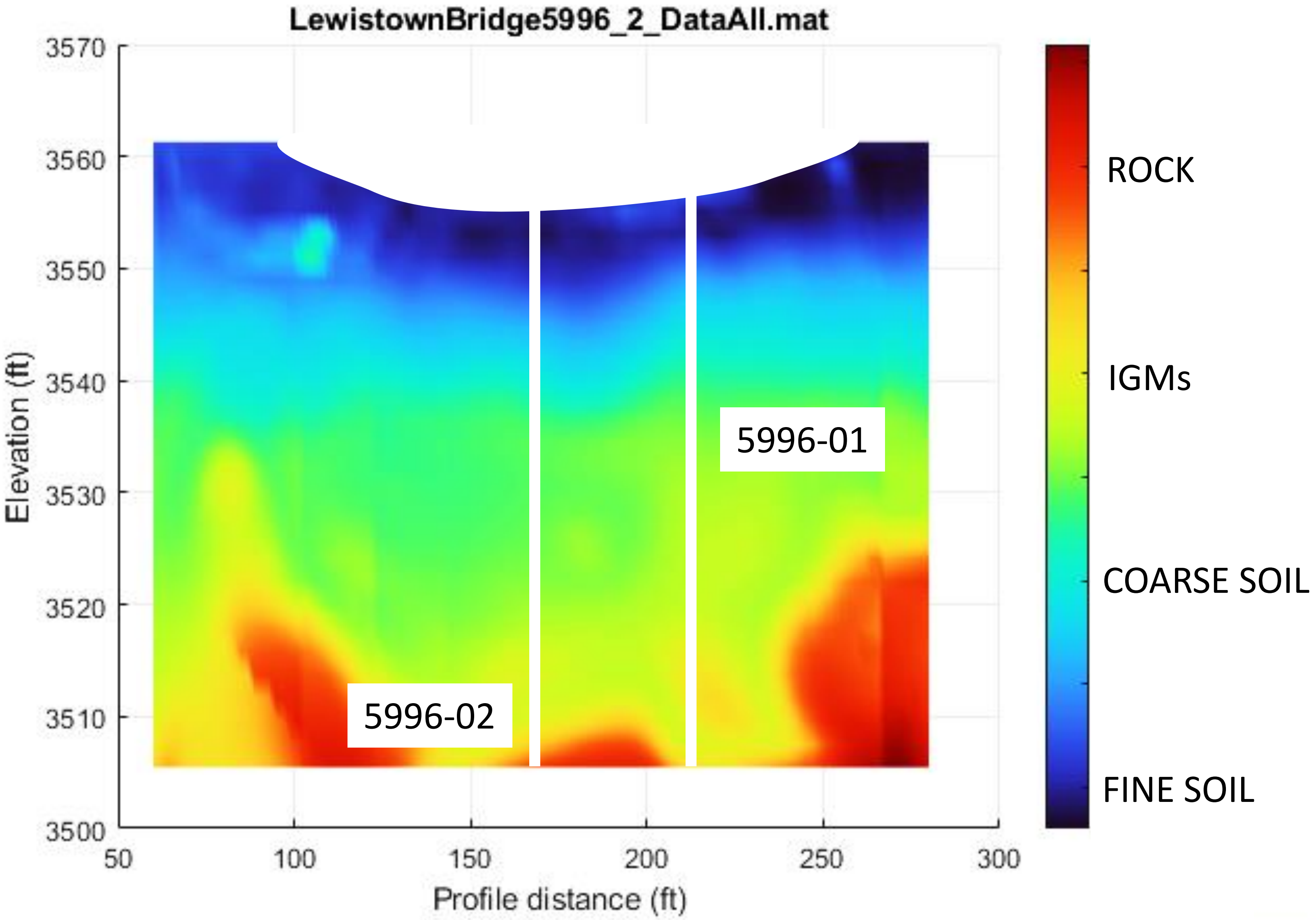
True Class \ Predicted Class	Coarse Soil	Dirty Coarse Soil	Fine Soil	IGM	Rock
Coarse Soil	31	6	4		
Dirty Coarse Soil	2	31	19	2	1
Fine Soil		3	73	1	5
IGM		1	2	23	7
Rock				4	37

Testing Confusion Matrix (Accuracy:72.90%)

True Class \ Predicted Class	Coarse Soil	Dirty Coarse Soil	Fine Soil	IGM	Rock
Coarse Soil	16	5			1
Dirty Coarse Soil	1	11	7	1	
Fine Soil		2	33	4	
IGM			2	8	4
Rock		1		1	10

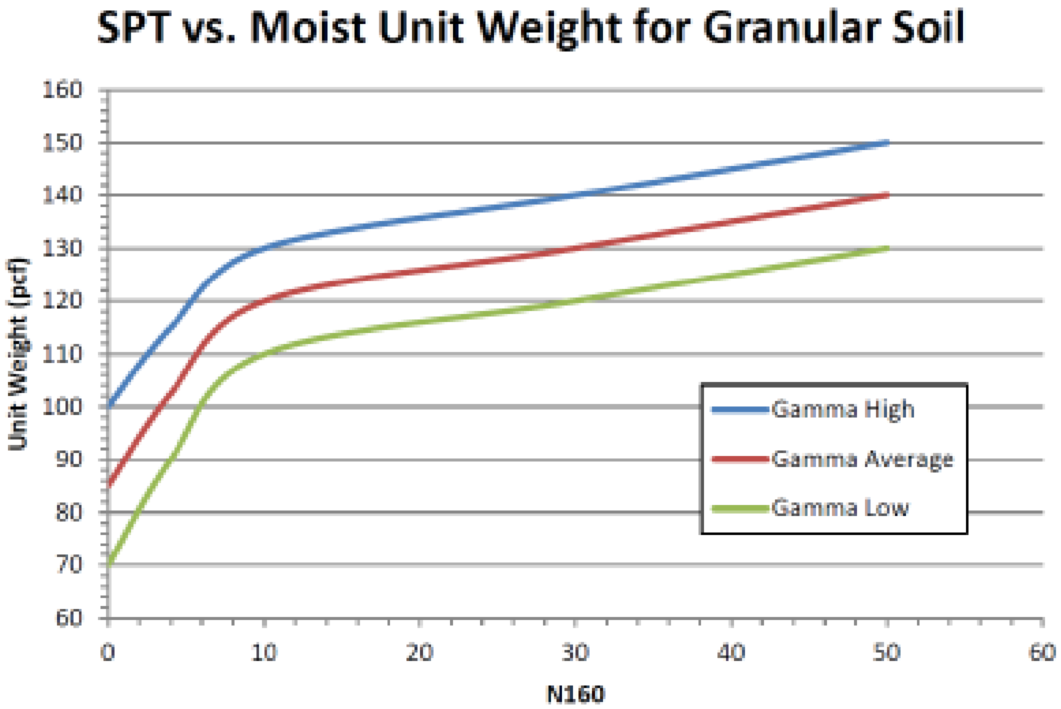
LITHOLOGY FROM BOREHOLE LOGS





Moist Unit Weight Prediction

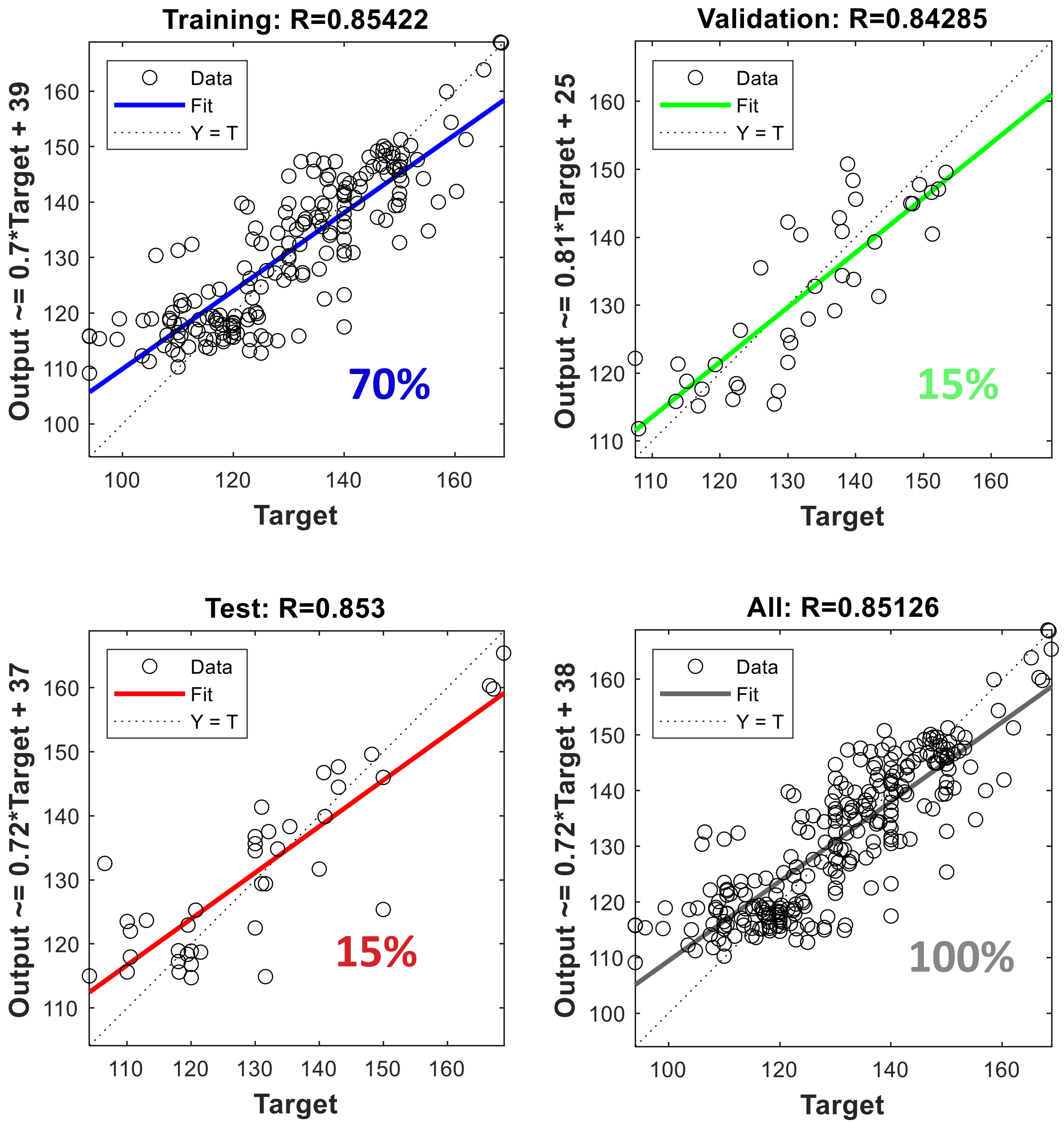
- **263 Samples**
  - Moist unit weights determined from:
    - Shelby tube samples – fine soil
    - Rock core samples
    - Correlations of SPT for granular soil



Source: Bowles, 1977

Moist Unit Weight Prediction

- 70% of original sample chosen randomly



- 15% used during training to determine if training is converging

- 15% used after training is completed to see if networks generalizes

- Visualize the outputs using regression plots

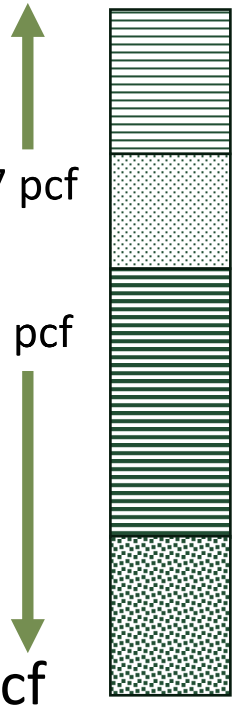
- Plot showing 100% of the data on one plot

Moist Unit Weight Profile

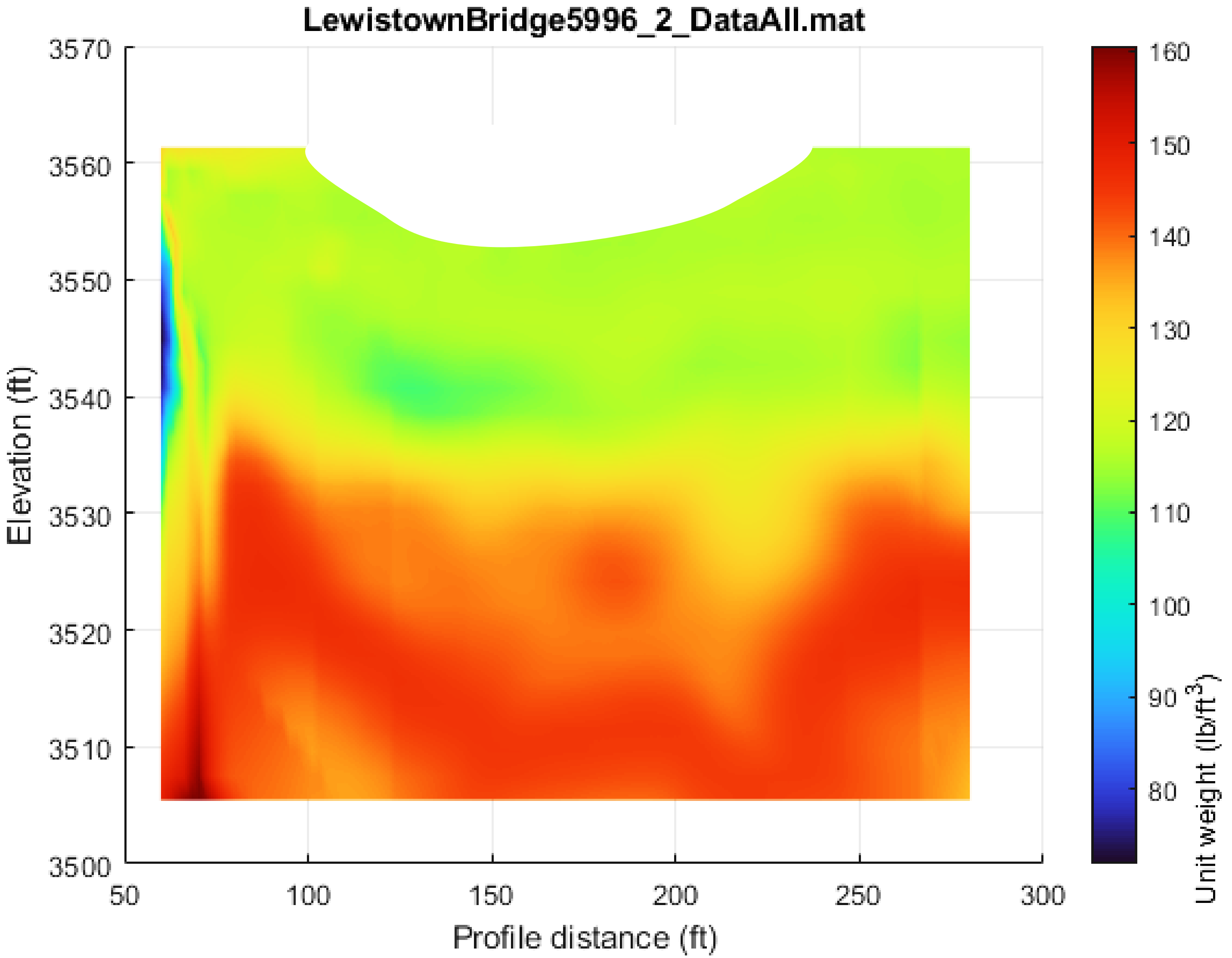
<u>Moist Unit Weights from Lab Testing</u>
<u>Pounds per Cubic Foot (pcf)</u>

Above EL. 3,540 feet = 117.8 to 120.7 pcf
Two Samples

Below EL. 3,530 feet = 133.0 to 159.3 pcf
Six Samples



Mean Absolute Error = 6.3 pcf
Root Mean Squared Error = 8.1 pcf
From 263 Samples



Conclusions and Future Research

- A potential method to provide geotechnical and civil/environmental engineers with subsurface profiles of geotechnical parameters
- Continue to improve machine learning models for predicting geotechnical parameters in areas without access to drill rigs.
  - Try an unsupervised approach to develop better lithology classes.
- Obtain geotechnical shear strength parameters (friction angle and cohesion) and try to predict them.
  - Have already attempted to predict static Young's modulus, initial void ratio, natural moisture content, preconsolidation pressures, compression index, and unconfined compressive strength.
- Of course, collect more data in different geological settings.