U.S. Department of Transportation
Federal Highway Administration

Turner-Fairbank
Highway Research Center

Application of Artificial Neural Network in Predicting Pavement Macrotexture

Behrokh Bazmara, Ph.D. student

Virginia Polytechnique and State University

Amir Golalipour, Ph.D., P.E., M.ASCE.

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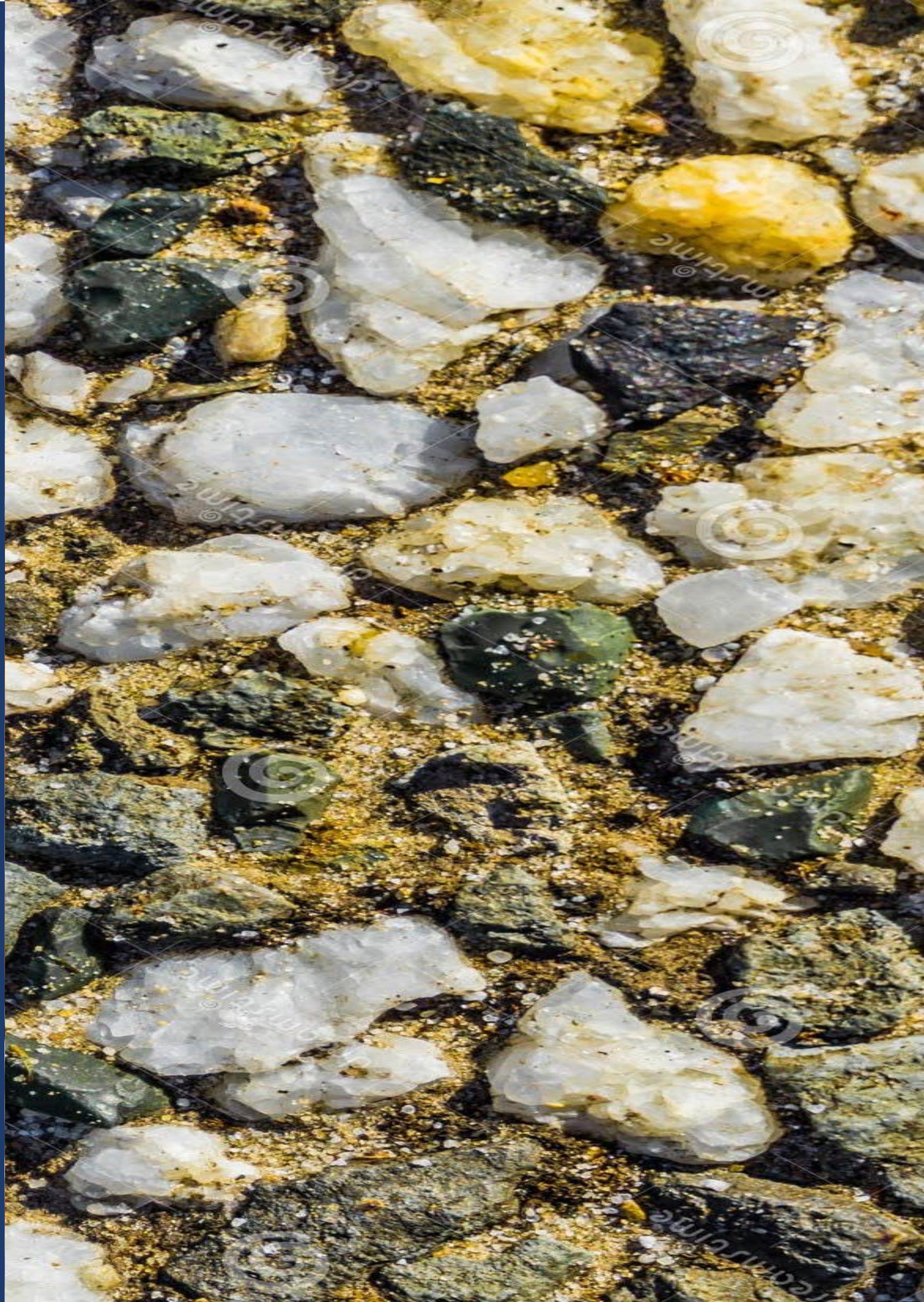


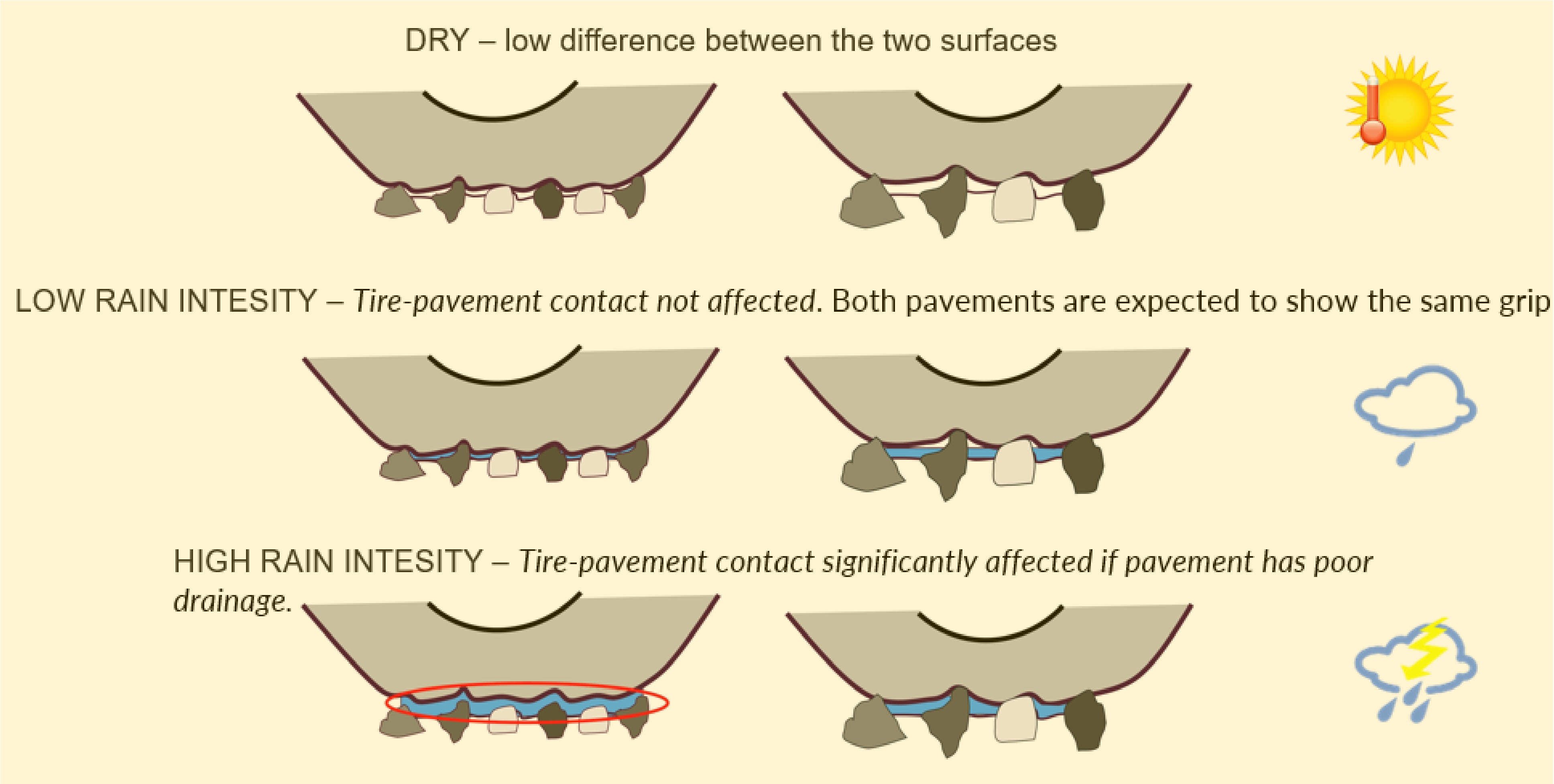
Project Scope

- Establish relationship/model between macrotexture that impacts safety and asphalt mix gradation.
- Using existing materials/surface mixes to develop validation process and verify the established relationship for the field data.

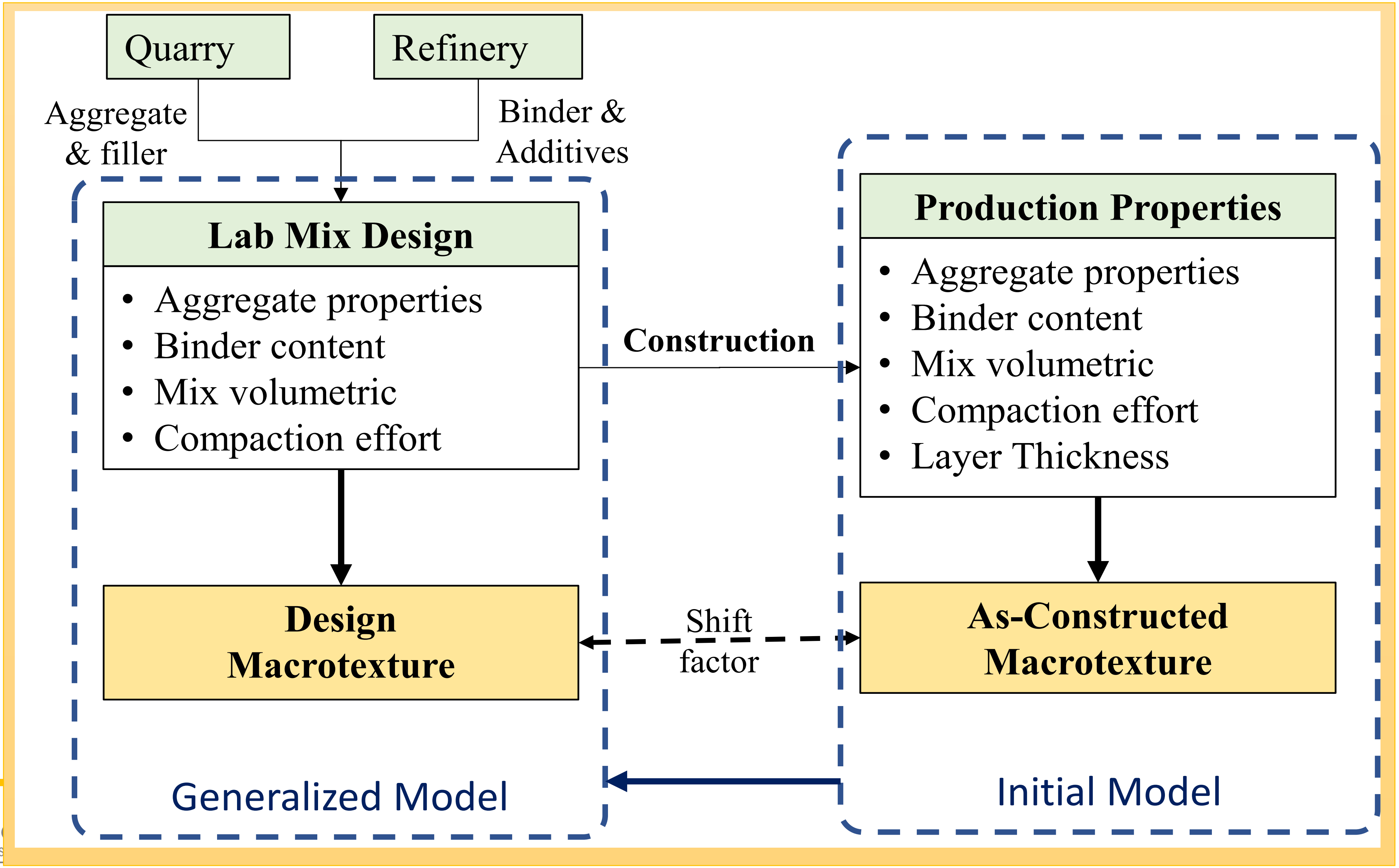
Project Objectives

- Develop, test examine and validate relationship/model between macrotexture and asphalt mix gradation.
- Develop, test examine and validate the promising methodologies to enable comprehensive evaluation of asphalt mix aggregate gradation impact on macrotexture and pavement safety
- Provide guidance related to the model modifications needed in case of field macrotexture data usage
- Provide guidance for agencies and construction contractors to use in designing asphalt mixes with a required value of macrotexture.

Macrotexture & Friction



Research Project Approach

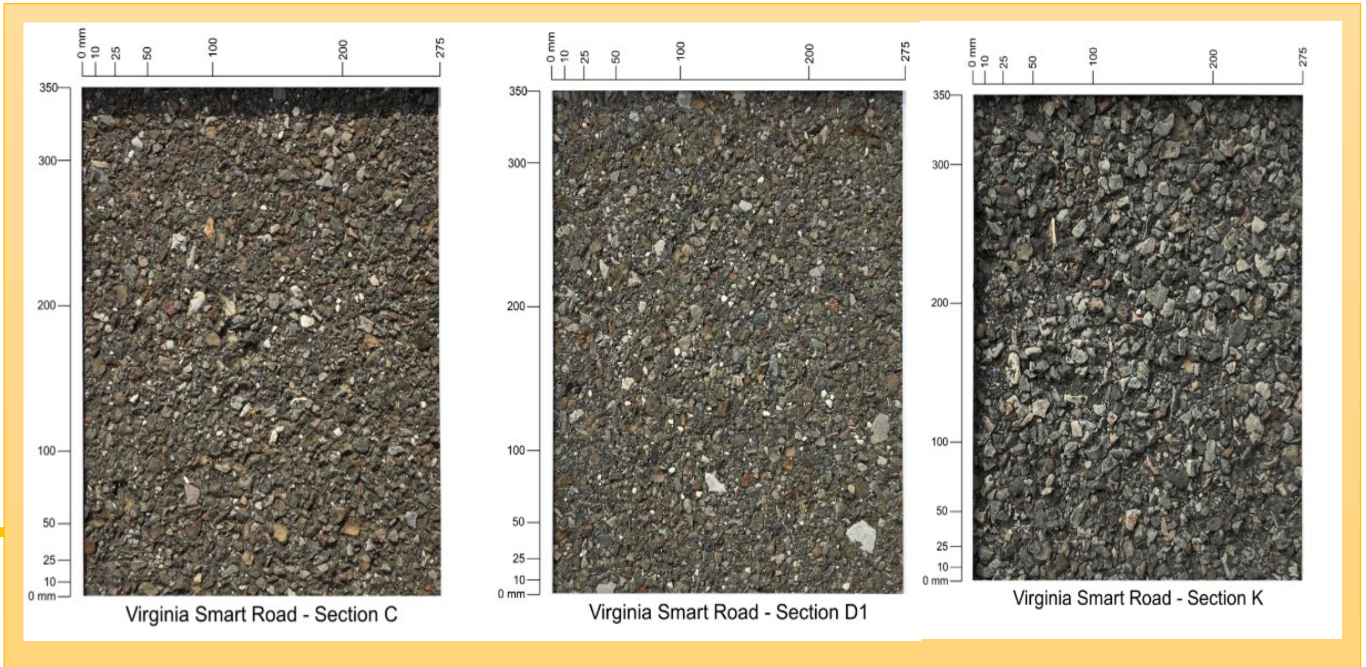


Selected Mixtures for Model Effort

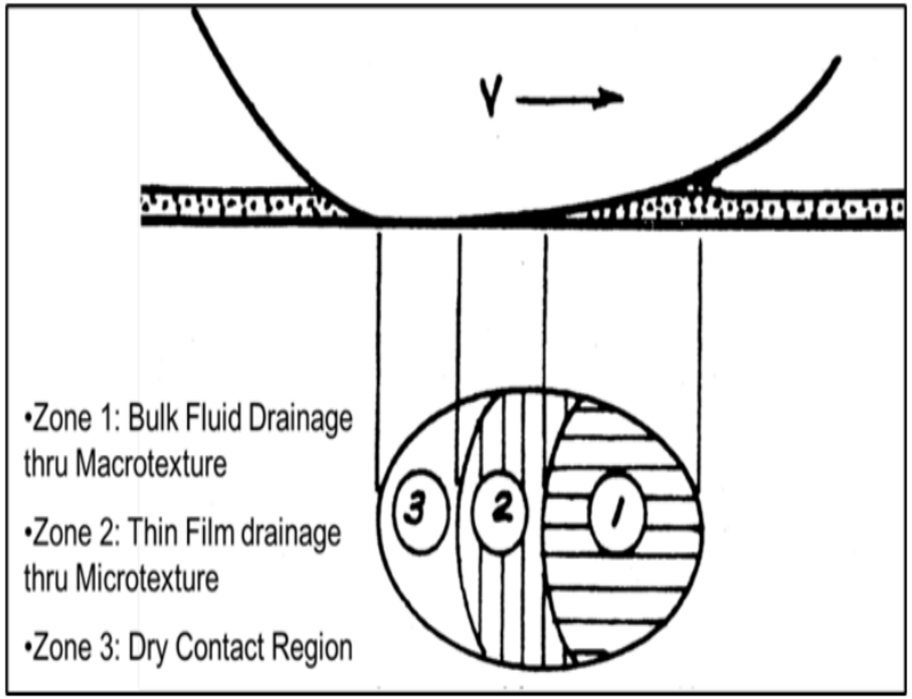
- **Dense-graded mixes**
  NMAS of 12.5, 9.5, 19, and 4.75 mm.

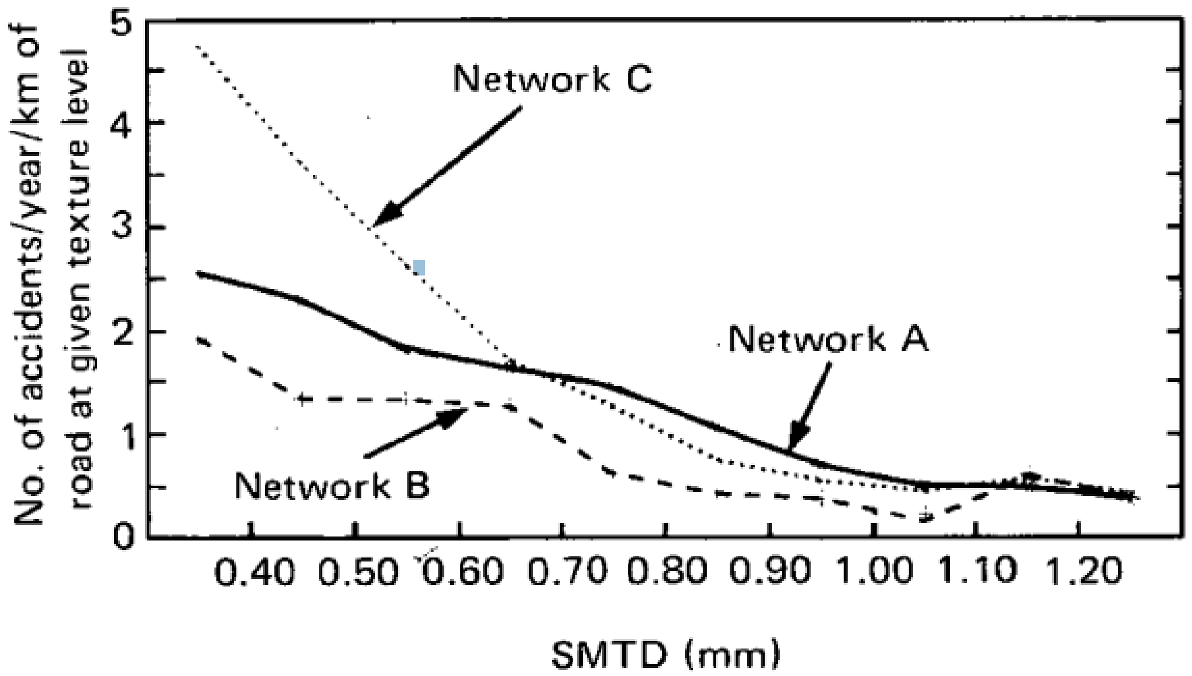
- **Gap-graded mixes** (e.g., Stone Matrix Asphalt)
  NMAS of 9.5, 12.5 and 19 mm.

- **Open-graded**
  NMAS of 9.5, 12.5 and
  19 mm (not included in the analysis so far).



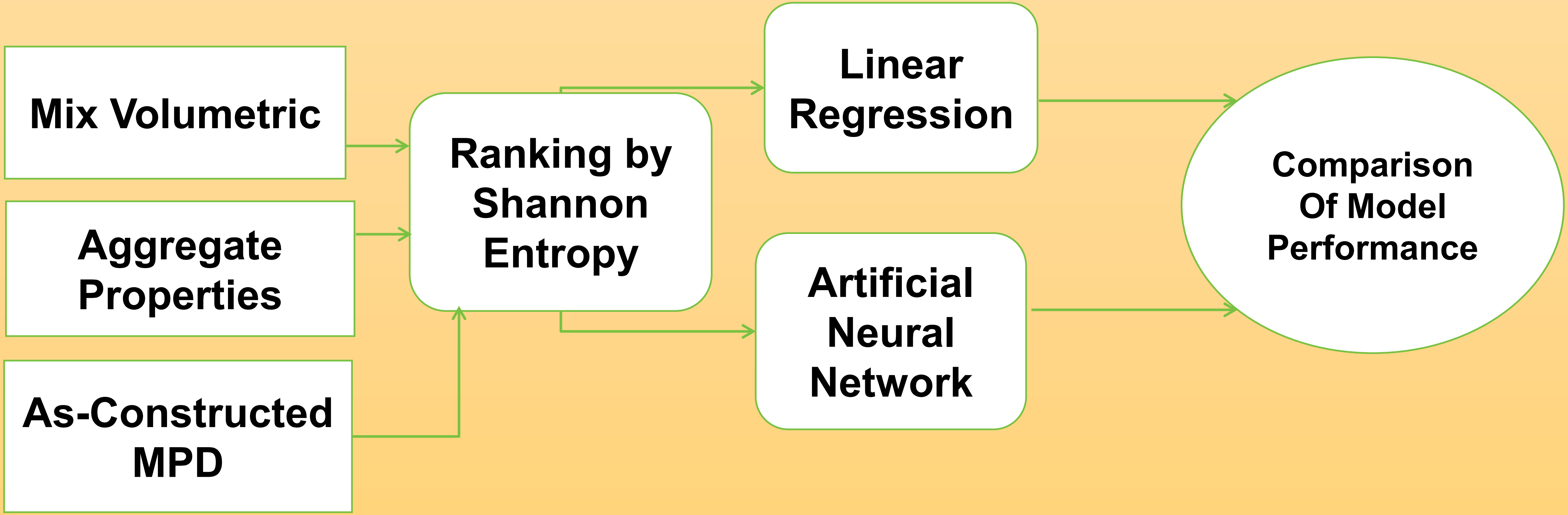
Macrotexture & Pavement Safety





Source: Moore, 1996., Roe et al. 1991.

Proposed Model Process



Dataset Compilation

1. Compiled dataset

- **Florida**
- **Kentucky**
- **North Carolina**
- **Virginia**
- **Vermont (MATC)**
- **North Dakota**
- Texas (not included so far)
- Illinois (not included so far)

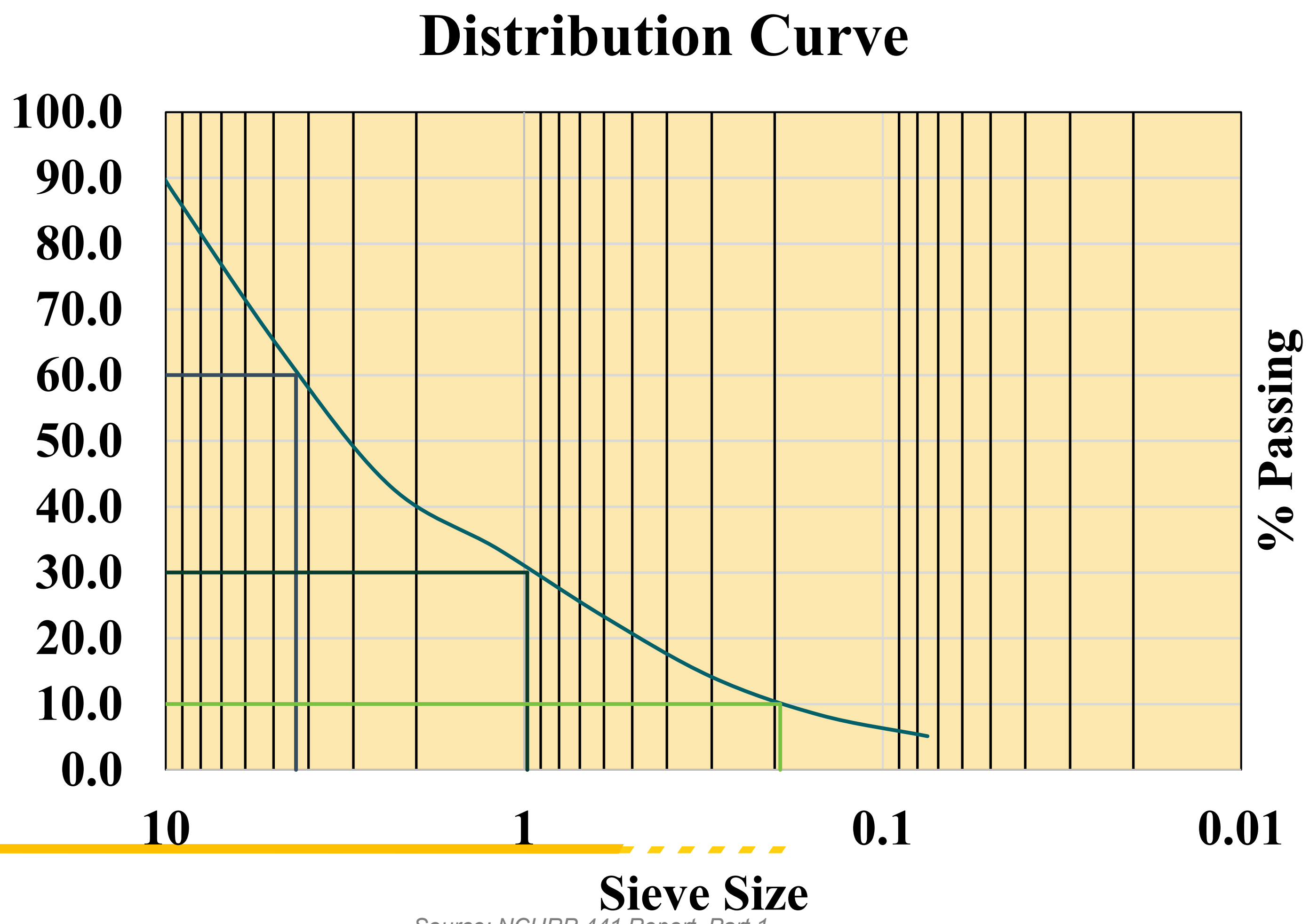
Mix Type	NMAS
DGAC	5/6/9.5/12.5
SMA	5/6/9.5

Parameter level	DOT provided parameters	Computed parameters
Aggregate Properties	Location/ Source	Sieve analysis
	Maximum Agg Size	Average Aggregate size
	Gradation type	Shape Measurements
Mix Volumetrics	Binder content	Air voids
		Void in Agg
		Void in Mix
Construction Consideration	Compaction	Layer Thickness

Dataset Compilation (Cont.)

2. Computed Parameters

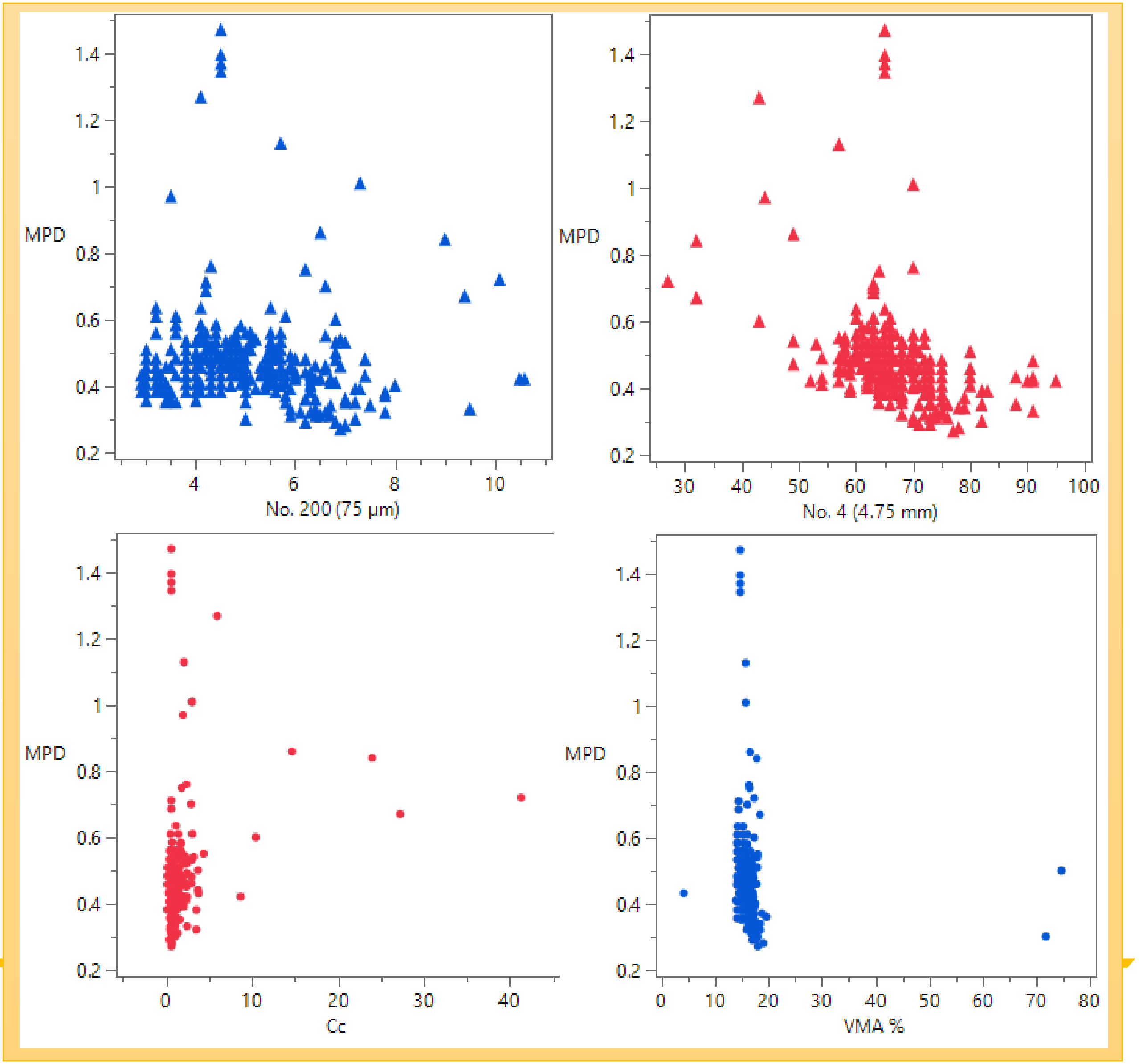
- Gradation



Source: NCHRP 441 Report, Part 1

Predictors Screening

- Outliers were detected to explore the power of machine learning techniques.



Predictors Screening (Cont.)

Predictor	Correlation
Asphalt Content	0.72
No. 30 (600 µm)	0.63
No. 16 (1.18 mm)	0.63
NMAS, mm	0.62
No. 8 (2.38 mm)	0.6
D60	0.56
D30	0.55
No. 4 (4.75 mm)	0.53
No. 50 (300 µm)	0.48
3/8 in (9.5 mm)	0.48
Cc	0.45
½ in (12.5 mm)	0.44
Cu	0.43
No. 200 (75 µm)	0.41
VFA	0.34
FM	0.32
VTM	0.3
VMA	0.24
No. 100 (150 µm)	0.22
D10	0.13

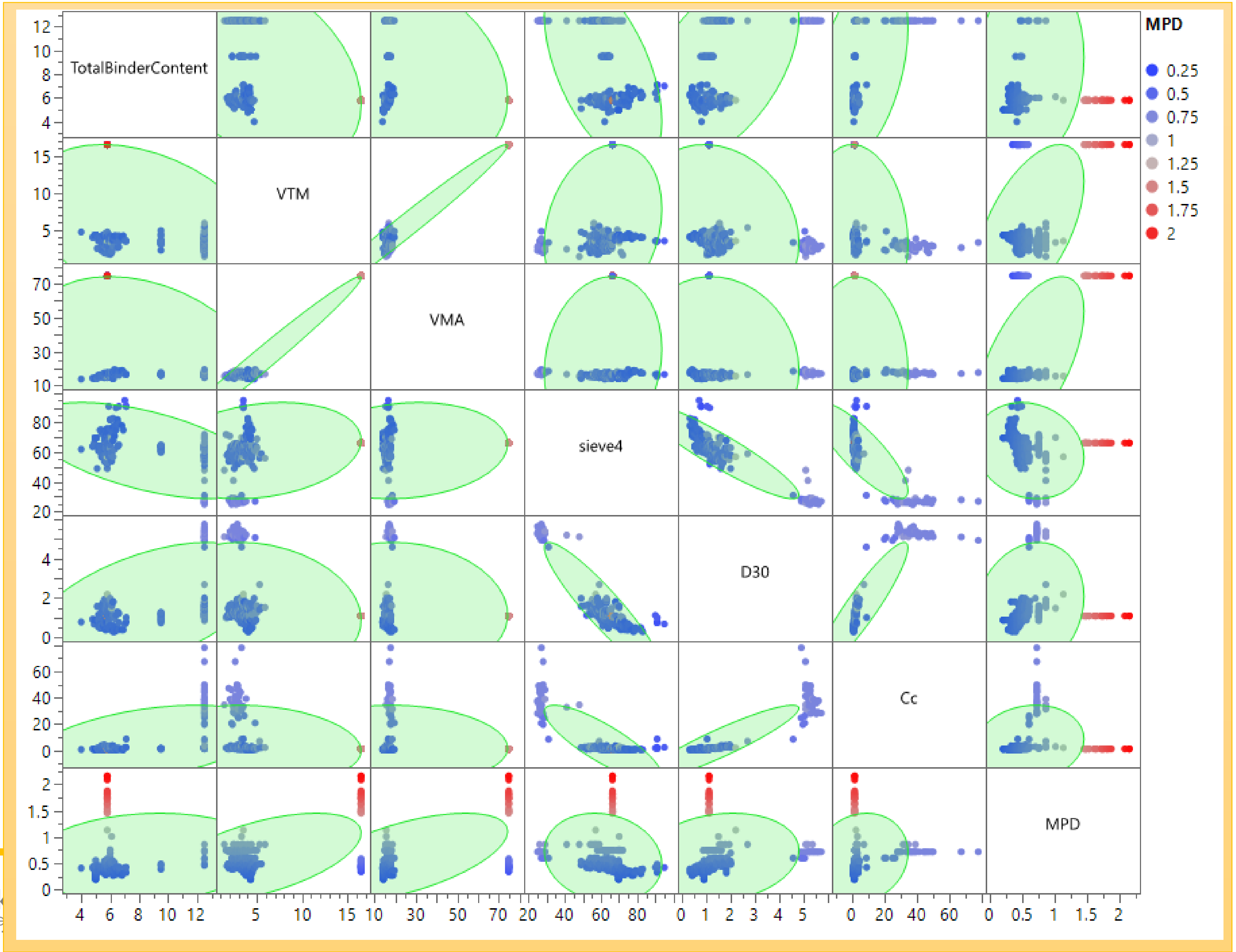
Correlated Variables to MPD

Analyze Linear Relationships

X	Y	Constant	Slope
NMAS	VTM %	2.75	0.1
NMAS	½ in (12.5 mm)	106.3	-0.67

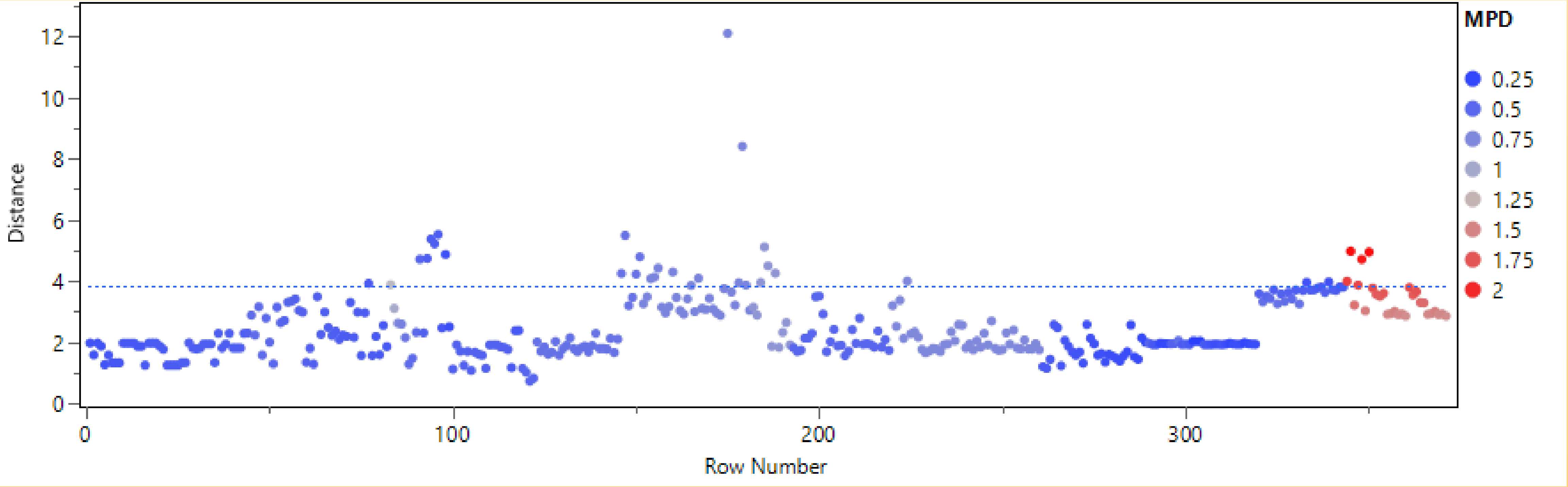
Predictors Screening (Cont.)

Bivariate Fit



Predictors Screening (Cont.)

Multivariate Detection



Methodology

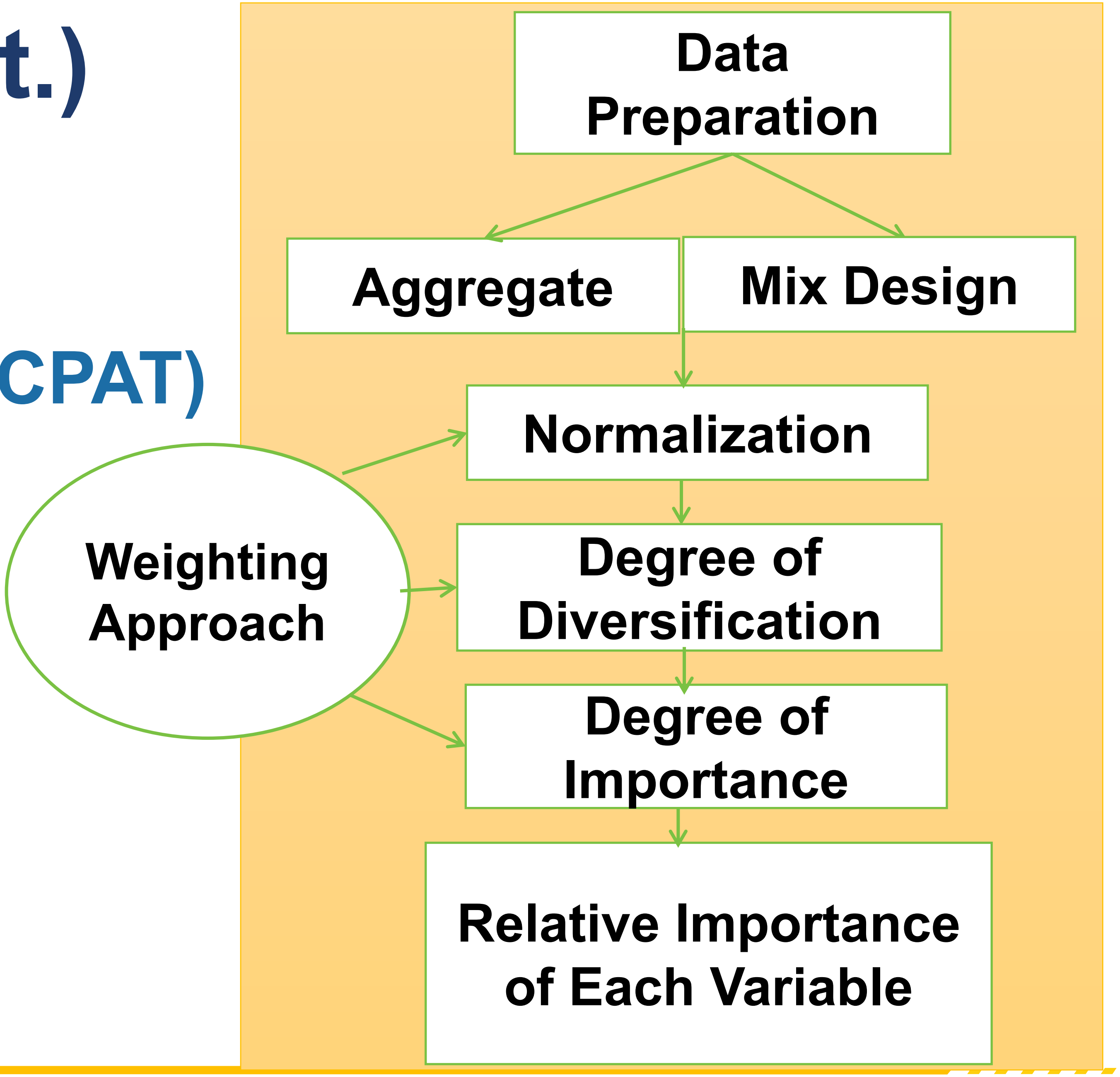
Linear Regression

Reference	Metric	MPD Range (mm)	R^2	Variables	Mix Type
Stroup-Gardiner et al. (2000)	MPD/ ETD	0.11-1.5	$R^2 =$ **0.07-0.65**	MAS, AC, Cc Cu, P4.75	HMA
Sullivan (2005)	MTD	0.23-1.5	$R^2 =$ **0.62**	Ω AC	HMA
Underwood et al. (2022)	MPD	0.3-0.43	$R^2 =$ **0.76**	VFA, Cc P200, AC	DGAC
Optimized Model	MPD	0.19-2.15	$R^2 =$ **0.51**	Mix Volumetric & Aggregate	All Mix Types
	MPD	0.19-1.13	$R^2 =$ **0.66**		DGAC
	MPD	0.6 -2.15	$R^2 =$ **0.93**		SMA

Methodology (Cont.)

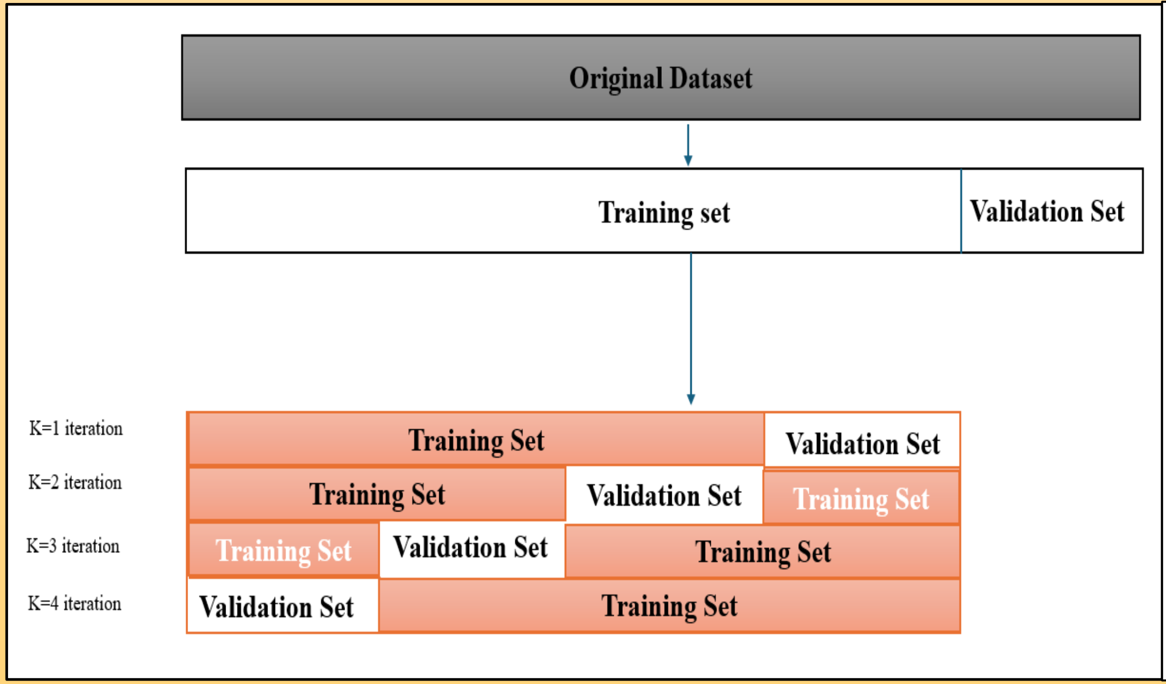
Complex Proportional Assessment Technique (CPAT)

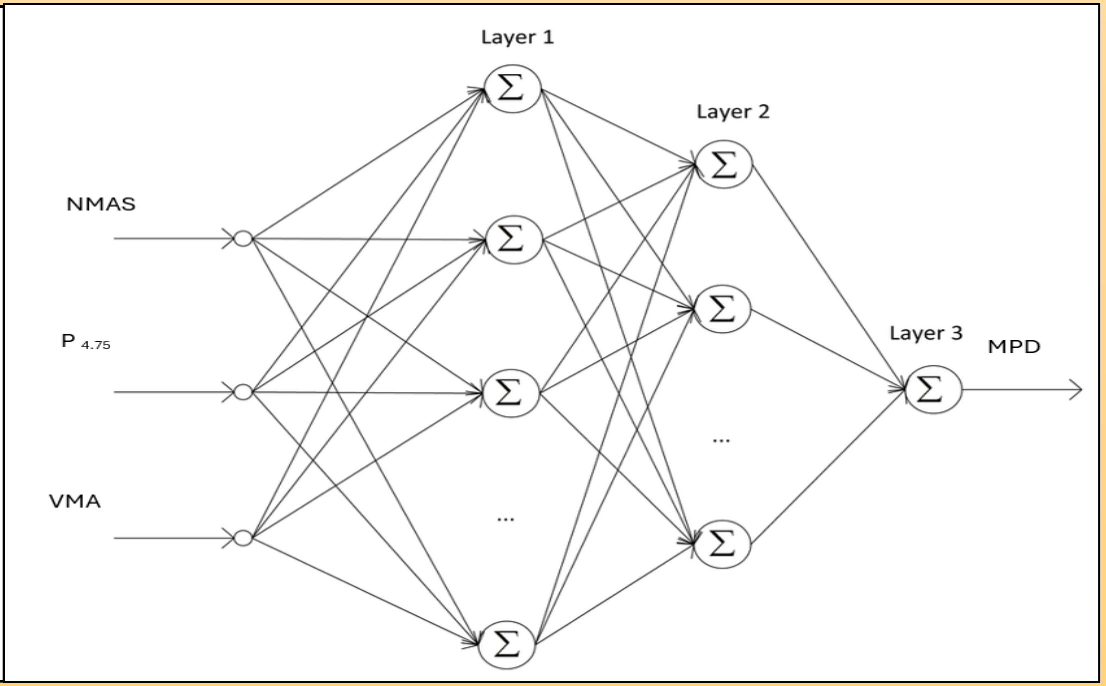
Weighting Approach by Shannon Entropy



Methodology (Cont.)

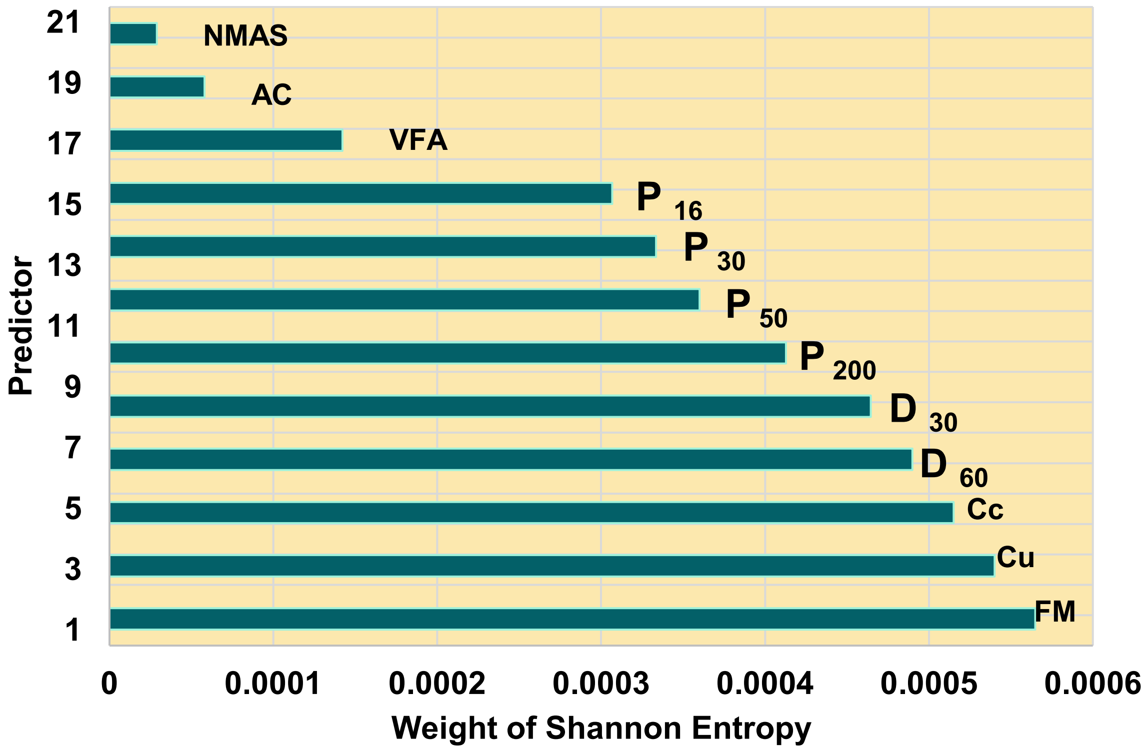
Artificial Neural Network (ANN)





Results

Ranking through CPAT Method



Variable	Importance
FM	0.00056
C_u	0.00054
C_c	0.00052
D_{60}	0.00049
D_{30}	0.00046
No. 200 (75 µm)	0.00041
No. 50 (300 µm)	0.00036
No. 30 (600 µm)	0.00033
No. 16 (1.18 mm)	0.00031
VFA	0.00014
Asphalt Content	0.000058
NMAS	0.000029

Results (Cont.)

Linear and ANN Before CPAT

Model	Mix Type	R^2	RMSE
Linear	All	0.50	0.25
	SMA	0.93	0.09
	DGAC	0.57	0.09
Neural Network	All	0.61	0.22
	SMA	0.89	0.16
	DGAC	0.80	0.05

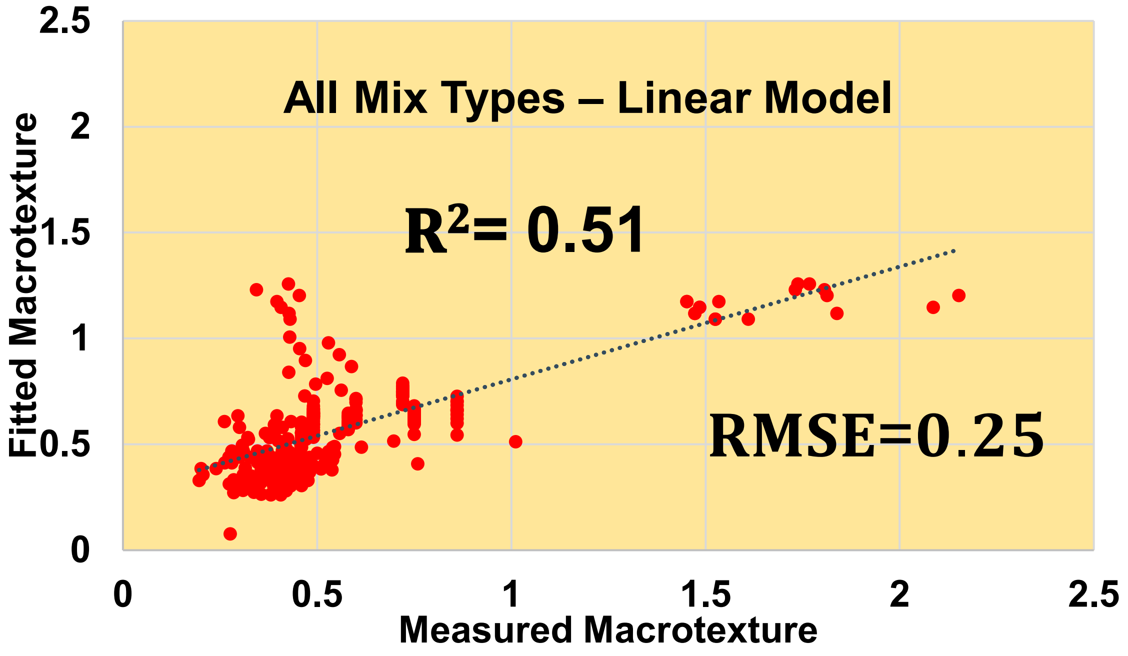
Linear and ANN after CPAT

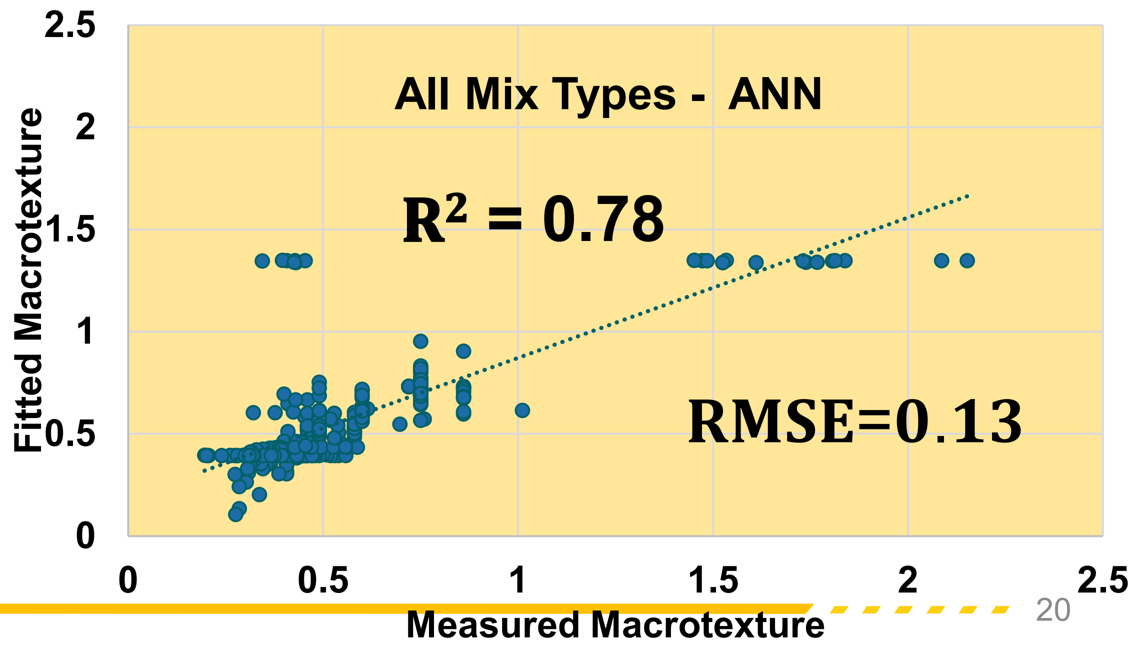
Model	Mix Type	R^2	RMSE
Linear	All	0.51	0.25
	SMA	0.93	0.04
	DGAC	0.67	0.05
Neural Network	All	0.78	0.13
	SMA	0.93	0.12
	DGAC	0.86	0.03

Conclusion

Model Performance Evaluation

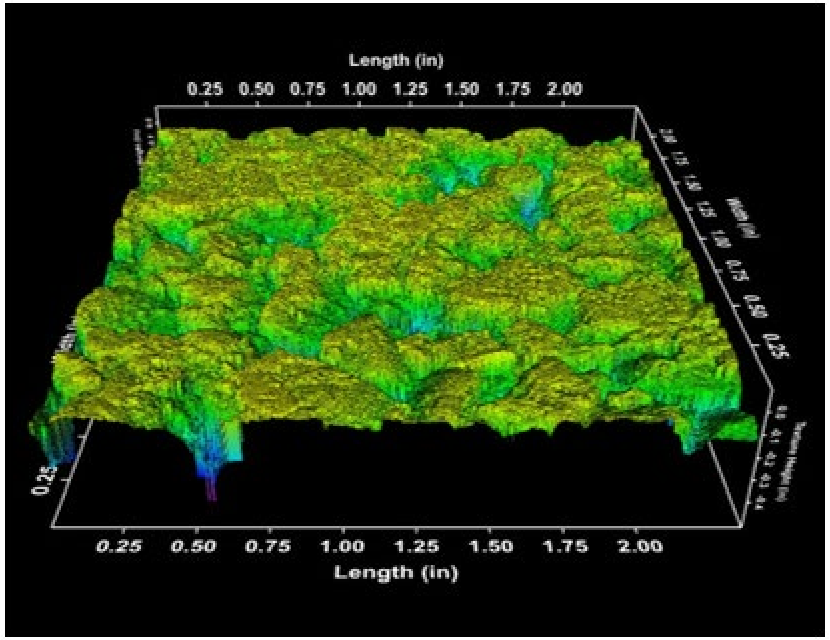
- Effectiveness of Shannon Entropy
- Improved Performance (ANN's outperforming)





Future Steps

- Explore other machine learning approaches
  - ▷ Random Forest
- Add laboratory characterization of AC cores from selected DOTs
  - ▷ Obtained cores from and will measure macrotexture by Ames Texture Meter
- Relationship of Lab vs. Field Measurements



(a) 608 Line Scans

Acknowledgements

Project Team

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Contact

Amir Golalipour, Ph.D., P.E.

amir.golalipour@dot.gov

Behrokh Bazmara

behrokhb@vt.edu

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