Polarimetric Decomposition Techniques and Machine Learning Modelling for Soil Moisture Retrieval from Simulated NASA-ISRO SAR (NISAR) L-Band Data

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INTRODUCTION / BACKGROUND

- Soil moisture plays a crucial role in sustaining a healthy ecosystem by supporting plant growth and survival, improving crop yields, and ensuring good crop quality.
- Soil Moisture is an influencing component in crop growth and development in the agricultural application as well as an early warning indicator of agricultural drought emergencies.
- An In-depth understanding of soil moisture dynamics has an essential significance for a wide range of meteorological, climatologic, and hydrologic applications.
- In addition, having a precise idea of the amount of moisture in the soil can help us manage our water resources better, make our irrigation practices more efficient, and give us a better understanding.

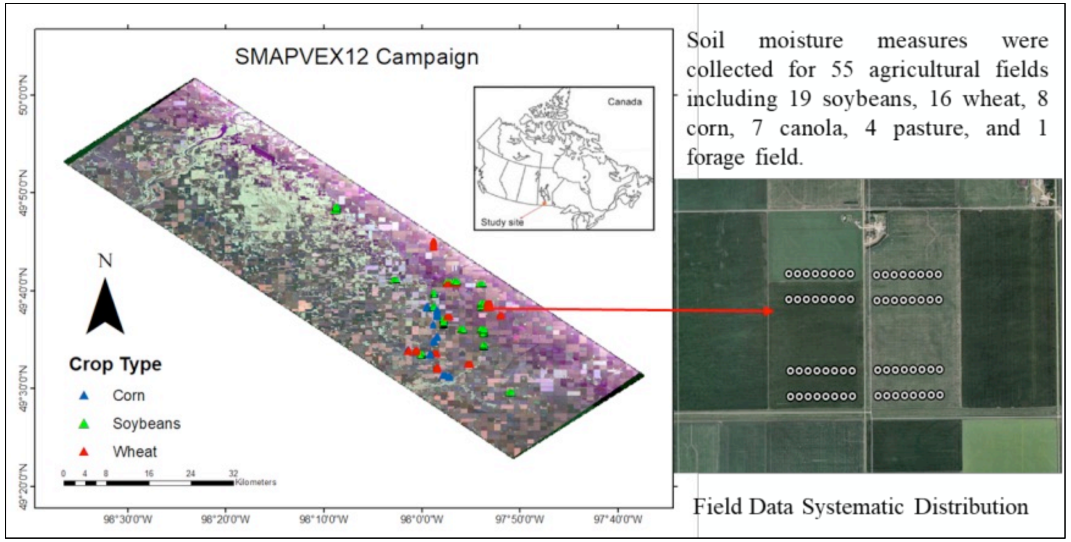
PROBLEM SATATEMENT / OBJECTIVE

- Manual mapping of soil moisture content (SWC) through field surveys is a difficult task as it consumes time and labour and provides limited data due to sampling constraints.
- Temporal mapping of large areas is also a challenging part as surface soil moisture is dynamic in nature and it changes frequently over time.
- Airborne and Space-borne remote sensing techniques keep track of the soil on a large scale and provide us with detailed data at reasonable temporal and spatial resolutions, allowing us to study soil moisture dynamics over a large area more effectively

Objective

1. The primary aim of this investigation is to assess the capacity of fully polarimetric Synthetic Aperture Radar data to examine L-Band for estimating soil moisture
2. To use Polarimetric decomposition technique and Machine Learning modelling to estimate soil dielectric and soil moisture.
3. To generate a high resolution soil dielectric and soil moisture map by using best performance algorithm

STUDY AREA



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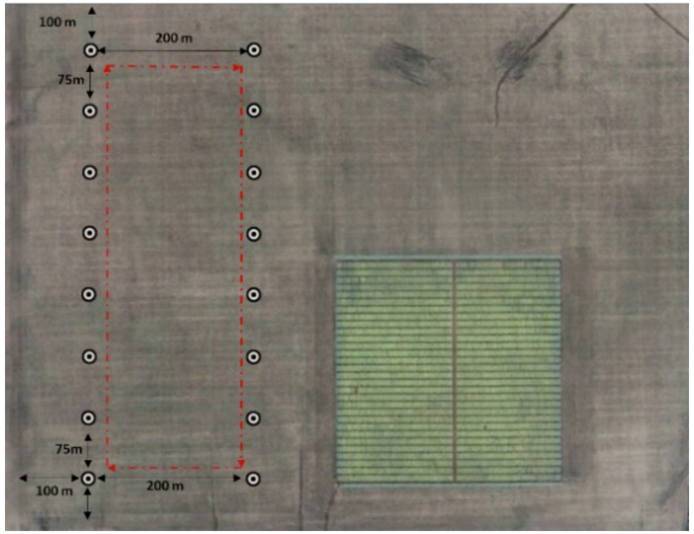

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The Soil Moisture Active Passive Experiment 2012 (SMAPVEX12), which was conducted in a region of Manitoba, Canada (98°00′23" W, 49°40′48" N) situated within the Red River Watershed and the Assiniboine River flows through the northern part of the area.

The region is primarily dominated by annual crops. The study area of SMAPVEX12 covers a distance of 12.8 km x 70 km and demonstrates substantial changes in surface soil moisture as a result of varying soil textures.

DATA USED

The Simulated "NISAR" data used in this study were collected by the "UAVSAR (Uninhabited Aerial Vehicle Synthetic Aperture Radar)" system as a part of the SMAPVEX12 Campaign.

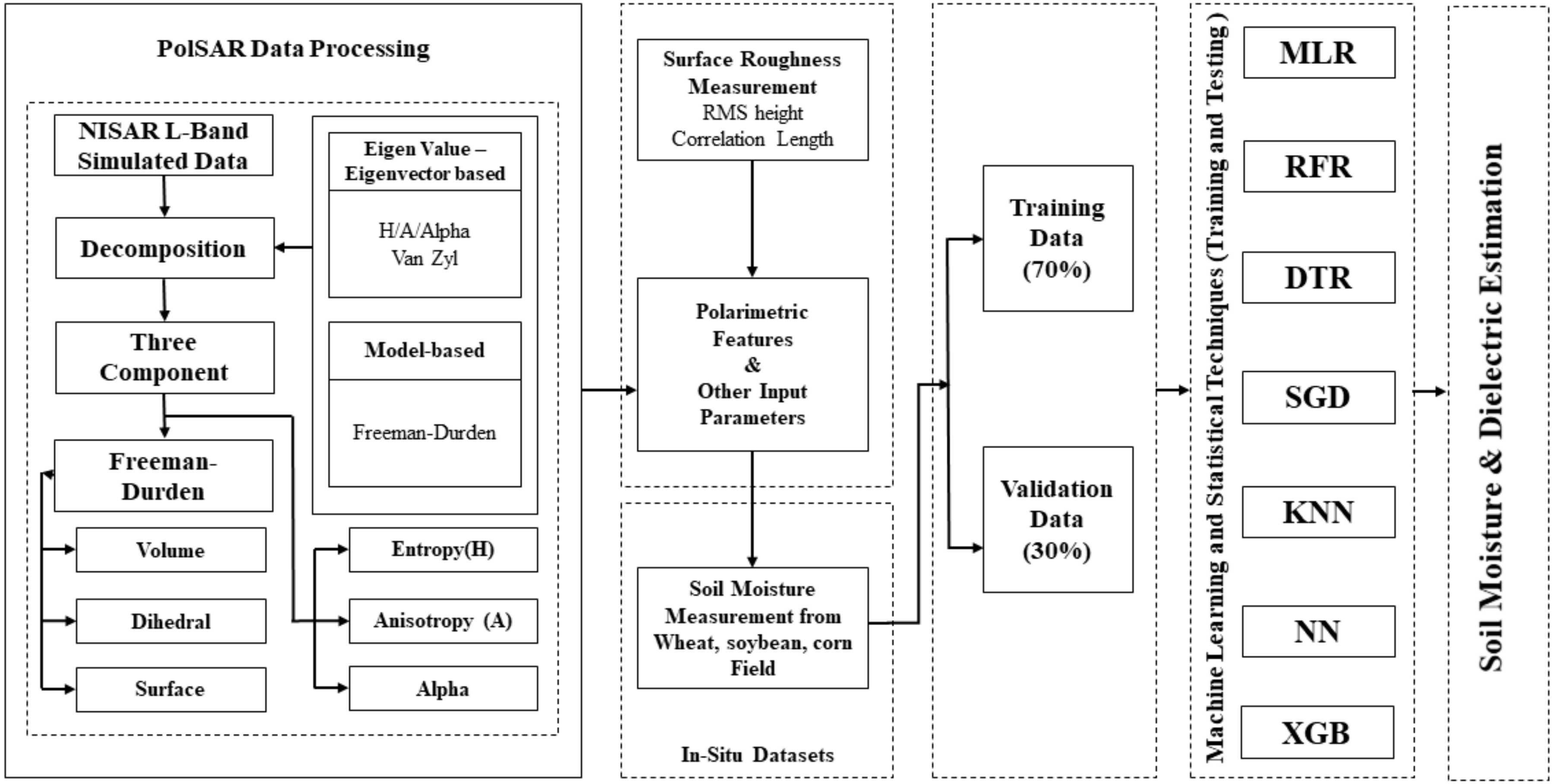
NISAR L-Band Data	
Sensor Type	SAR
Band	L-Band
Simulated NISAR Mode	138A (frequency A)
Frequency	1.253 Ghz
Polarization	Quad Pol Data
Angle of incidence	Near – 33.88, Far – 47.2
Look Direction	Left
Resolution	7.3 m x 7.3 m (Ground Range Detected)
Data Provider	Jet Propulsion Laboratory (JPL), NASA

Date	(Flight Line ID: 31606) Flight ID	Soil Moisture Measurement (Available)	Roughness Measurement (Available)	Simulated NISAR Data Availabale
7th June	--	Yes	--	--
10th June	--	--	Yes	--
11th June	--	--	Yes	--
12th June	--	Yes	Yes	--
13th June	--	--	Yes	--
15th June	--	Yes	Yes	--
16th June	--	--	Yes	--
17th June	Flight 12044	Yes	Yes	Yes
18th June	--	--	Yes	--
19th June	--	--	Yes	Yes
21st June	--	--	Yes	--
22nd June	Flight 12046	Yes	--	Yes
23rd June	Flight 12047	Yes	--	Yes
24th June	--	--	Yes	--
25th June	Flight 12048	Yes	--	Yes
27th June	Flight 12049	Yes	--	Yes
29th June	Flight 12050	Yes	--	Yes
30th June	--	--	Yes	Yes
3rd July	Flight 12055	Yes	--	Yes
5th July	Flight 12056	Yes	--	Yes
7th July	--	--	Yes	--
8th July	Flight 12057	Yes	--	Yes
10th July	--	Yes	--	Yes
13th July	Flight 12059	Yes	--	Yes
14th July	Flight 12060	Yes	--	Yes
17th July	Flight 12061	Yes	--	Yes
19th July	--	Yes	--	--

Data Processed

https://uavsar.jpl.nasa.gov/

METHODOLOGY



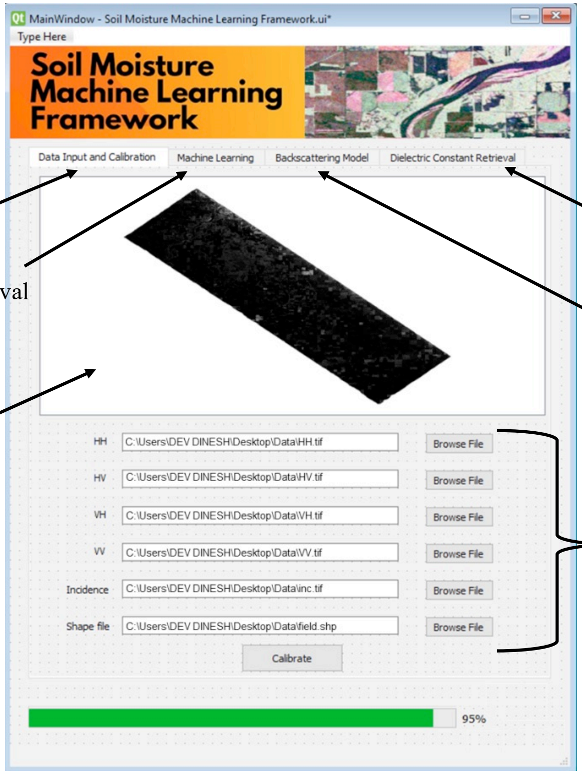
MLR: Multi-Linear Regression
RFR: Random Forest Regression
DTR: Decision Tree Regression
SGD: Stochastic gradient descent
KNN : K-Nearest Neighbor
NN: Neural Network
XGB : Extreme Gradient Boosting

DEVELOPMENT OF ML FRAMEWORK

Input Parameter Tab

Machine Learning based Retrieval Section

Display Section for data



Dielectric Constant Retrieval by ML

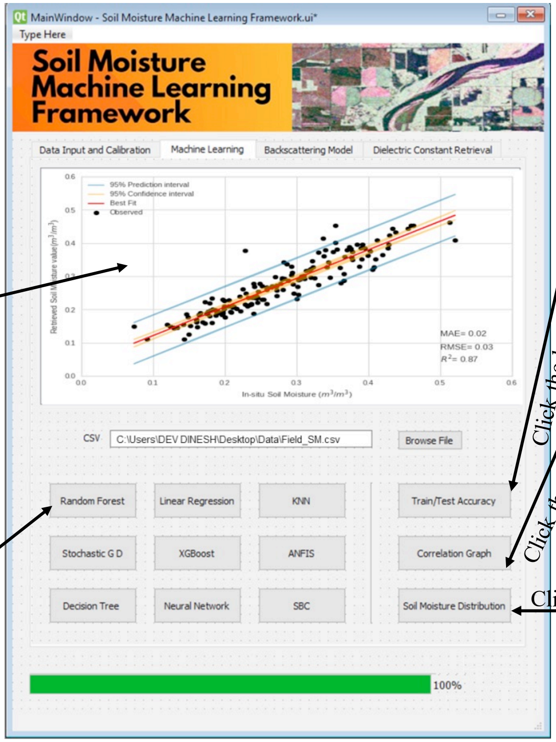
Classical Models SM retrieval technique section

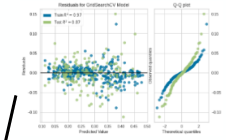
Input and Browse data section

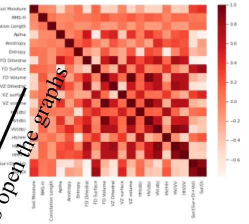
Machine Learning based Retrieval Section

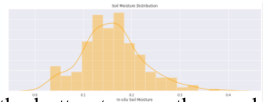
Displaying Graph with CI/PI values

Just one Click









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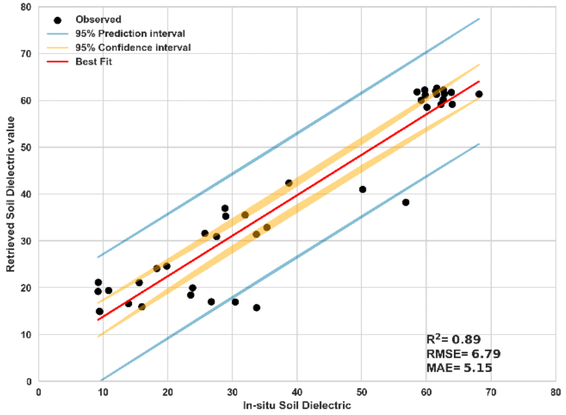
ML Software for soil Moisture

RESULTS: Soil Dielectric

Soybean Field



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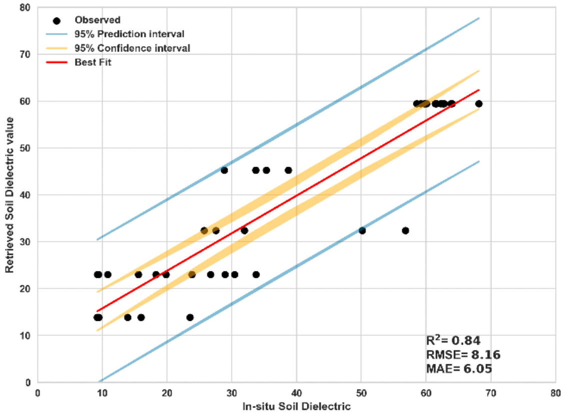

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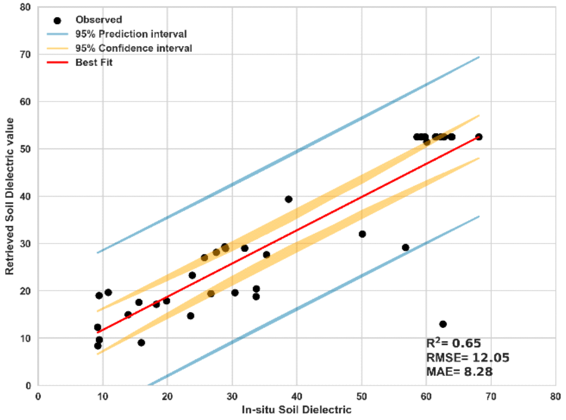

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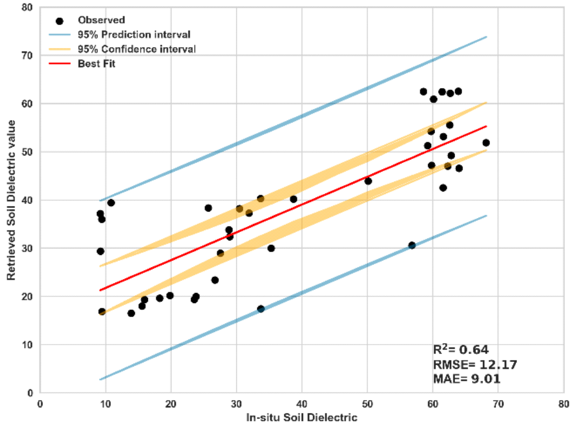

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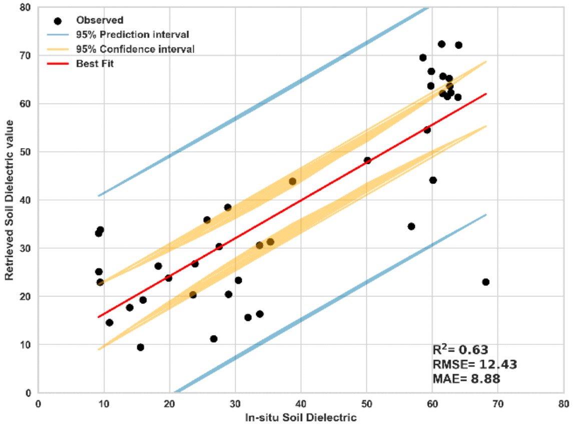

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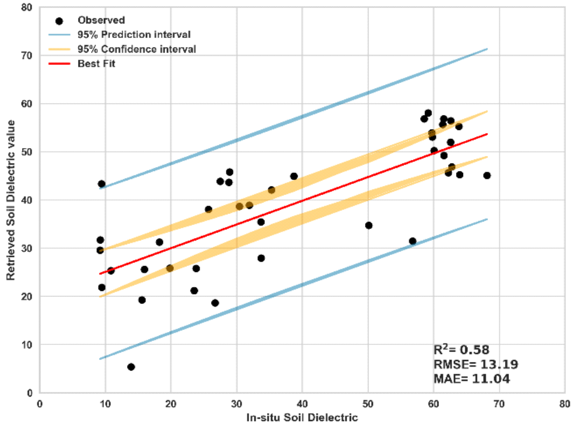

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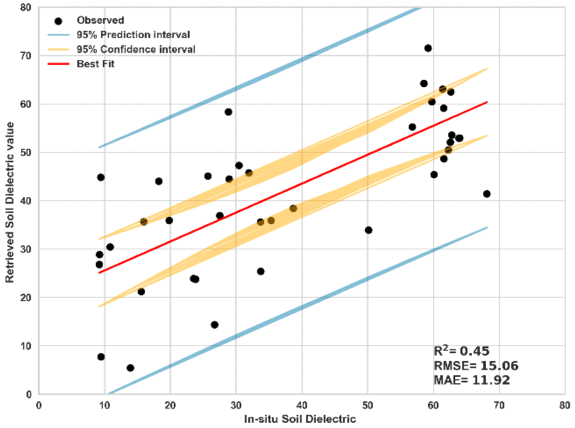


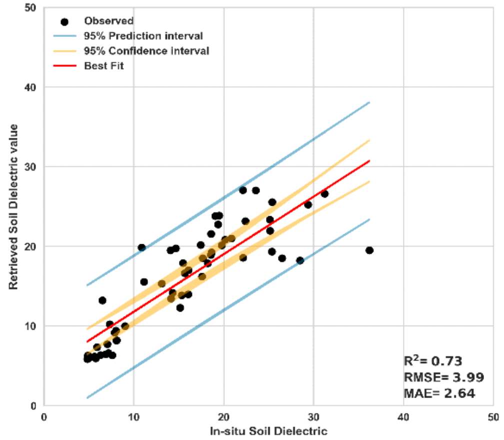
(g)

Soil Dielectric Retrieval from Soybean Field

(a) Random Forest (b) Decision Tree (c) XGBoost (d) KNN (e) Neural Network (f) SGD (g) MLR

RESULTS: Soil Dielectric

Wheat Field



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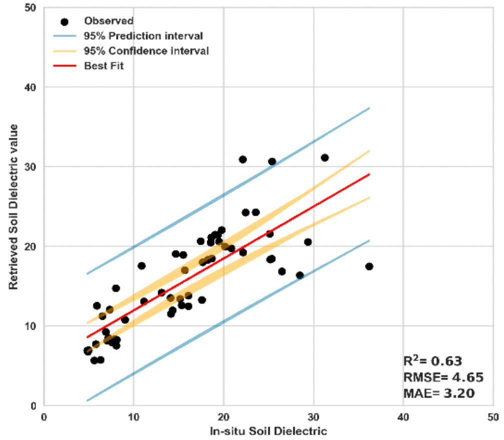

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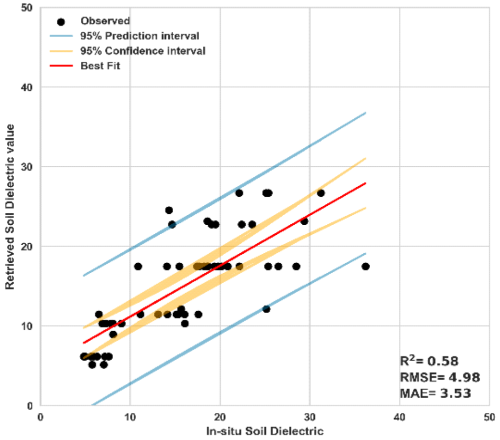

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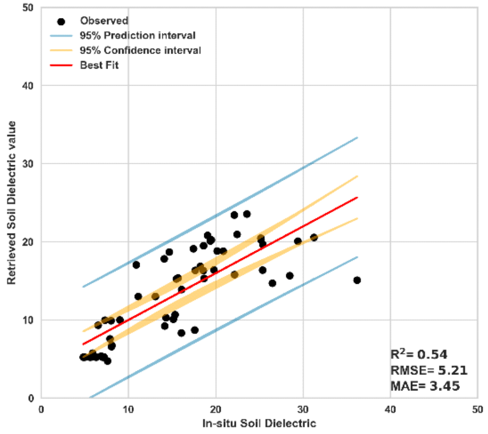

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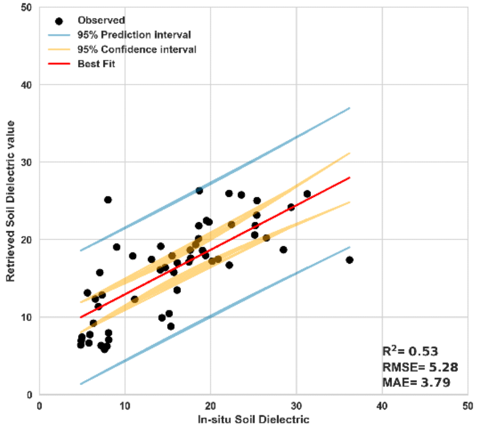

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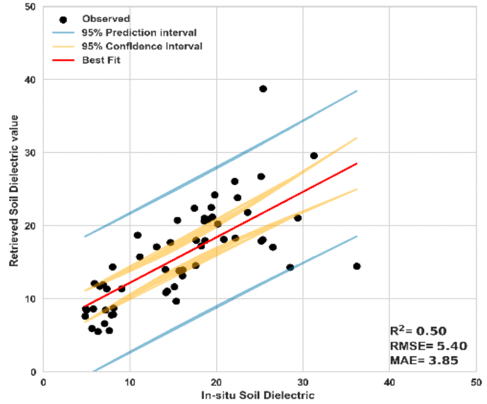

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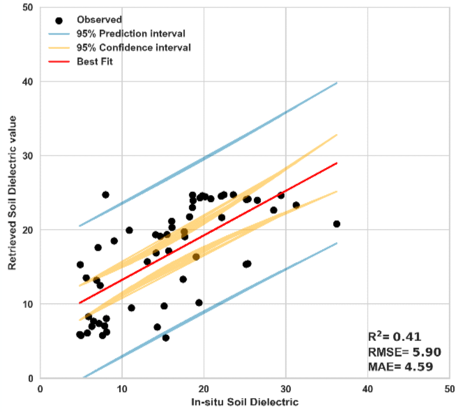


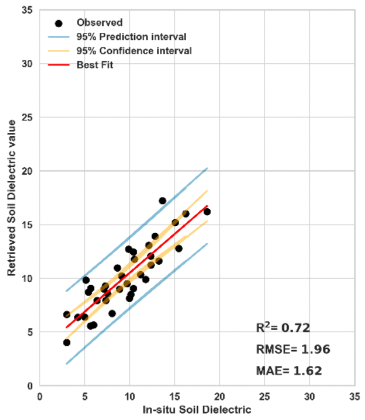
(g)

Soil Dielectric Retrieval from Wheat Field

(a) Random Forest (b) SGD (c) Decision Tree (d) XGBoost (e) KNN (f) MLR (g) Neural Network

RESULTS: Soil Dielectric

Corn Field



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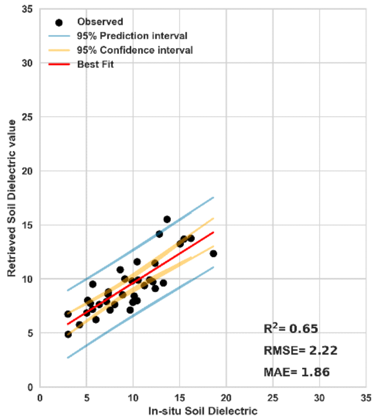

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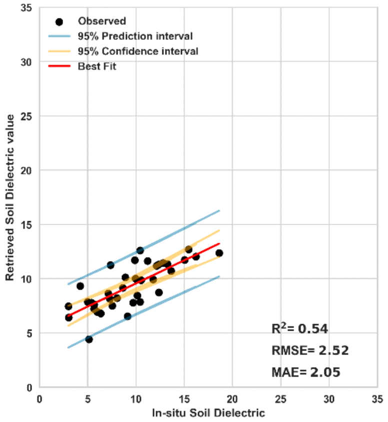

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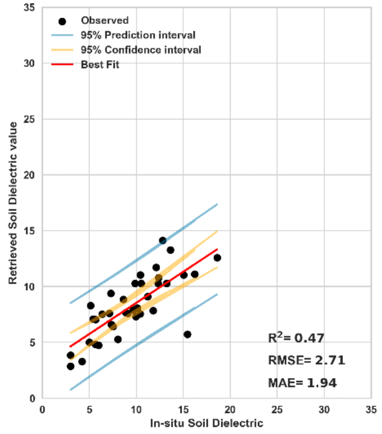

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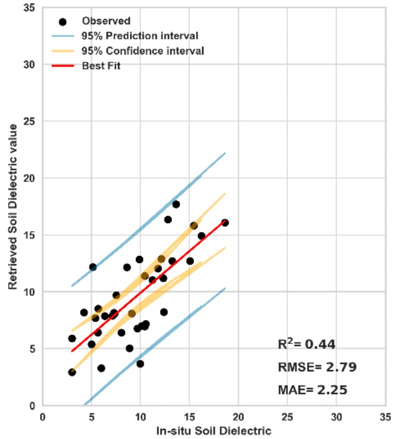

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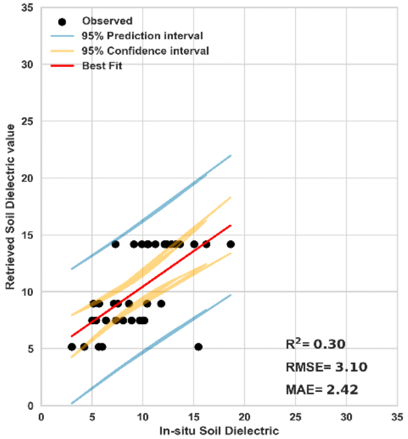

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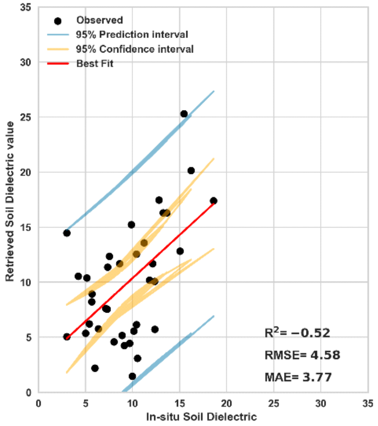

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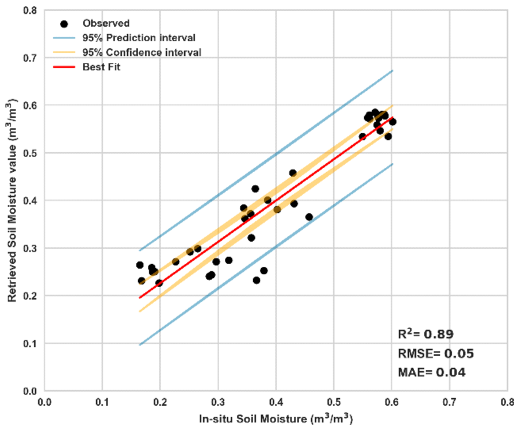
Soil Dielectric Retrieval from Corn Field

(a) Random Forest (b) KNN (c) Neural Network (d) XGBoost (e) SGD (f) Decision Tree (g) MLR

RESULTS: Soil Moisture

Soybean Field



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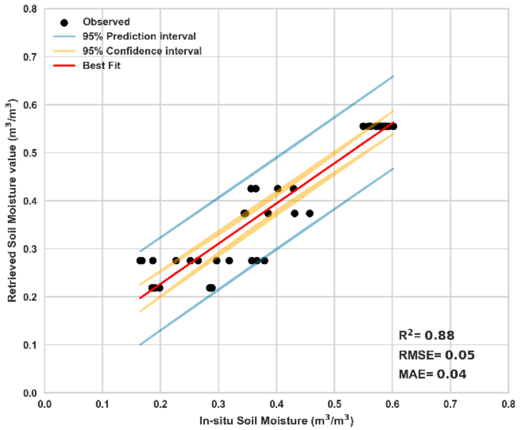

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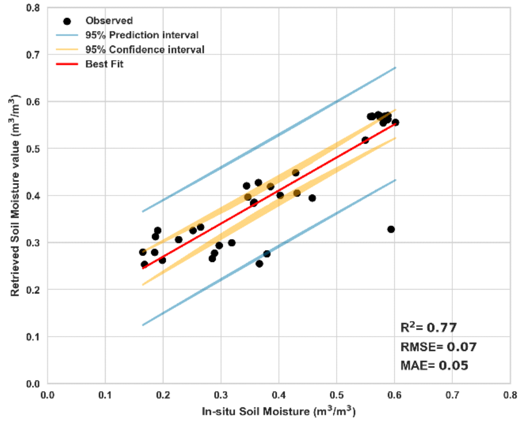

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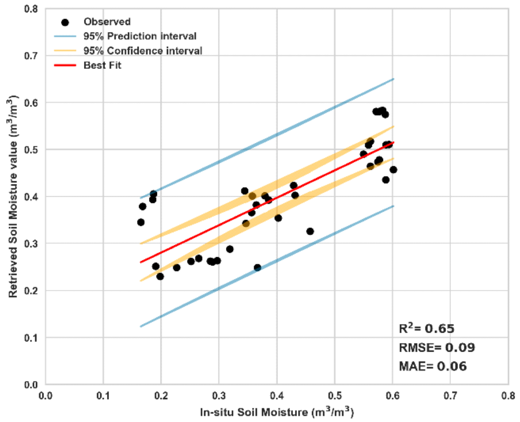

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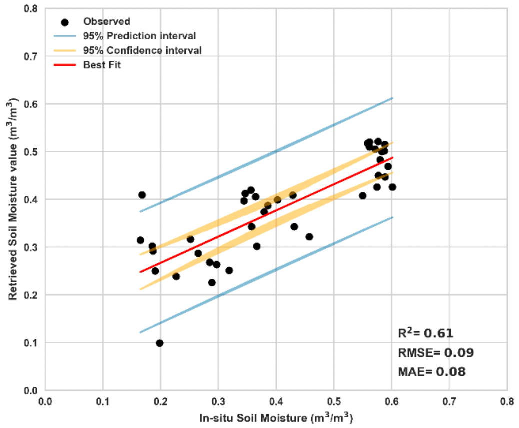

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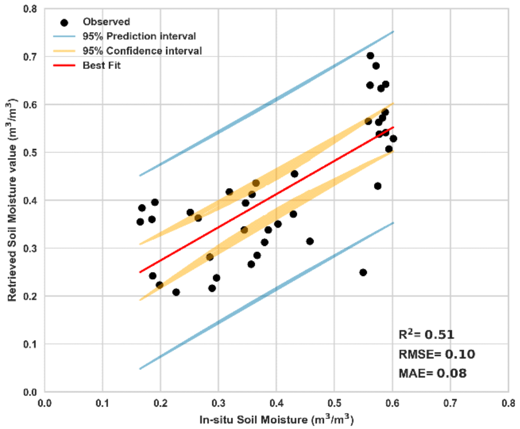

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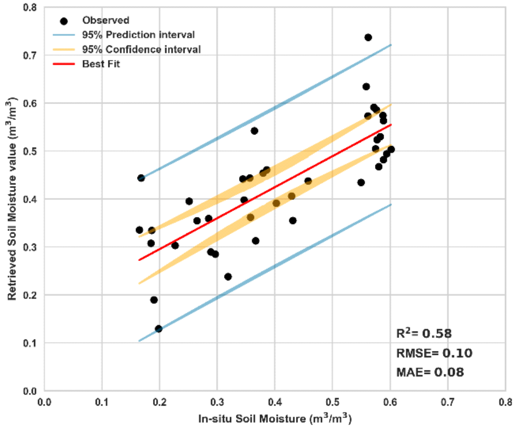

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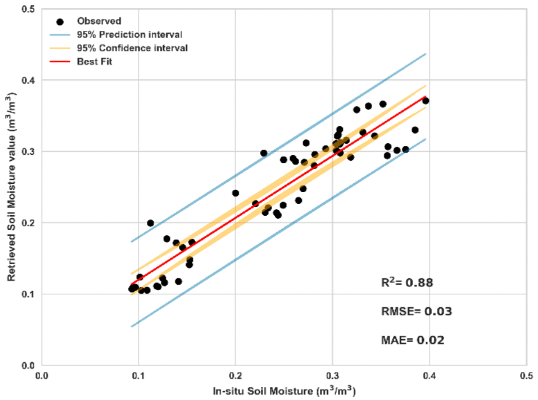
Soil Moisture Retrieval from Soybean Field

(a) Random Forest (b) Decision Tree (c) XGBoost (d) KNN (e) SGD (f) Neural Network (g) MLR

RESULTS: Soil Moisture

W heat

Wheat Field



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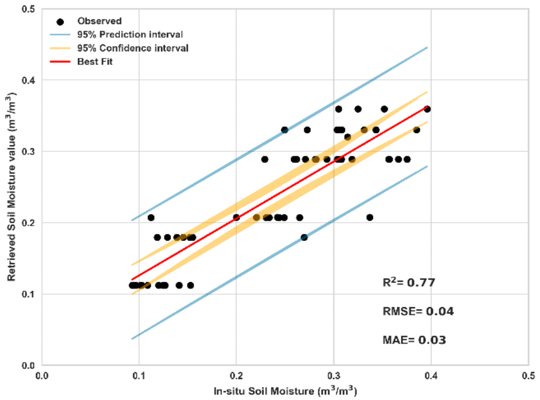

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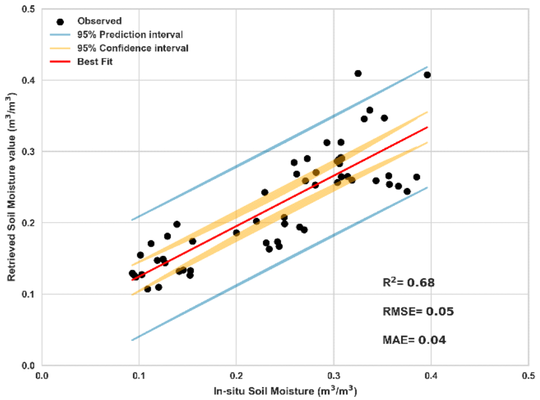

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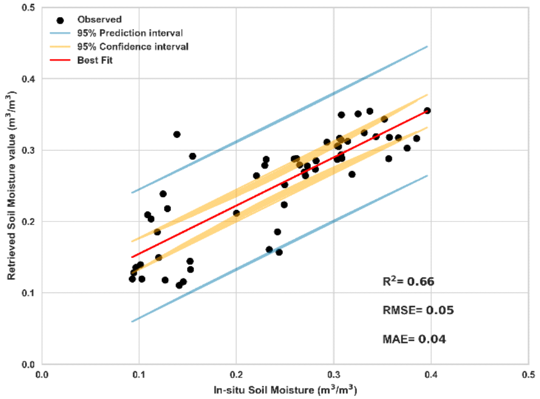

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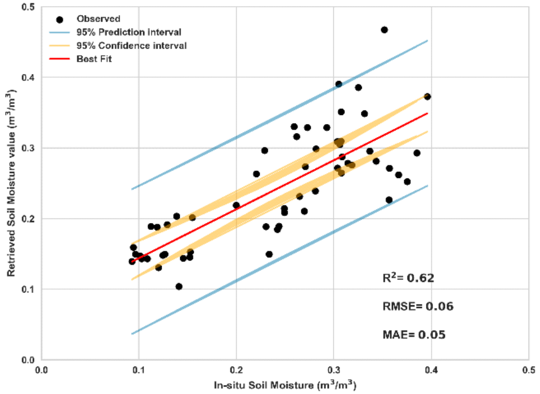

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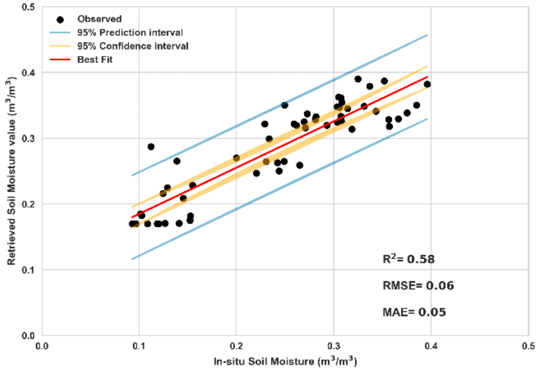

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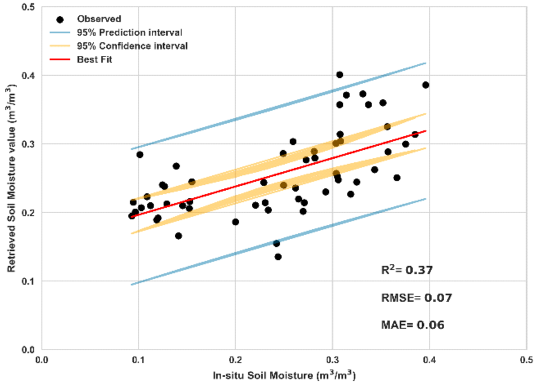

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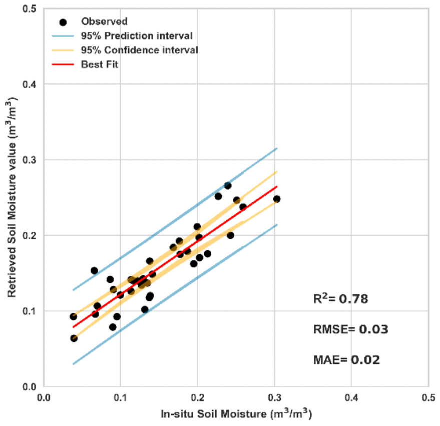
Soil Moisture Retrieval from the Wheat Field

(a) Random Forest (b) Decision Tree (c) SGD (d) KNN (e) MLR (f) XGBoost (g) Neural Network

RESULTS: Soil Moisture

Corn Field



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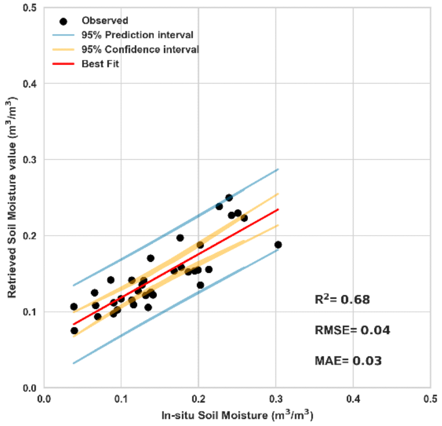

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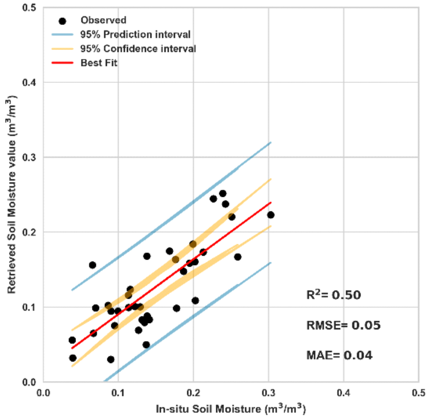

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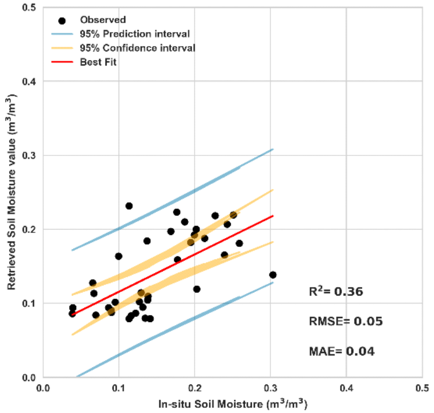

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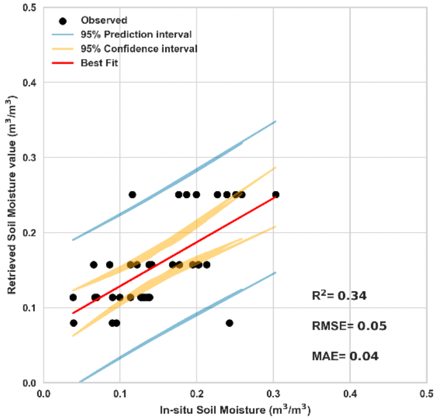

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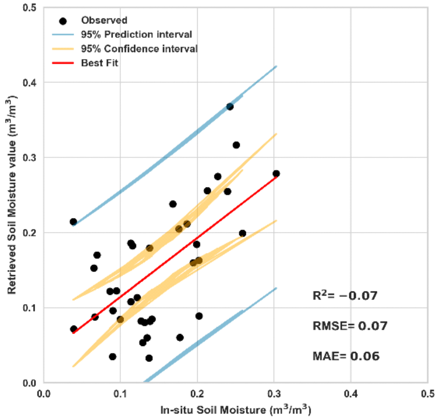

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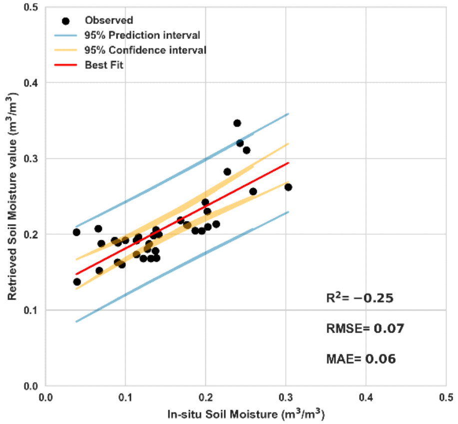


(g)

Soil Moisture Retrieval from Corn Field

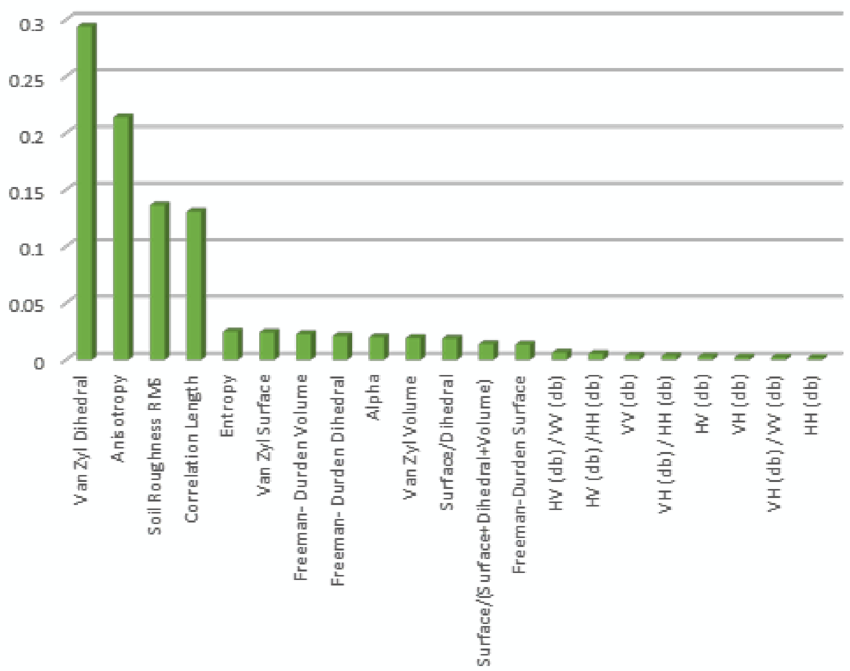
(a) Random Forest (b) KNN (c) SGD (d) Neural Network (e) Decision Tree (f) MLR (g) XGBoost

RESULTS

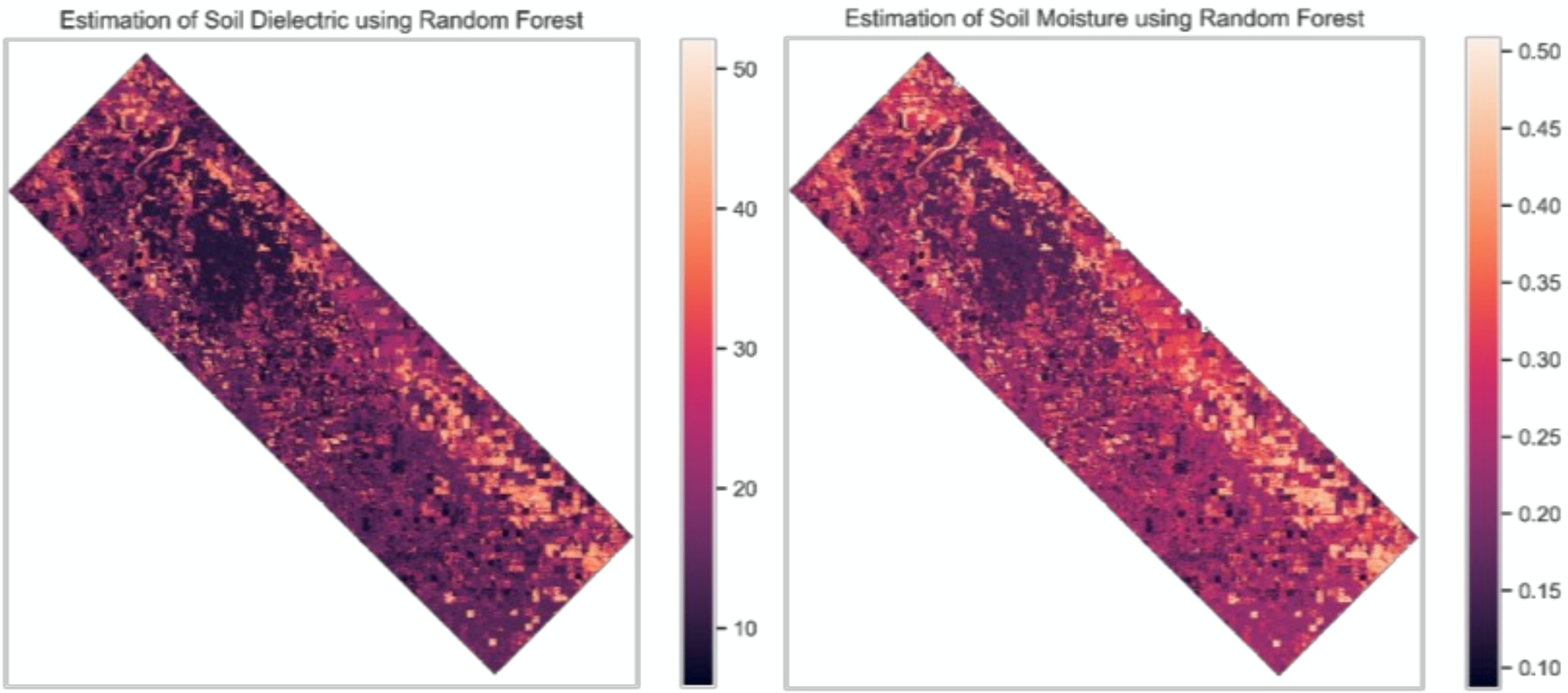
Algorithms	Field Type	Soil Dielectric R^2	Soil Dielectric RMSE	Soil Dielectric MAE	Soil Moisture R^2	Soil Moisture RMSE (m^3/m^3)	Soil Moisture MAE (m^3/m^3)
Random Forest	Soybeans	0.89	6.79	5.15	0.89	0.05	0.04
	Wheat	0.73	3.99	2.64	0.88	0.03	0.02
	Corn	0.72	1.96	1.62	0.78	0.03	0.02
Decision Tree	Soybeans	0.84	8.16	6.05	0.88	0.05	0.04
	Wheat	0.58	4.98	3.53	0.77	0.04	0.03
	Corn	0.30	3.10	2.42	0.34	0.05	0.04
XGBoost	Soybeans	0.65	12.05	8.28	0.77	0.07	0.05
	Wheat	0.54	5.21	3.45	0.58	0.06	0.05
	Corn	0.47	2.71	1.94	-0.25	0.07	0.06
Stochastic Gradient Descent	Soybeans	0.58	13.19	11.04	0.61	0.09	0.08
	Wheat	0.63	4.65	3.20	0.68	0.05	0.04
	Corn	0.44	2.79	2.25	0.50	0.05	0.04
KNN	Soybeans	0.64	12.17	9.01	0.65	0.09	0.06
	Wheat	0.53	5.28	3.79	0.66	0.05	0.04
	Corn	0.65	2.22	1.86	0.68	0.04	0.03
Multi Linear Regression	Soybeans	0.45	15.06	11.92	0.58	0.10	0.08
	Wheat	0.50	5.40	3.85	0.62	0.06	0.05
	Corn	-0.52	4.58	3.77	-0.07	0.07	0.06
Neural Network	Soybeans	0.63	12.49	8.88	0.51	0.10	0.08
	Wheat	0.41	5.90	4.59	0.37	0.07	0.06
	Corn	0.54	2.52	2.05	0.36	0.05	0.04

Analysis of modelled output of soil dielectric & soil moisture

Feature Importance in Random Forest



RESULTS



Estimated Soil Dielectric and Soil Moisture using Random Forest

CONCLUSION

- The results were obtained for three crop types: wheat, soybean, and corn fields, for soil dielectric estimation, the random forest again provided better results in the soybean crop field with an R^2 of 0.89, RMSE of 6.79, and MAE of 5.15.
- Random forest showed best results for the soybean field with a coefficient of determination of 0.89, RMS of 0.033 $m^3\ m^{-3}$, MAE of 0.001 $m^3\ m^{-3}$.
- For the wheat field, a coefficient of determination of 0.87 was observed. Random forest performed better in the soybean field compared to the wheat field, but it still outperformed the other machine learning (ML) algorithms.
- The Adverse performance was reported for neural networks, XGBoost, and multi-linear regression.
- One of the reasons random forest performed better than other ML algorithms was its ability to handle a larger number of input variables without overfitting.

THANK YOU

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