Modeling Oxygen Dynamics During Anaerobic Soil Disinfestation for Soilborne Pathogen Control

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Introduction

Phytophthora capsici is a persistently harmful pathogen impacting Michigan's vegetable crops [1]. Anaerobic soil disinfestation (ASD) is effective in controlled settings but is untested in Michigan fields. Soil oxygen measurement is essential to evaluate ASD performance and pathogen survival. Advanced soil oxygen sensors and predictive machine-learning models can identify the influence of irrigation, soil, and environmental factors on pathogen survival and ASD effectiveness in Michigan fields [2-3].

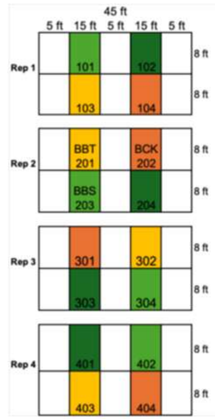
Objectives

The objectives of this study were to:

1) develop a data-driven pathogen transport prediction model using field sensors

2) evaluate pathogen dynamics under ASD treatments to predict treatment endpoints

Field Work



Treatments		
Factor A	**Factor B**	**Plots**
Std	Inoculated	102 204 303 401
Std	Non-Inoculated	101 203 304 402
ASD	Inoculated	104 202 301 404
ASD	Non-Inoculated	103 201 302 403

Fig. 1. Plot layout (left) and treatments

Treatment	Sum of healthy	Sum of unhealthy
ASD	7	1
STD	3	5
Total	10	6

Table 1. Plant (pepper) health based on treatment

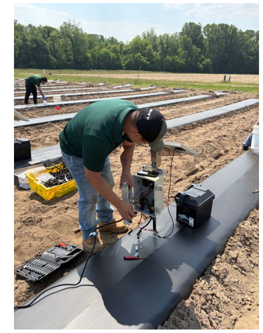


Fig. 2. Sensors installed in plots

Fig. 3. ASD treatment in the field

Soil Sensor Data Collected Over Time

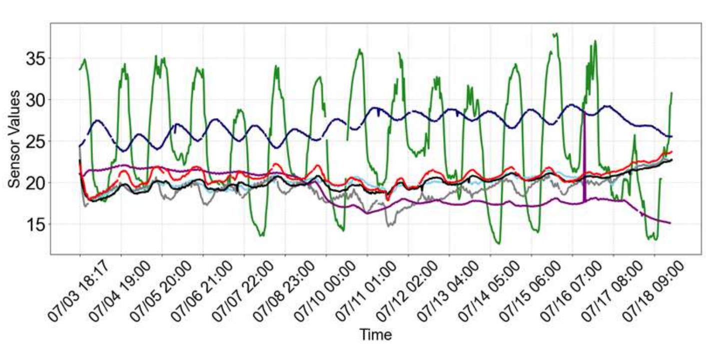


Fig. 4. Soil sensor data and oxygen contents plotted over time

Fig. 5. IRIS tubes used to determine anaerobic conditions

Conclusions

SVR and RFR prediction were tested for accuracy. SVR's root mean square error was 2.155, R^2 of -6.342. RFR had a root mean square error of 1.620 and R^2 of -3.149. LSTM had the highest accuracy with root mean square error is .0395 and R^2 of .755. Based on these results, oxygen levels may be predicted using these models.

Acknowledgements

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References

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3. Shireshi, S. S., & Raman, R. (2024). Soil-borne pathogens management in cloud-connected agriculture: An IoT and decision tree algorithmic approach. In 2024 International Conference on Emerging Smart Computing and Informatics (ESCI) (pp. 1-5). IEEE.

Machine Learning Prediction of Oxygen Content Based on Initial Soil Temperature and Moisture

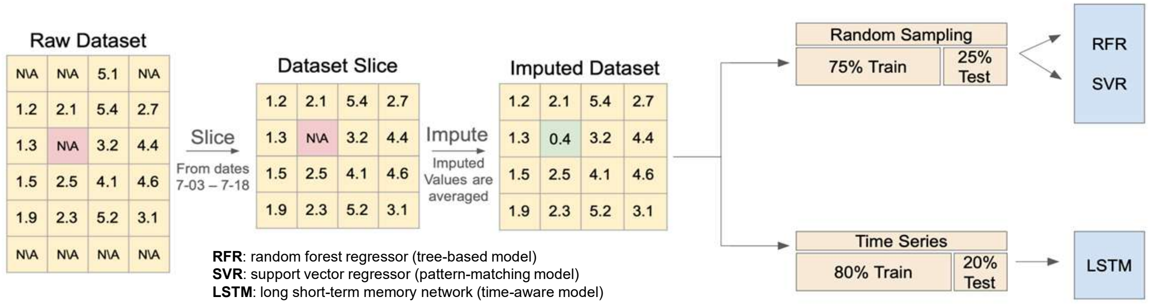

Fig. 6. Schematic diagram of overall workflow

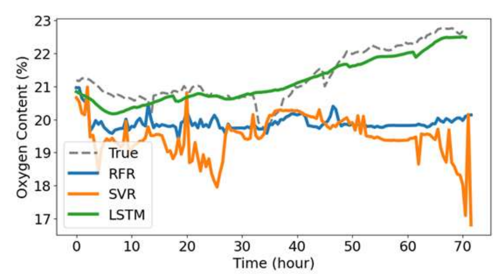

Fig. 7. Model prediction of oxygen contents between 7/15/25 to 7/18/25

Model	R² Value	RMSE
LSTM	0.75445 ± 0.00051	.039458 ± 0.00029
RFR	-3.14929 ± 0.00162	1.62019 ± 0.00001
SVR	-6.34161	2.15516

Table 2. Model performance