Enhancement of Data Analysis Procedure of Traffic Speed Deflection Device for Pavement Structural Evaluation

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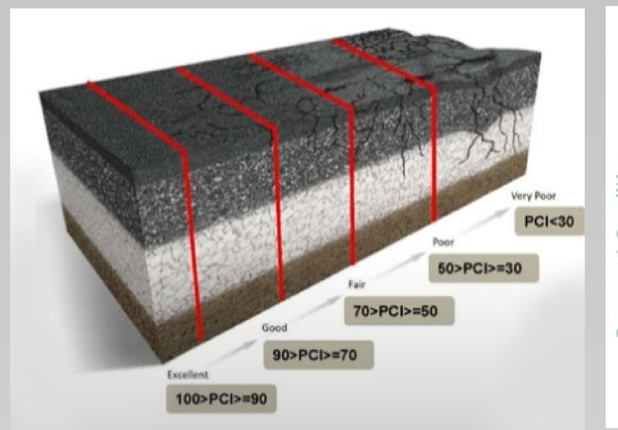
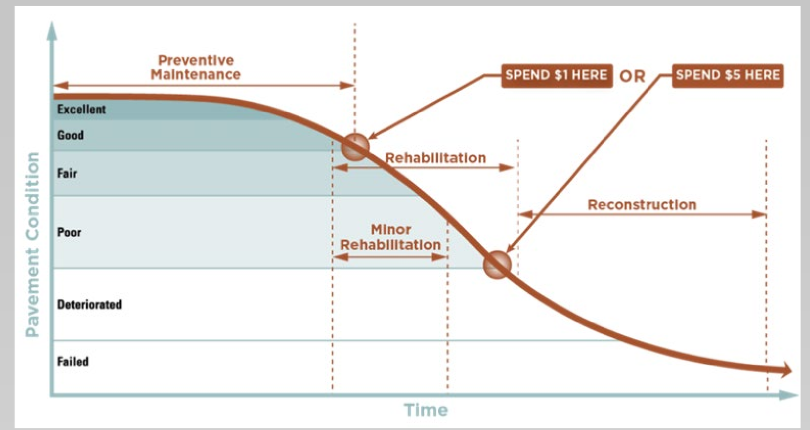
1. Introduction

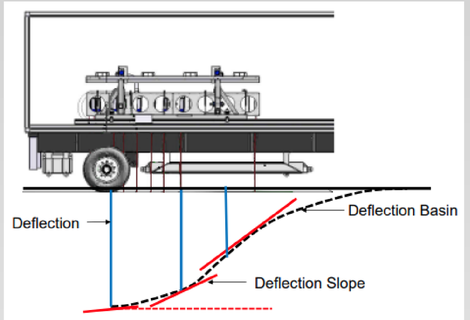
Pavement management is "the effective and efficient directing of the various activities involved in providing and sustaining pavements in a condition acceptable to the traveling public at the least life cycle cost (AASHTO)"

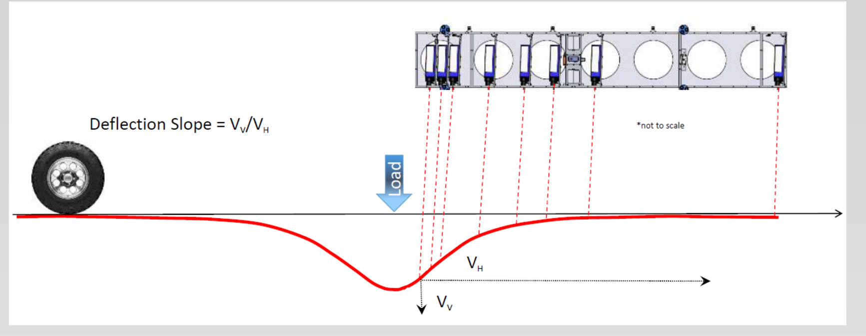




(Snyder, 2022)

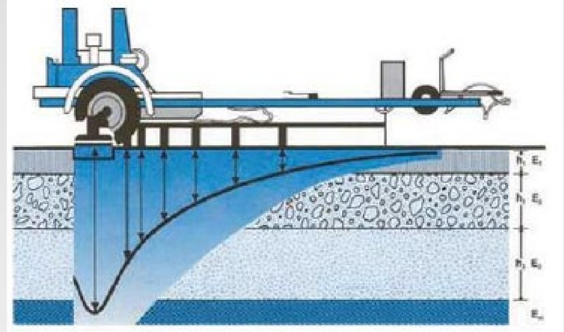
2. Fast Falling Weight Deflectometer & Traffic Speed Deflection Device (FFWD & TSDD)

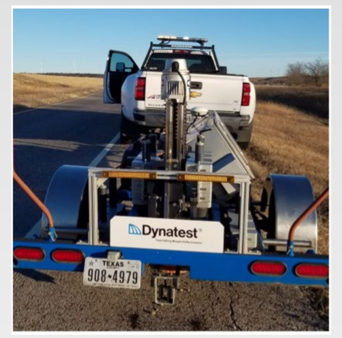




(Katicha, et al., 2017)

- Continuous measurements
- Force applied trough wheels
- Deflections integrated from velocity measurements with Doppler lasers
- Accuracy loss compensated by averaging
- High measurement speed
- Dynamic load is more representative of traffic loading
- Vectors for stress and strain rotate during test





- Discrete locations
- Force applied trough stationary plate
- Deflections measured with geophones
- High accuracy
- Zero speed measurement (impact)
- Directions of stress and strains vectors remain constant during testing

3. Literature Review

E Moduli → MODCOMP®, ELMOD®, and BACKCALC®, MODULUS®

Parameter	Formula
1. Maximum deflection	D_0 as measured
2. Base Layer Index (BLI) also known as Surface Curvature Index (SCI)	$SCI = BLI = D_0 - D_{300}$
3. Middle Layer Index (MLI) also known as Base Damage Index (BDI)	$BDI = MLI = D_{300} - D_{600}$
4. Lower Layer Index (LLI) also known as Base Curvature Index (BCI)	$BCI = LLI = D_{600} - D_{900}$
5. Spreadability, S	$S = \frac{\{\left[\frac{D_0 + D_{300} + D_{600} + D_{900}}{5}\right] 100\}}{D_0}$
6. Area, A	$A = \frac{6[D_0 + 2D_{300} + 2D_{600} + D_{900}]}{D_0}$
7. Shape factors	$F1 = (D_0 - D_{600})/D_{300}$ $F2 = (D_{300} - D_{900})/D_{600}$
8. Slope of Deflection	$SD = \tan^{-1}(D_0 - D_{600})/600$
9. Additional shape factor	$F3 = (D_{600} - D_{1200})/D_{900}$
10. Area under pavement profile	$AUPP = \frac{(5D_0 - 2D_{300} - 2D_{600} - D_{900}}{2}$
11. Additional areas	$A2 = \frac{6(D_{300} + 2D_{450} + D_{600})}{D_0}$ $A3 = \frac{6(D_{600} + 2D_{900} + D_{1200})}{D_0}$
12. Area indices	$AI1 = (D_0 + D_{300})/2D_0$ $AI2 = (D_{300} + D_{600})/2D_0$ $AI3 = (D_{600} + D_{900})/2D_0$ $AI4 = (D_{900} + D_{1200})/2D_0$

(Schnoor & Horak, 2012)

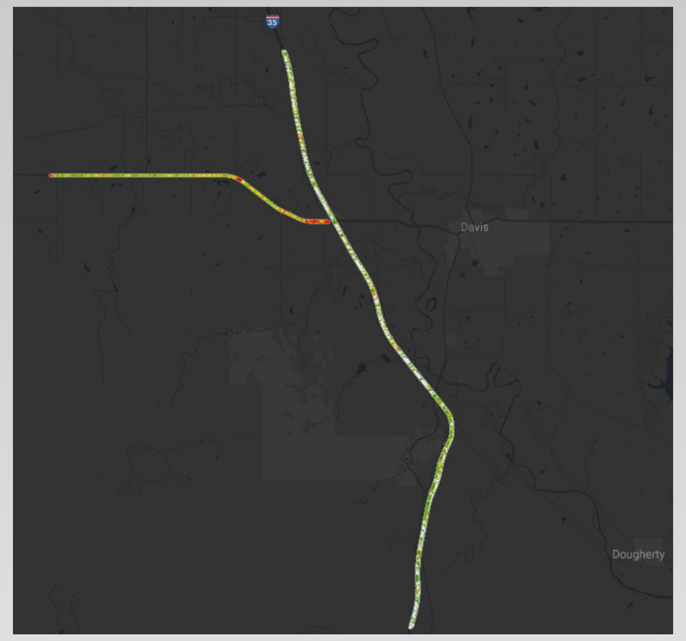
Comparison	Criteria	Reference
High correlation for deflections under the central loads	D0	Virginia DOT (2017) Flintsch et al. (2012)
Structural Number Effective (SNeff) highly correlated for FWD and TSDD	SNeff	Zihan et al. (2018)
SCI12 or SC300 highly correlated for FWD and TSDD	SCI12	Muller (2013
E moduli backcalculation well correlated for FWD and TSDD	E	Elbagalti et al. (2017)

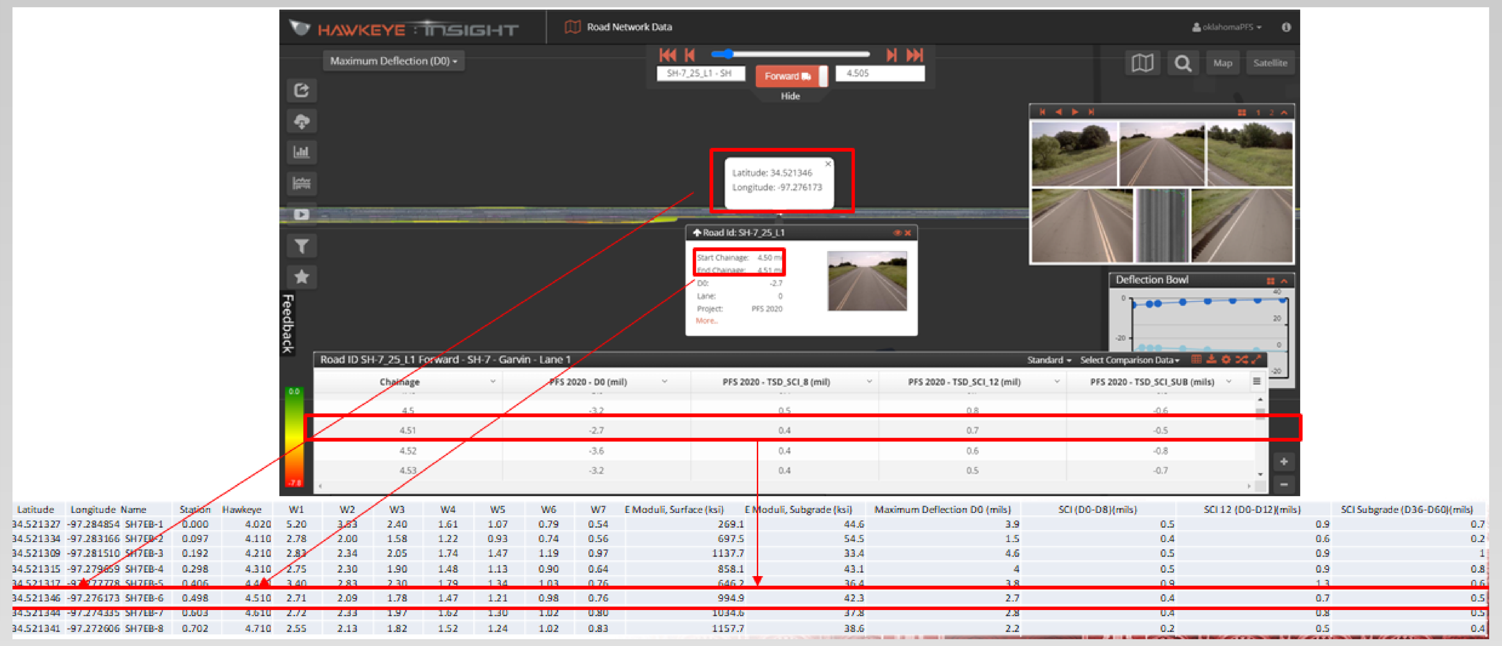
$$\lambda = \frac{SCI_{Ref}}{SCI_T} = \frac{10^{-0.0521 T_{Ref} + 0.0322 T_{Ref} \log(h_{AC})}}{10^{-0.0521 T + 0.0322 T \log(h_{AC})}}$$ (Nasimifar, et al., 2018)

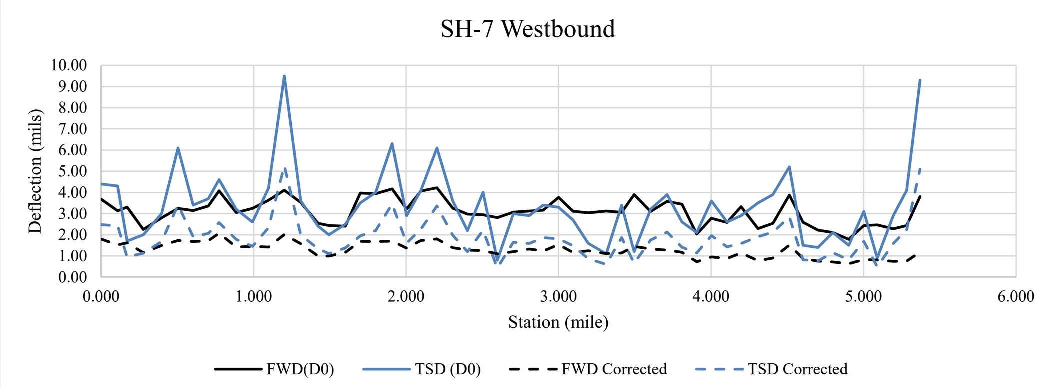
where
λ = Temperature adjustment factor
SCI_{Ref} = Adjusted SCITSD at reference temperature
T_{Ref} = Reference temperature, ° C
T= Mid-depth AC layer temperature at time of measurement, ° C
h_{AC}= Asphalt layer thickness, mm

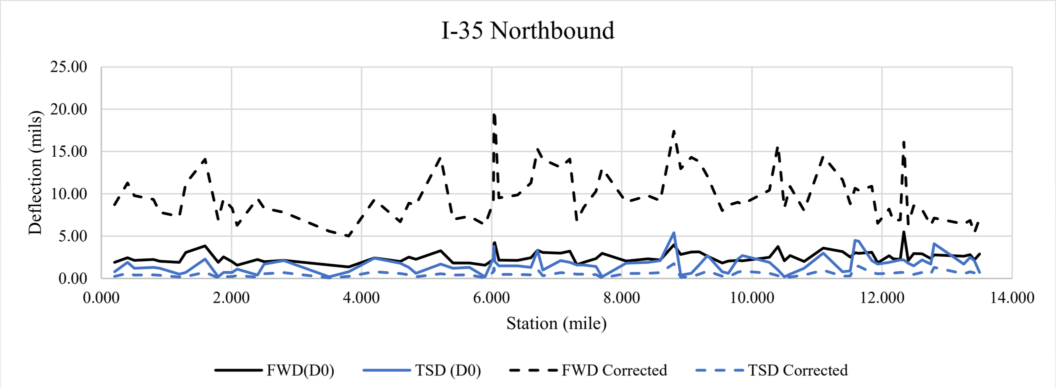
4. Data and Results

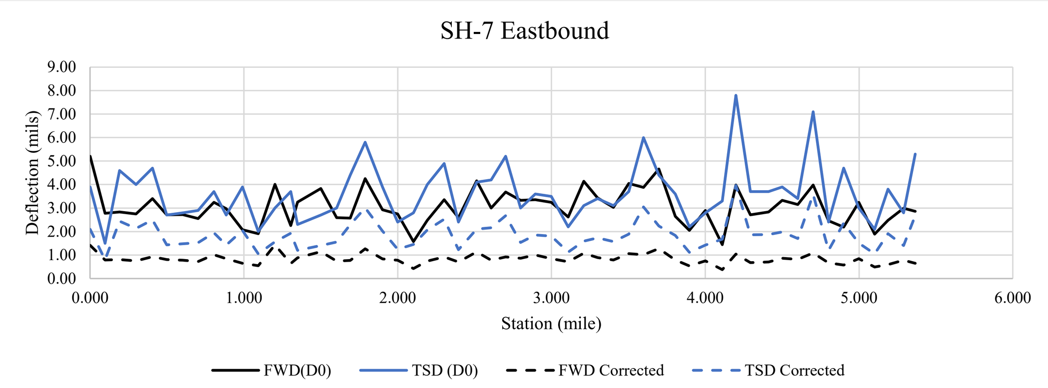
This study covers a 14.5-mile section on I-35 and a 5-mile section on SH-7. TSDD data was collected on the same segments of I-35 and SH-7 by the Oklahoma Department of Transportation (ODOT) as part of a pooled fund study conducted by Virginia Tech Transportation Institute (VTTI). FFWD and coring was conducted by the University of Oklahoma in collaboration with ODOT. Texas Transportation Institute (TTI) at Texas A&M University (TAMU) collected subsurface data by using a 1-GHz air-coupled GPR (TTI-GPR).

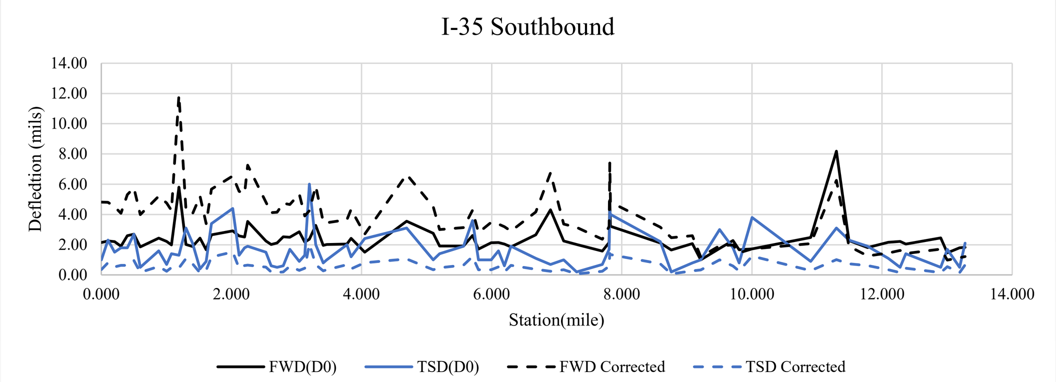


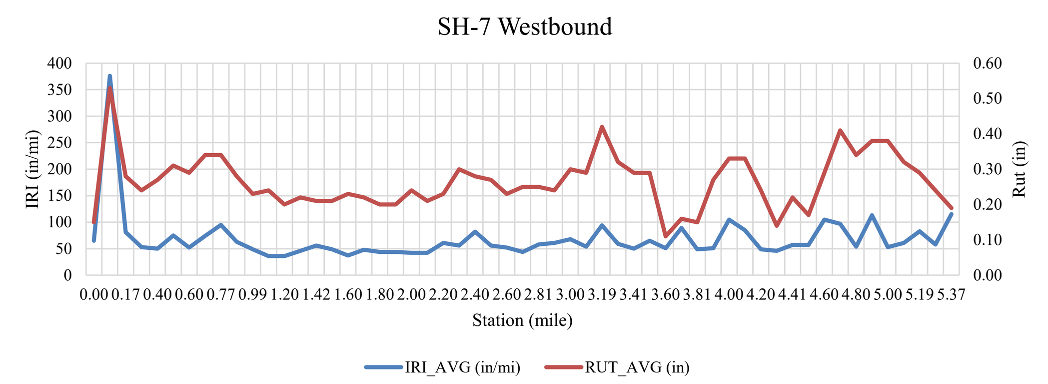


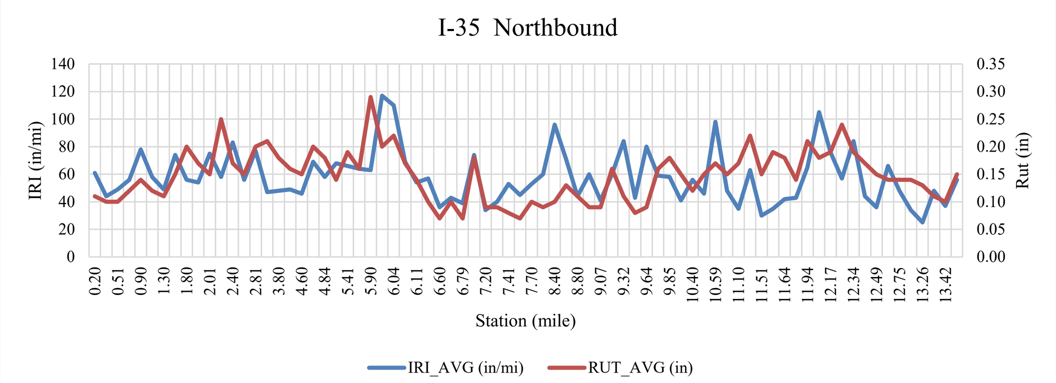


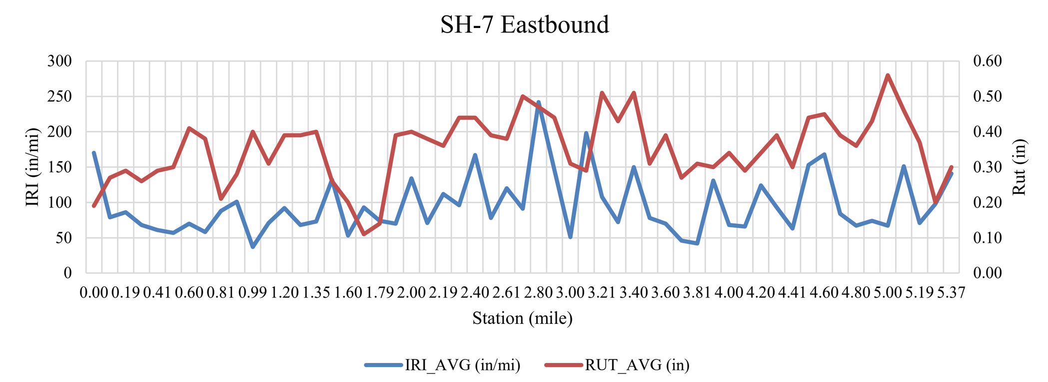


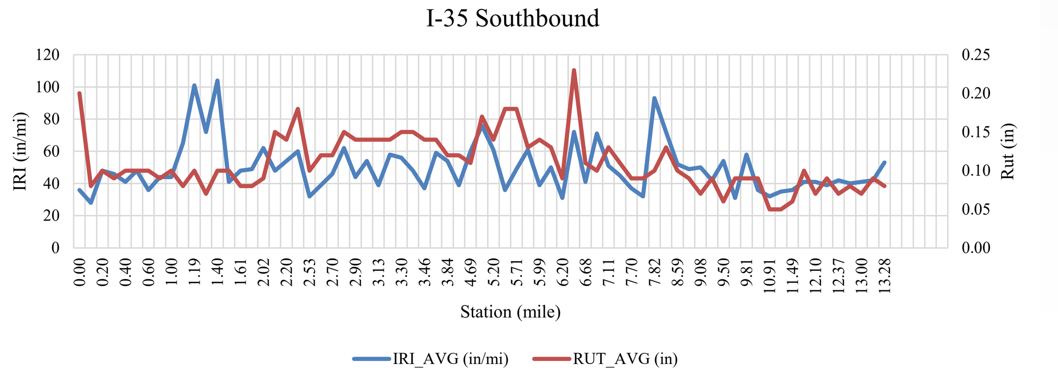


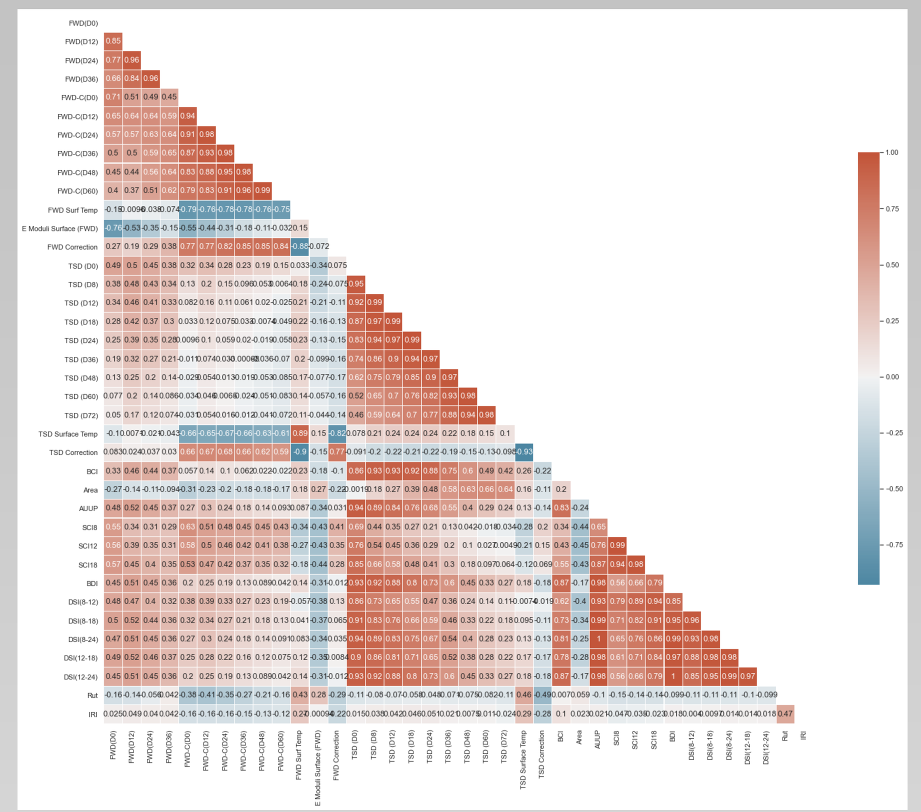


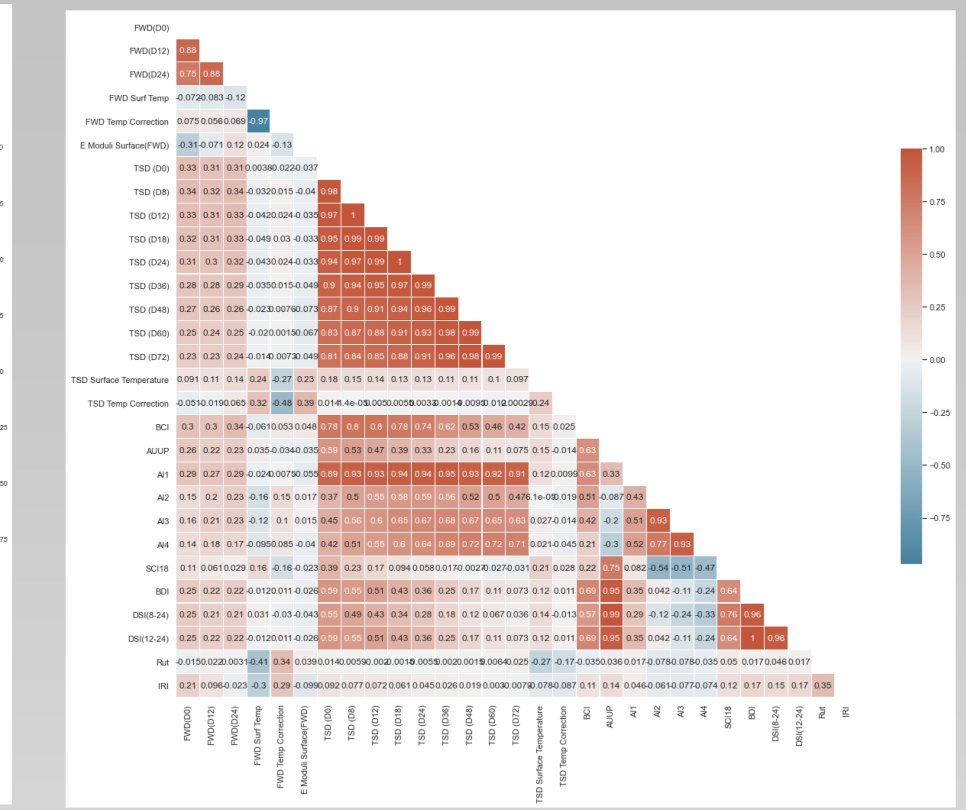








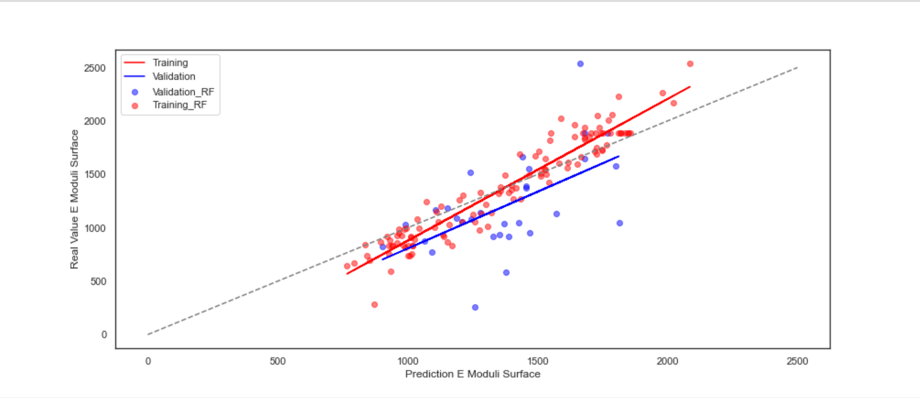




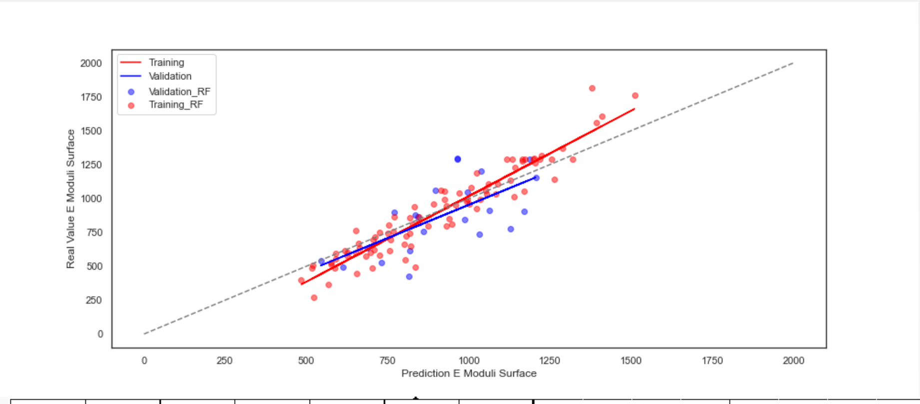
4. Random Forest (RF) Model and Linear Regressions for E and SNeff

It is a nonparametric and tree-based approach. This model is minimally influenced by the hyper parameters and has a faster convergence speed.. A python model was created to compare the different combinations.

For E Moduli I-35 and SH-7

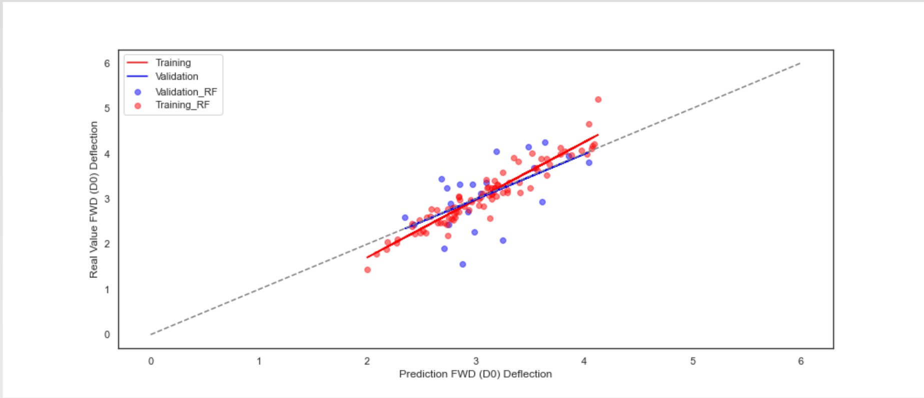


Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6	Variable 7	Variable 8	Random Forest				Linear Regression			
								MAE Train	MAE Val	RMSE Train	RMSE Val	MAE Train	MAE Val	RMSE Train	RMSE Val
TSD (D8)	TSD (D12)	TSD (D24)	TSD Surface Temperature	TSD Temp Correction	AI1	IRI		131.6	290.6	171.0	382.7	335.4	338.1	420.6	435.0
TSD (D0)	TSD (D8)	TSD (D12)	TSD (D24)	TSD Surface Temperature	TSD Temp Correction	AI1	IRI	128.7	291.5	170.4	387.0	335.7	337.6	420.5	434.6
TSD (D18)	TSD (D24)	TSD Surface Temperature	TSD Temp Correction	AI1	IRI			129.2	295.2	175.4	392.8	337.9	340.3	421.0	436.1

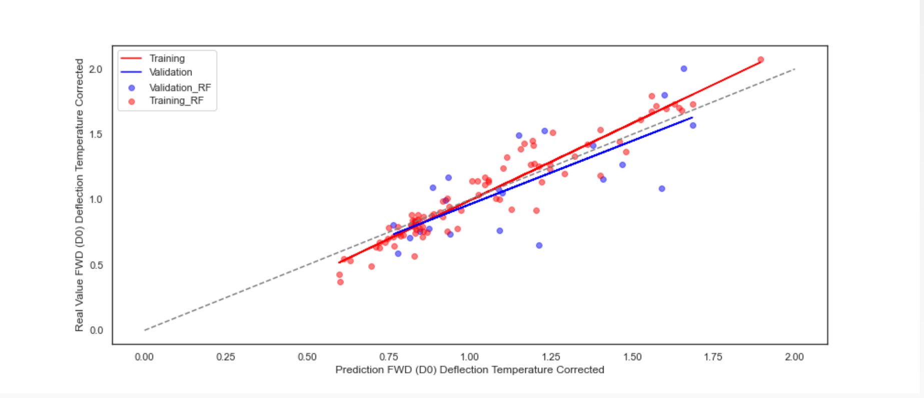


Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6	Variable 7	Random Forest				Linear Regression			
							MAE Train	MAE Val	RMSE Train	RMSE Val	MAE Train	MAE Val	RMSE Train	RMSE Val
TSD (D12)	SCI18	DSI(8-12)	Rut				87.2	160.9	109.9	220.9	214.4	202.5	272.0	275.7
TSD (D8)	TSD (D12)	SCI18	DSI(8-12)	Rut			87.8	161.6	115.1	228.3	214.4	202.5	272.0	275.7
TSD (D0)	TSD (D12)	SCI12	SCI18	DSI(8-12)	Rut		89.0	163.0	114.3	229.6	212.4	208.9	270.7	283.2

For FWD (D0) SH-7 Only



Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6	Random Forest				Linear Regression			
						MAE Train	MAE Val	RMSE Train	RMSE Val	MAE Train	MAE Val	RMSE Train	RMSE Val
TSD (D8)	AUUP	SCI8	SCI12			0.19	0.41	0.26	0.61	0.41	0.50	0.53	0.63
TSD (D8)	TSD (D12)	AUUP	SCI8	SCI12	DSI(8-18)	0.19	0.42	0.26	0.63	0.40	0.48	0.53	0.61
AUUP	DSI(8-18)	BCI				0.27	0.43	0.35	0.53	0.48	0.45	0.60	0.55



Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6	Variable 7	Random Forest				Linear Regression			
							MAE Train	MAE Val	RMSE Train	RMSE Val	MAE Train	MAE Val	RMSE Train	RMSE Val
Area	SCI8	SCI12	DSI(8-12)	AI2			0.09	0.19	0.11	0.27	0.22	0.20	0.28	0.25
AUUP	SCI8	AI2					0.10	0.20	0.12	0.28	0.22	0.20	0.28	0.25
S	Area	SCI8	DSI(8-12)	AI2			0.09	0.20	0.12	0.27	0.21	0.22	0.27	0.28

5. Conclusions

•Random forest models performed better than Linear regression for training and validation sets. A better performance of RF models was observed in SH-7 compared to I-35.
•The temperature correction did improve the model significantly. The relationship between FWD (D0
•Roughness and rut showed a similar trending. As per influence in the models, IRI showed to be an important variable for I-35 and rut for SH-7.
•Prediction of pavement condition parameters is possible by using Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL) methods.

Acknowledgements

- Oklahoma Department of Transportation (ODOT), Texas Transportation Institute (TTI), Virginia Tech Transportation Institute (VTTI)