Solute Transport in Seawater Flooded Soils: Environmental Impacts and Insights from Experiments, Numerical Modeling, and Machine Learning

Greater Everglades Restoration Conference

Girma W. Awoke
Niguss S. Hailegnaw
Mulatu L. Berihun
Haimanote K. Bayabil

UF|IFAS UNIVERSITY of FLORIDA
TREC Tropical Research and Education Center

Water Resources Research Group

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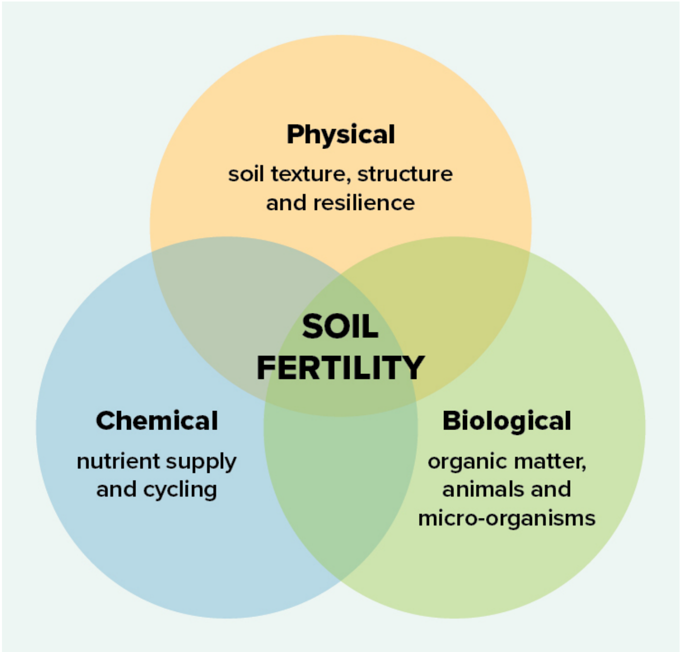
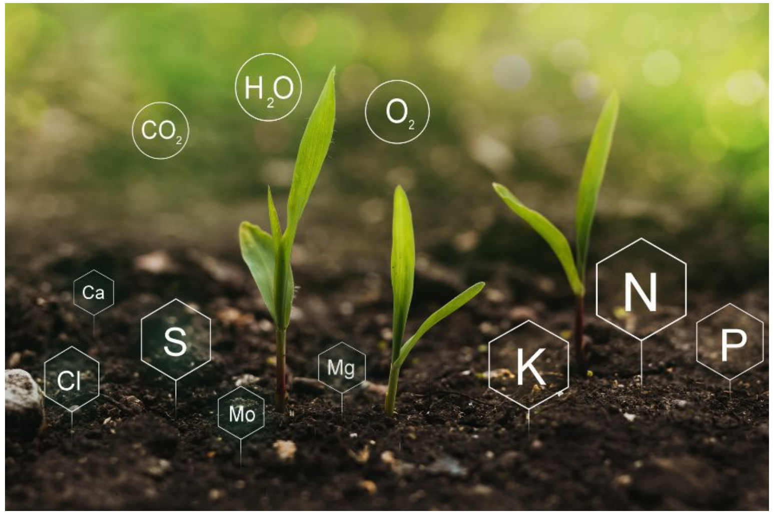
Solute transport

- Impacts agricultural productivity
- Disrupts optimal condition
- Effects of agricultural management practices
- Impacts of seawater flooding





Motivation: Soil hydrology

- Rock plowing

https://www.nrcs.usda.gov/Internet/FSE_MANUSCRIPTS/florida/FL686/0/Dade.pdf

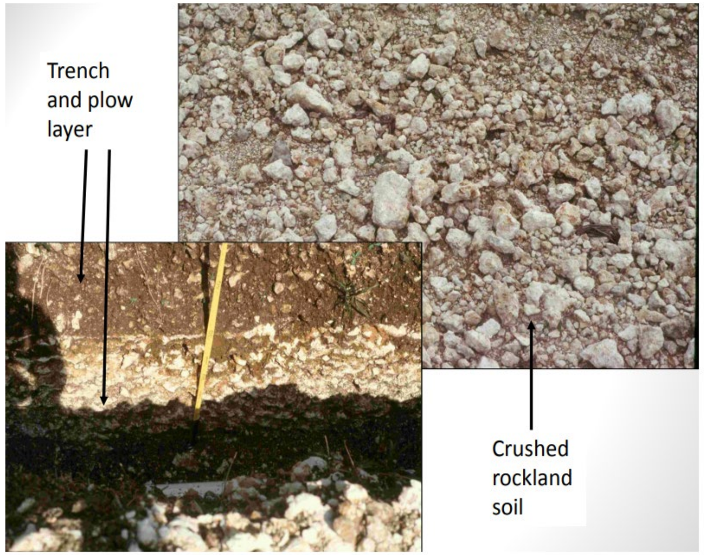
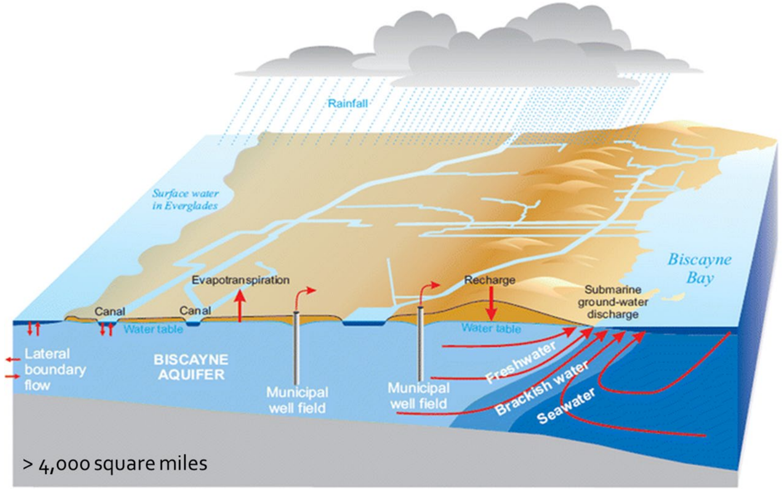
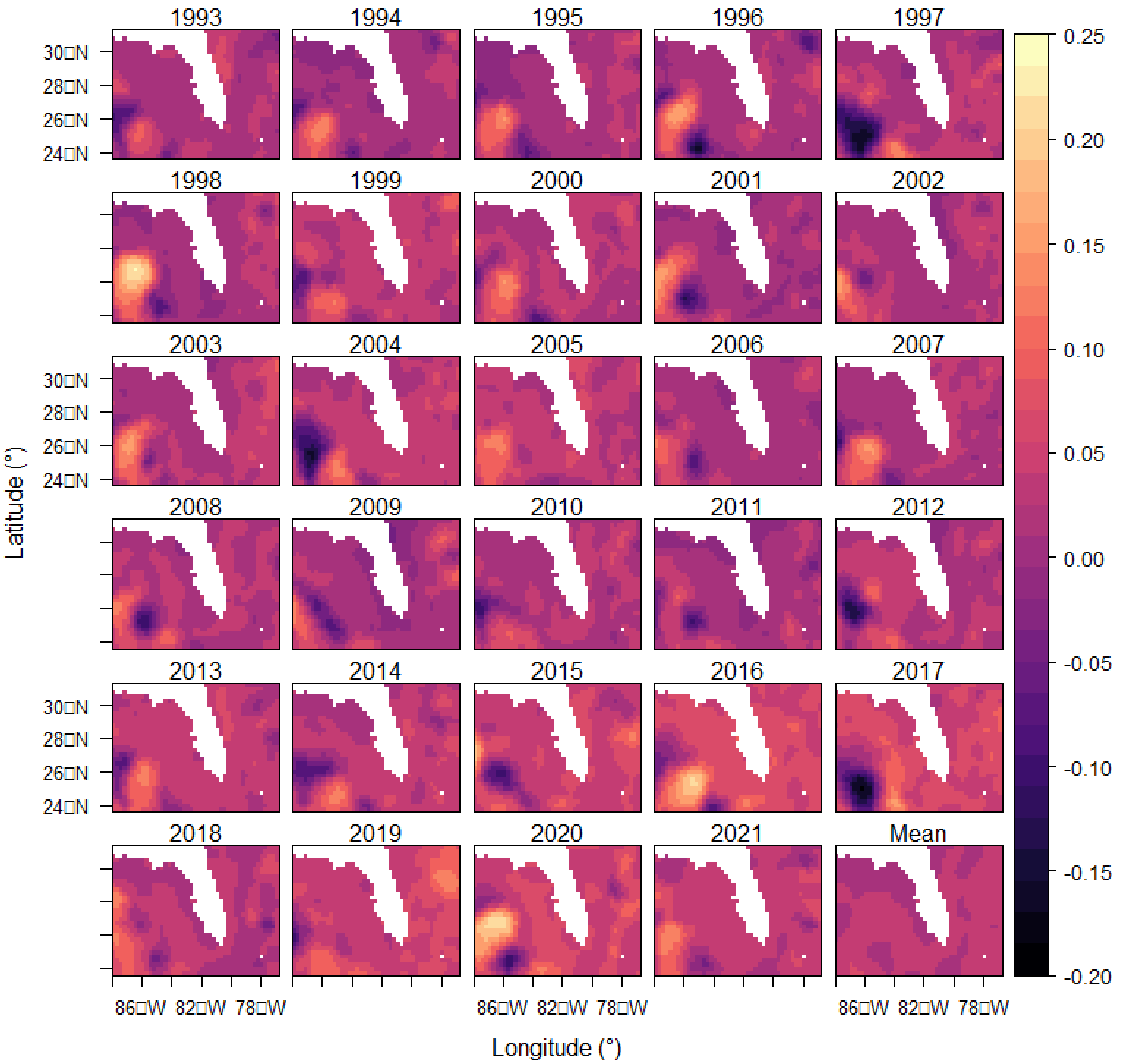
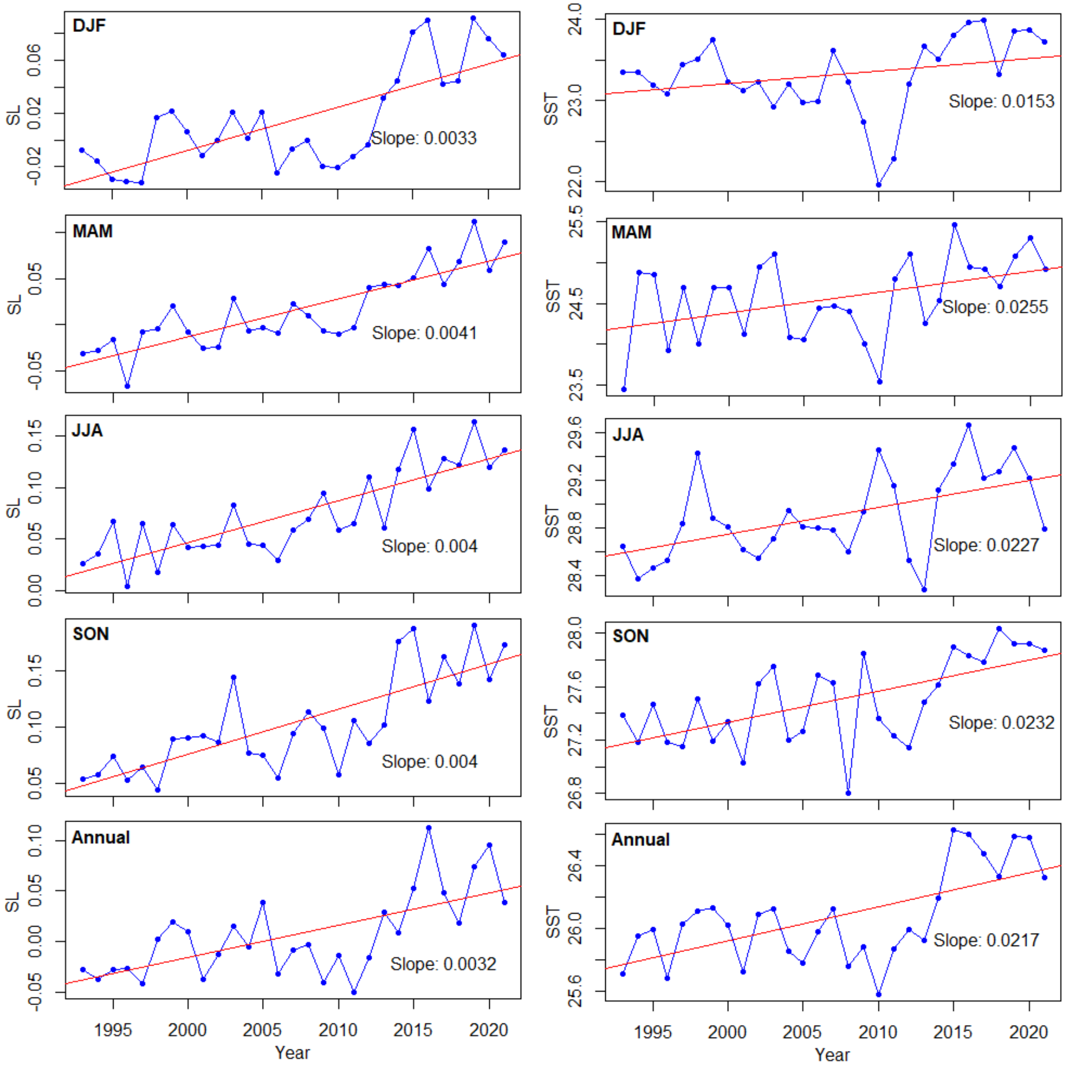


Photo credit: Prof. J. Crane (UF/IFAS)



Motivation: Sea level rise in the past

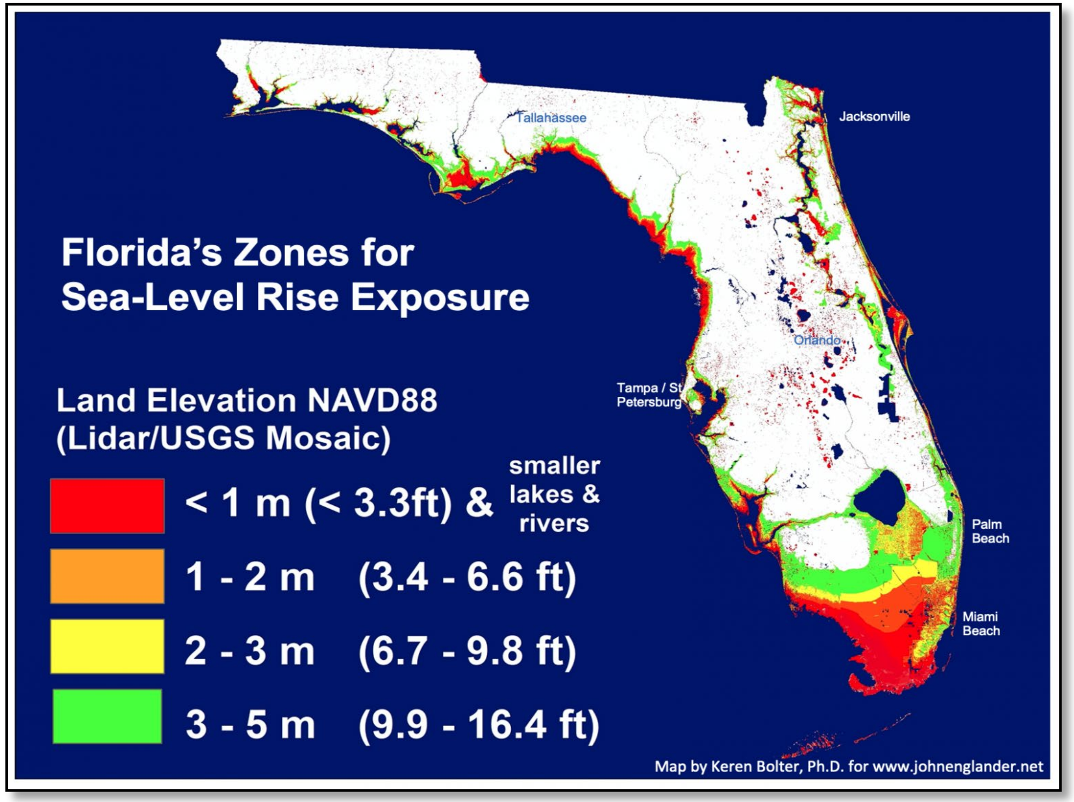


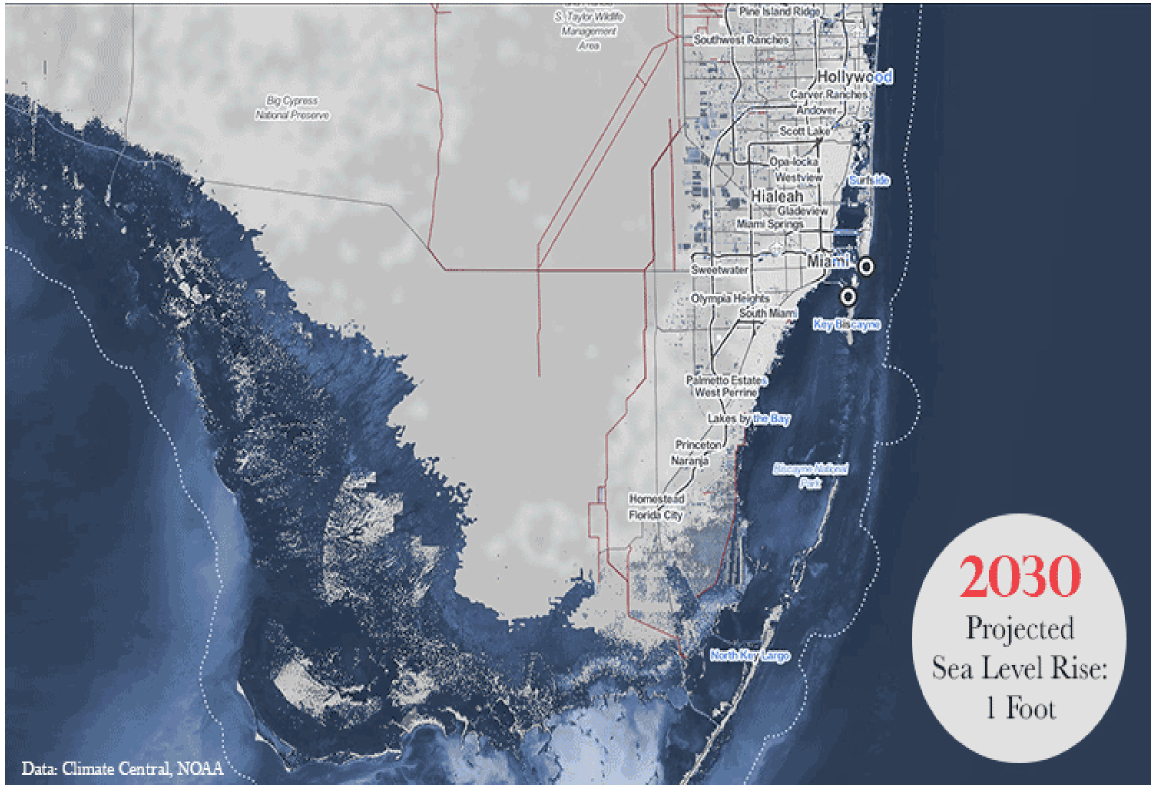


- A cumulative spatial and temporal SLR by up to 25 cm and 10 cm over 29 years

Berihun et al. (under review)

Motivation: Sea level rise in the future





https://oceanservice.noaa.gov/hazards/sealevelrise/sealevelrise-tech-report.html

- Sea level along the U.S. coastline is projected to increase by 25 – 30 cm
- Flooding: 10x as often as it does today

Flooding in South Florida

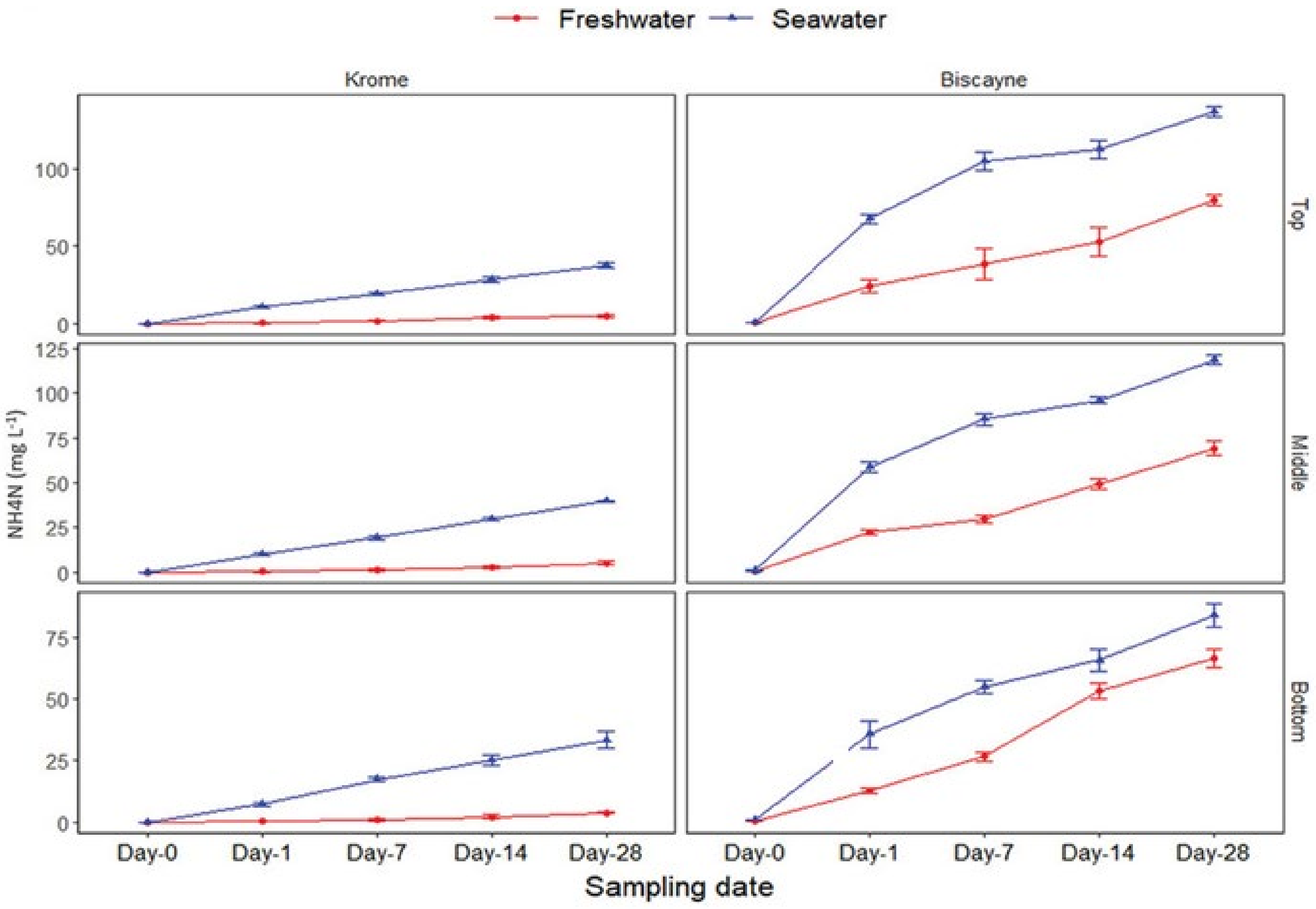
- Extreme weather, hurricane, and flooding

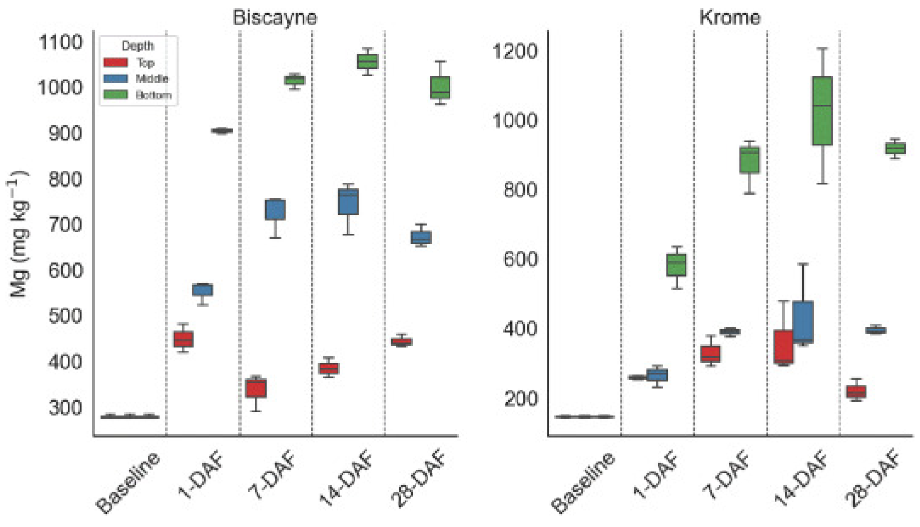
Photo by: Don Pybas

Photo by Bruce Schaffer

© Miami Herald, 2015 Flooding in Miami-Dade, Florida

Impacts of Seawater flooding





(Hailegnaw et al., 2023&2024)

Objective

- Simulate solute transport within saturated soil columns

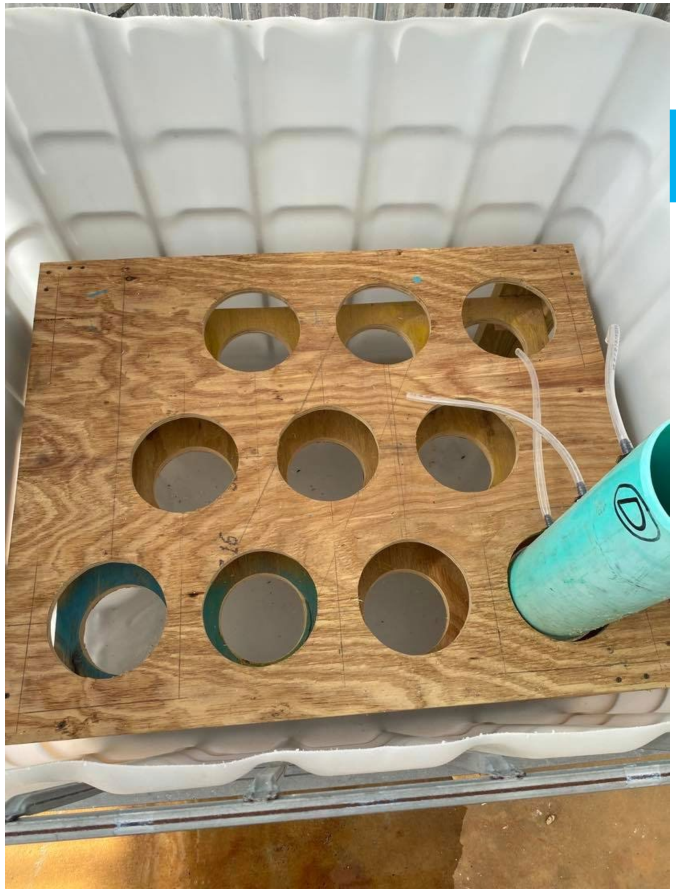
Experiment design

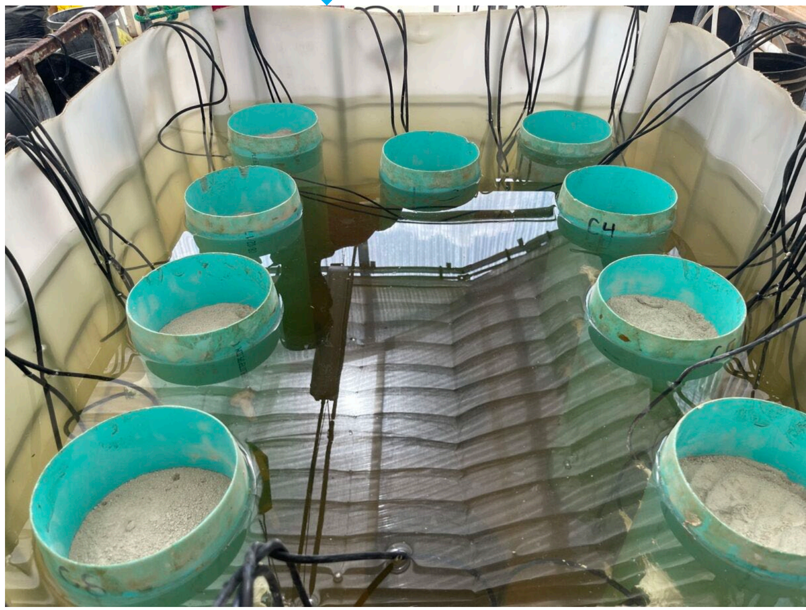
Krome

Biscayne

< 2mm

61cm, ⌀15 cm





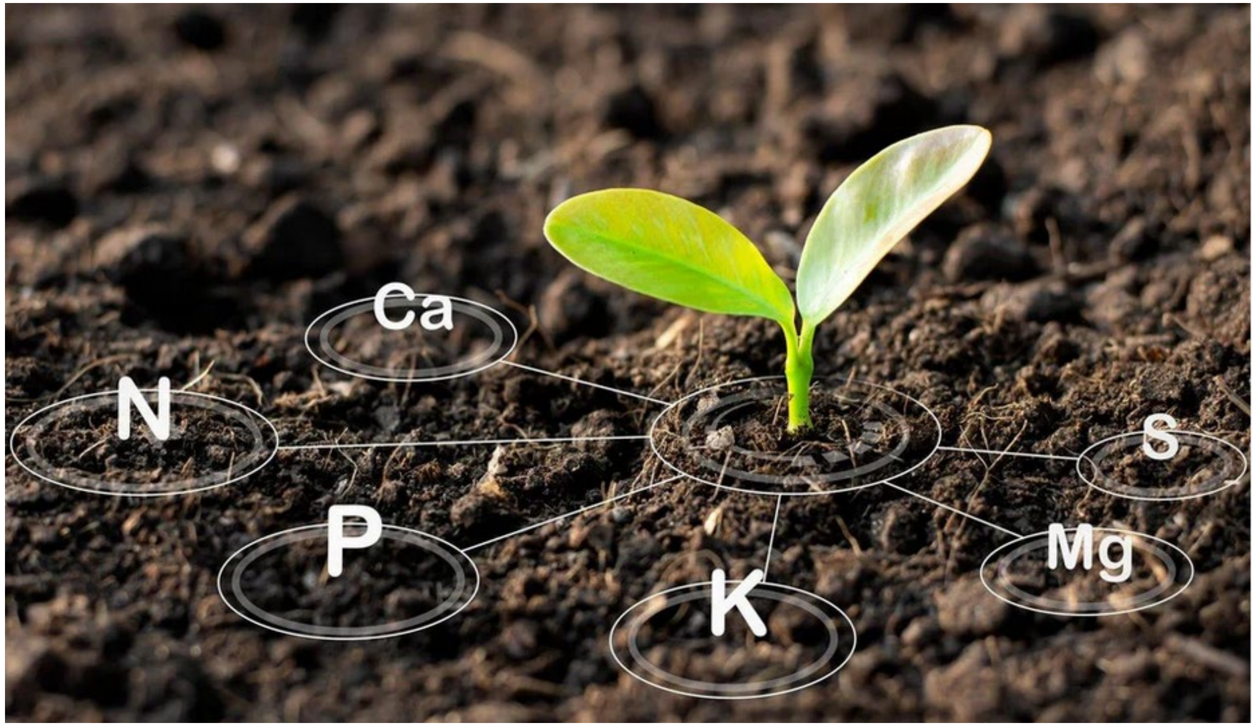
Porewater sampling and analysis

- Samples collected at three levels

- ICP – OES and segmented flow analyzer

Solute transport modeling

- Solute transport modeling
  - Hydrus-1D
  - Machine Learning Models



Hydrus-1D

- Water flow, solute and heat transport

- Experiments in greenhouse and actual field setting

- Water flow: Richard’s equation

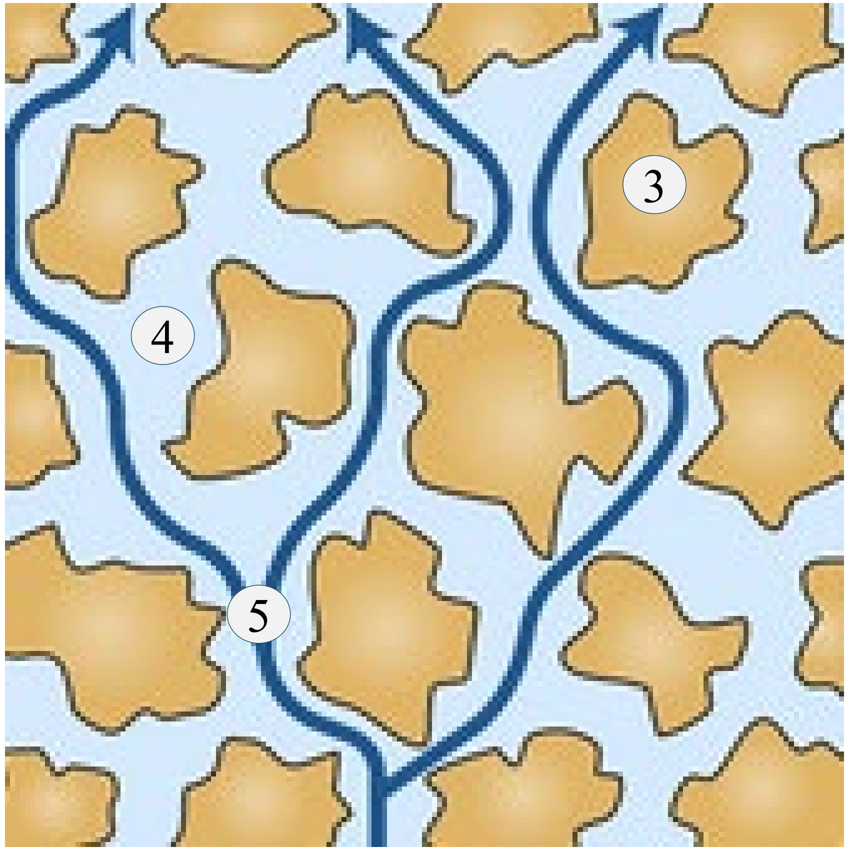
$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z}\left[K\left(\frac{\partial h}{\partial z} + 1\right)\right] \tag{1}$$

- Solute transport: advection dispersion type of equations

$$\frac{\partial \rho S}{\partial t} + \frac{\partial \theta C}{\partial t} = \frac{\partial}{\partial z}\left(\theta D \frac{\partial C}{\partial z}\right) - q\frac{\partial C}{\partial z} \tag{2}$$

Boundary conditions

1 Constant pressure - unsaturated



2 Constant pressure - saturated

3
Baseline
information
Soil texture
Ks

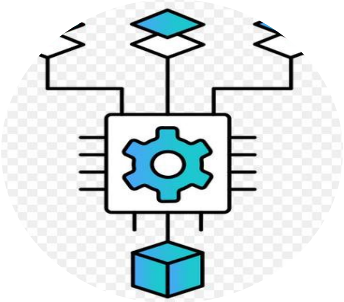
4
Baseline
information
Chemical
properties

5
Solute transport
and reaction
parameters

Machine learning algorithms

- Decision Tree (DT) – regression and classification problems
- Random Forest (RF) – constructs multiple decision trees
- Extreme Gradient Boost (XGB) – powerful to capture non-linear relationships

Statistical analysis

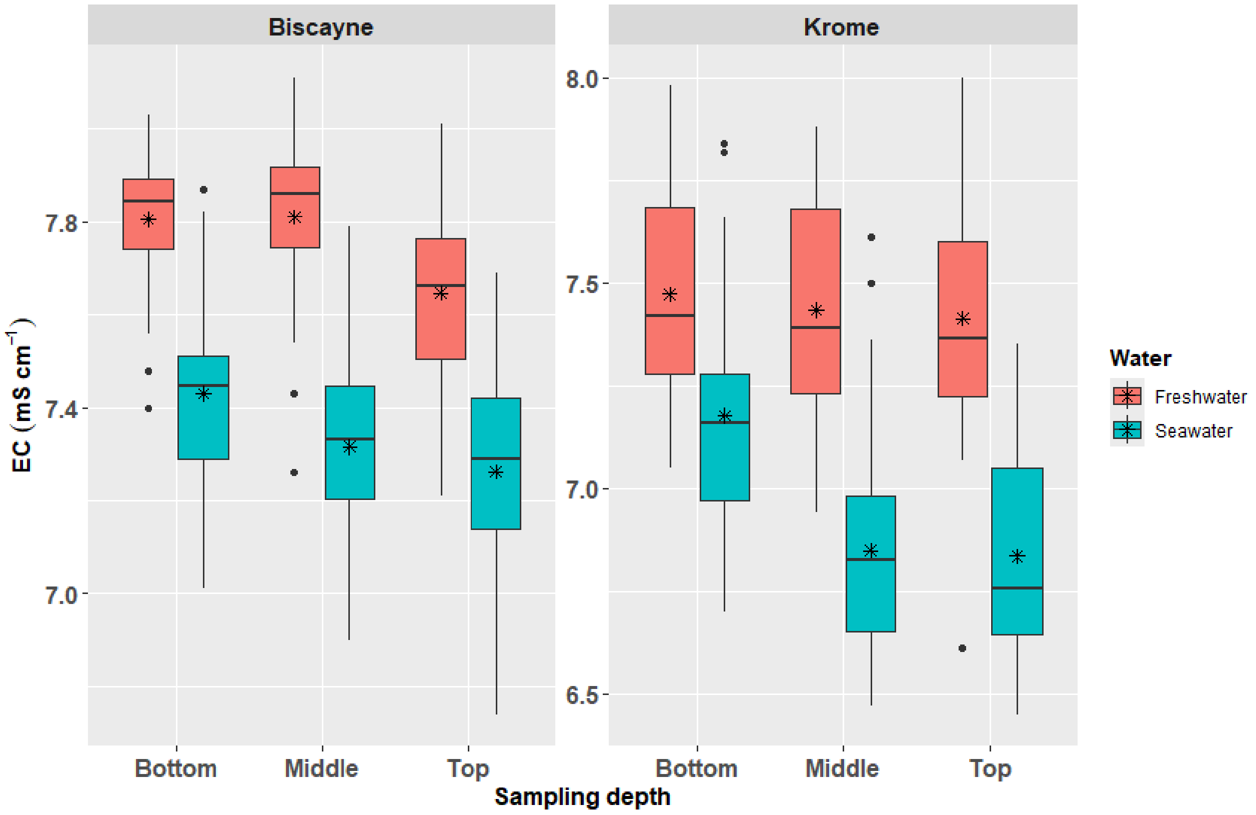


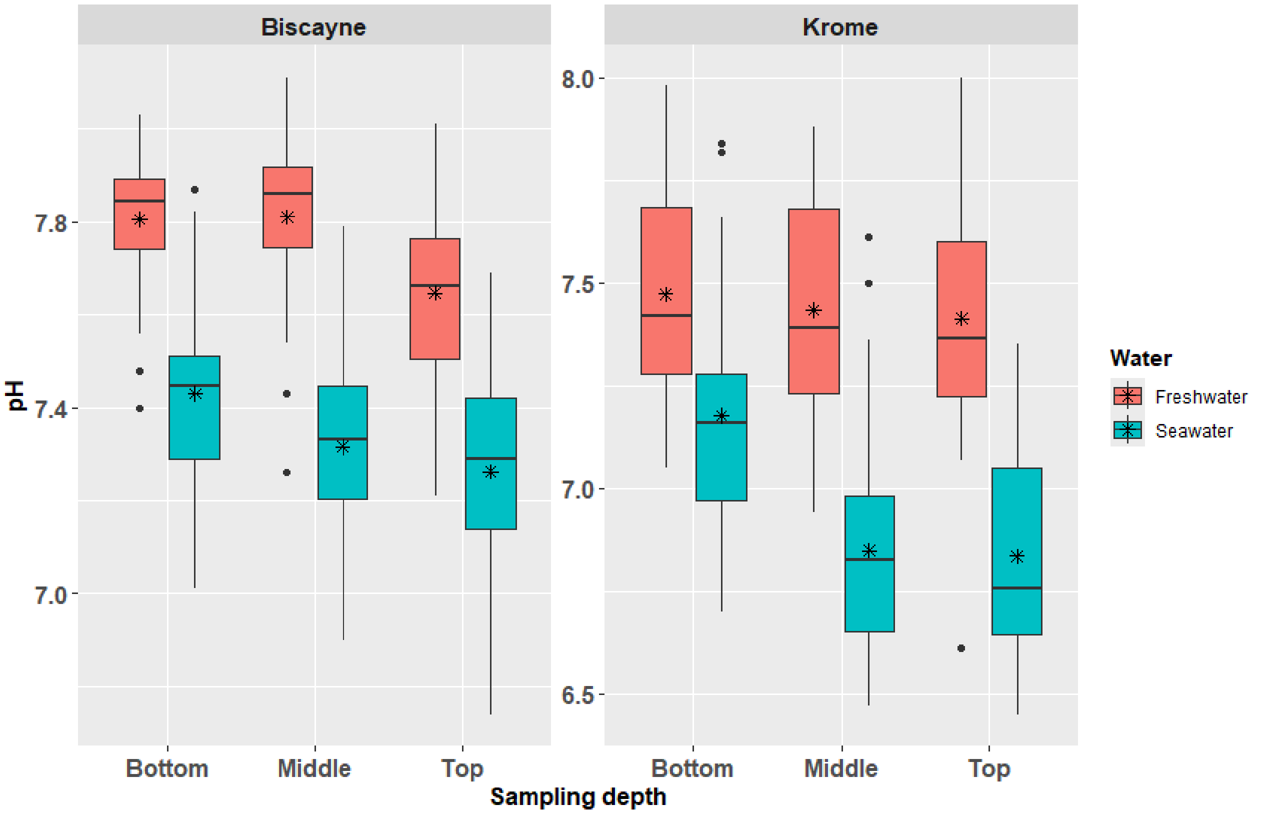
Seventy percent of the data is used for training

Model performance evaluation: R^2 and RMSE

All statistical analyses are performed in R and Python

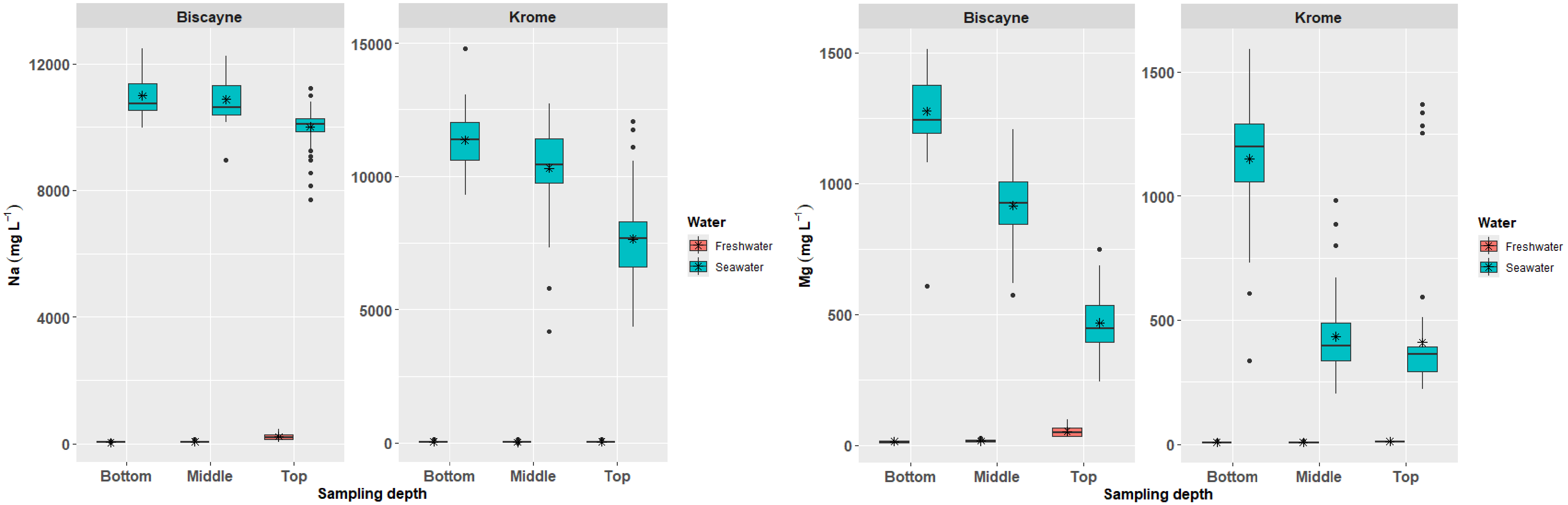
EC and pH





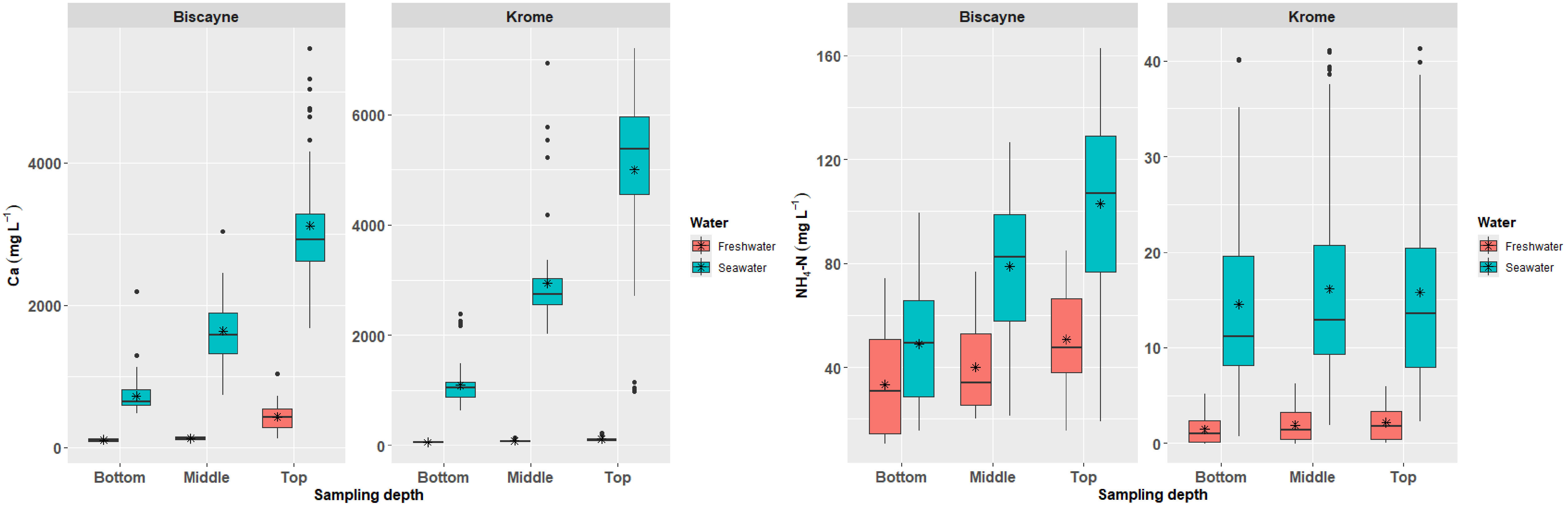
- High EC and pH values in freshwater flooded soils

Na and Mg concentrations



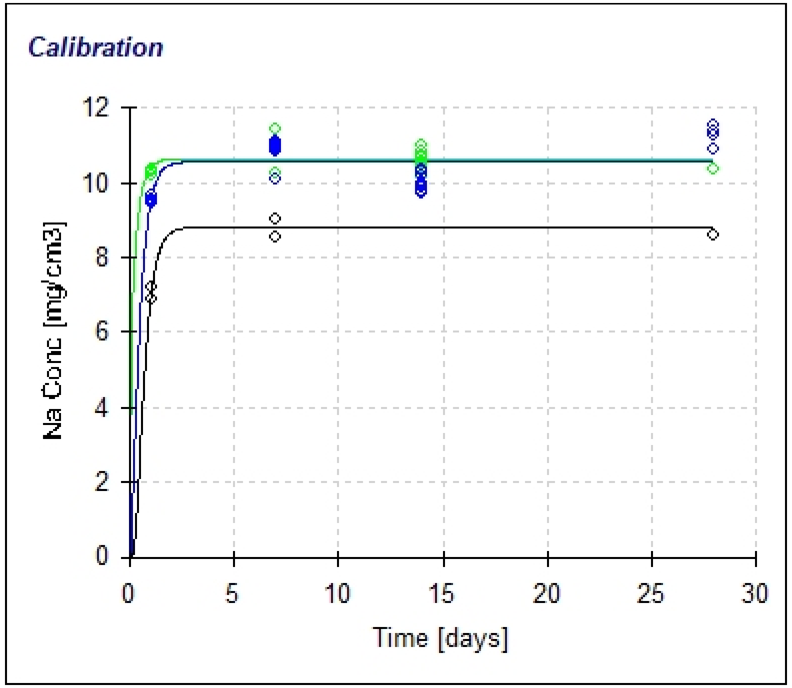
- High release of Na and Mg in seawater flooded soils

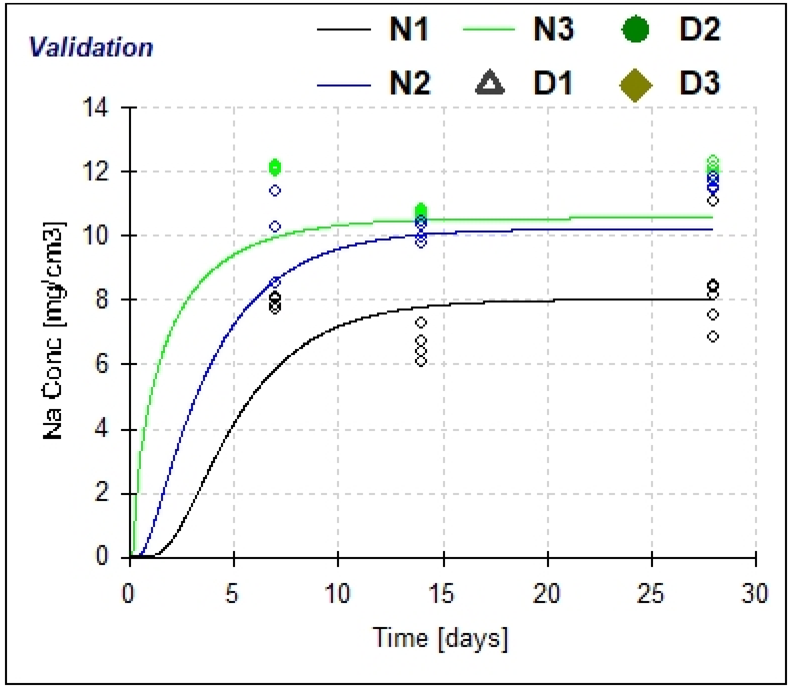
Ca and NH_4-N concentrations



- High release of Ca and NH_4-N in seawater flooded soils

Sodium Transport modeling in Krome soil

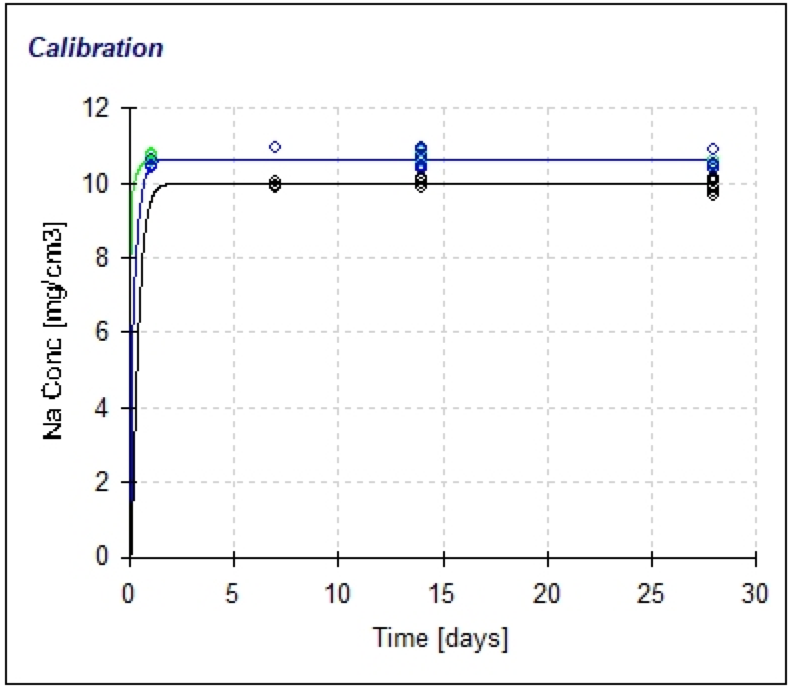


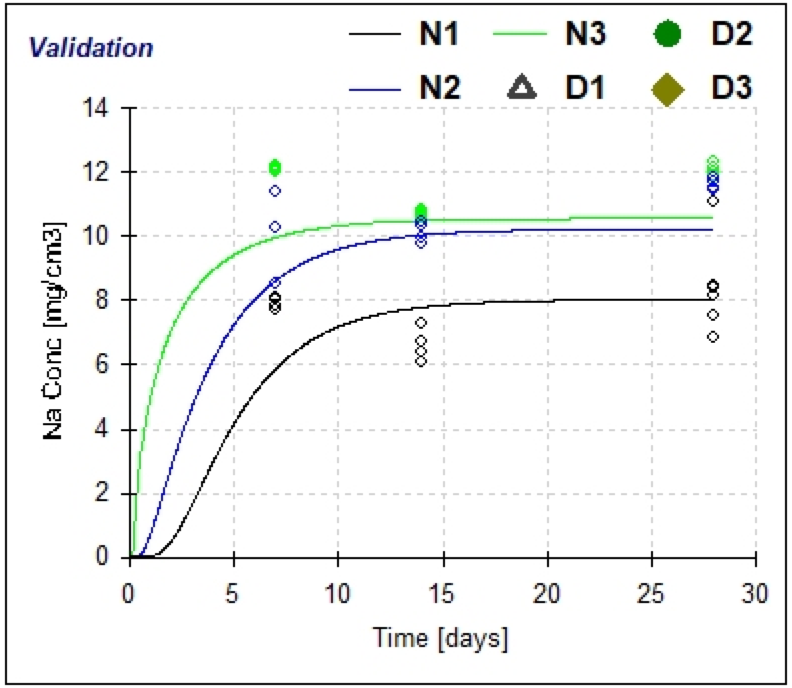


$R^2 = 0.77$, RMSE=0.44 mg cm^{-3}

$R^2 = 0.59$, RMSE=1.44 mg cm^{-3}

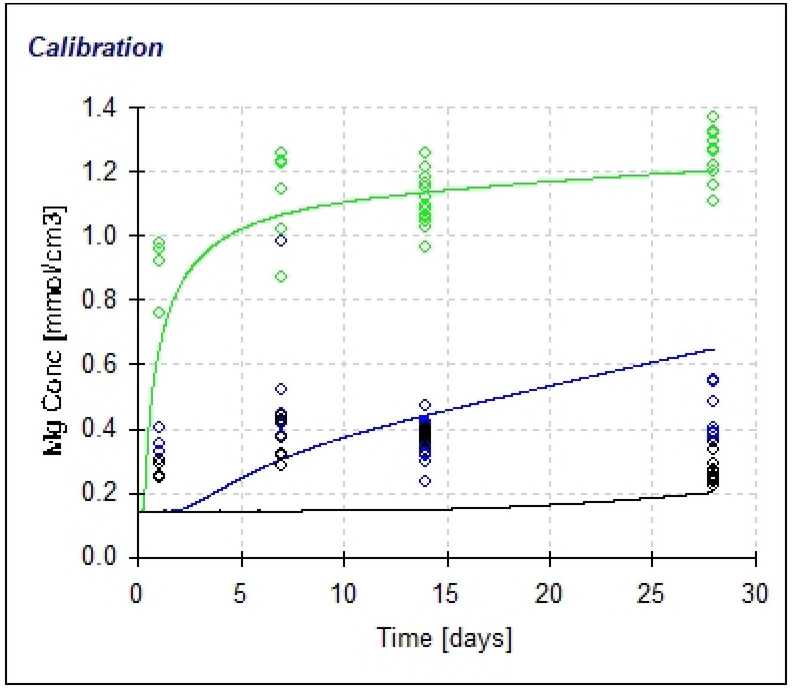
Sodium transport modeling in Biscayne soil

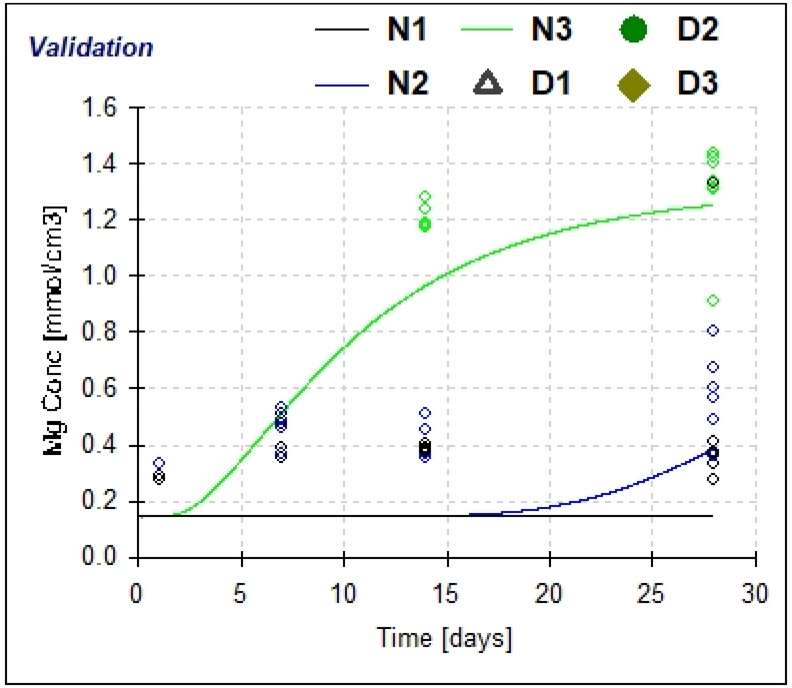




$R^2 = 0.75$, RMSE=0.17 mg cm^{-3} $R^2 = 0.55$, RMSE=0.96 mg cm^{-3}

Magnesium transport modeling in Krome soil

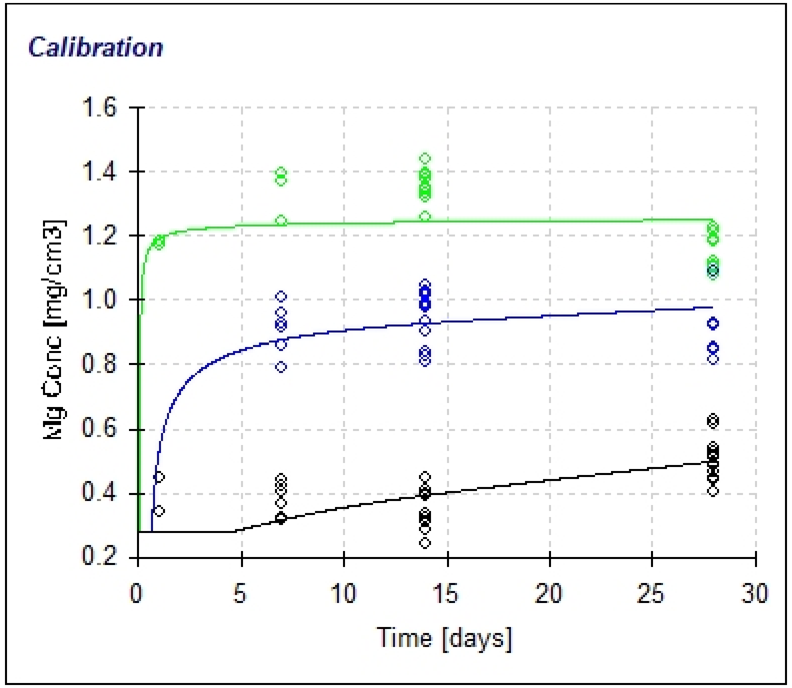


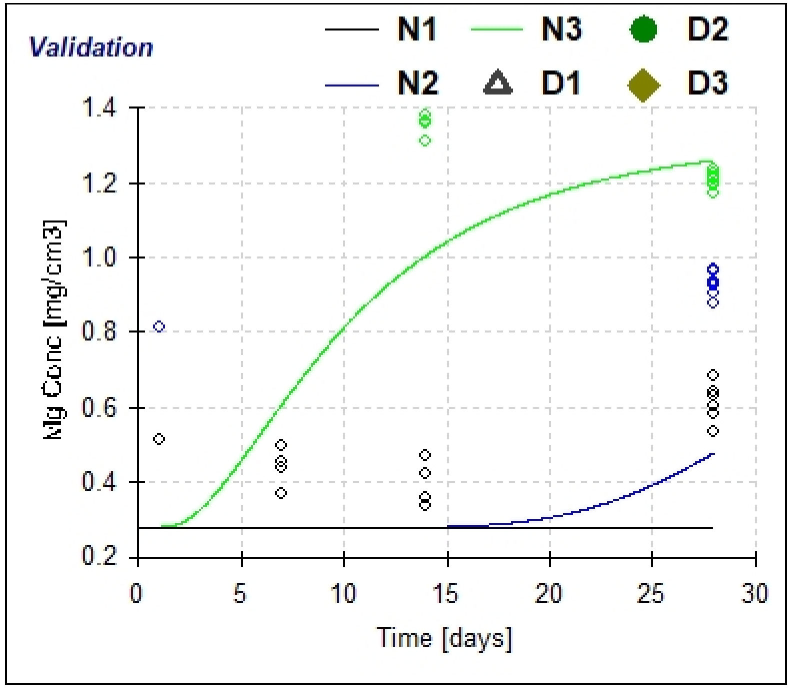


$R^2 = 0.85$, RMSE=0.17 mg cm^{-3}

$R^2 = 0.81$, RMSE=0.29 mg cm^{-3}

Magnesium transport modeling in Biscayne soil

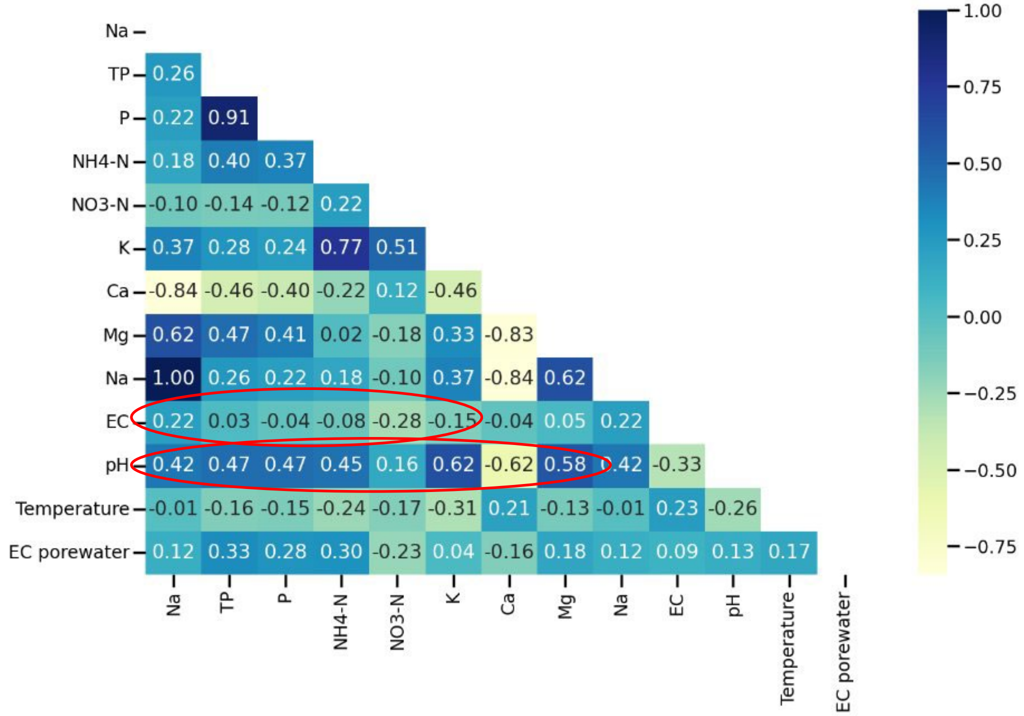


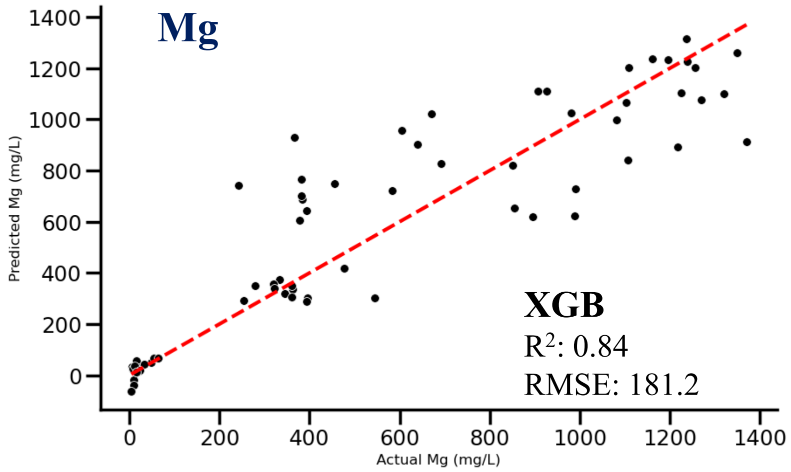


$R^2 = 0.94$, RMSE=0.09 mg cm^{-3}

$R^2 = 0.77$, RMSE=0.34 mg cm^{-3}

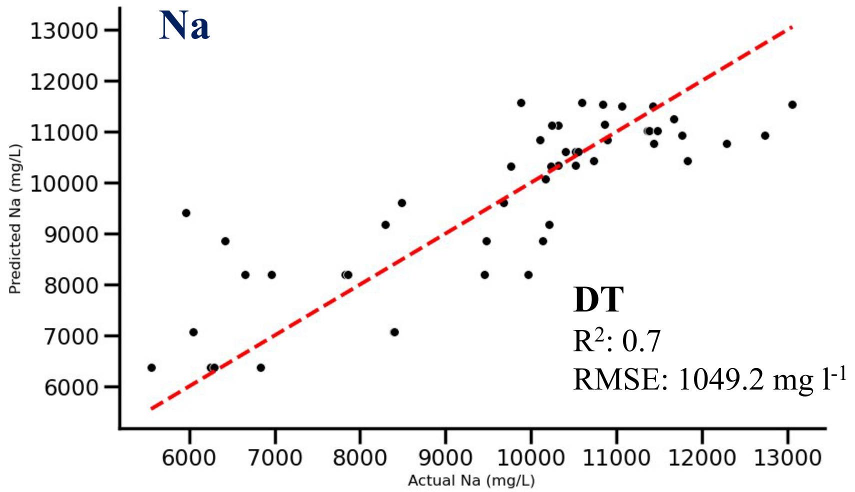
ML models





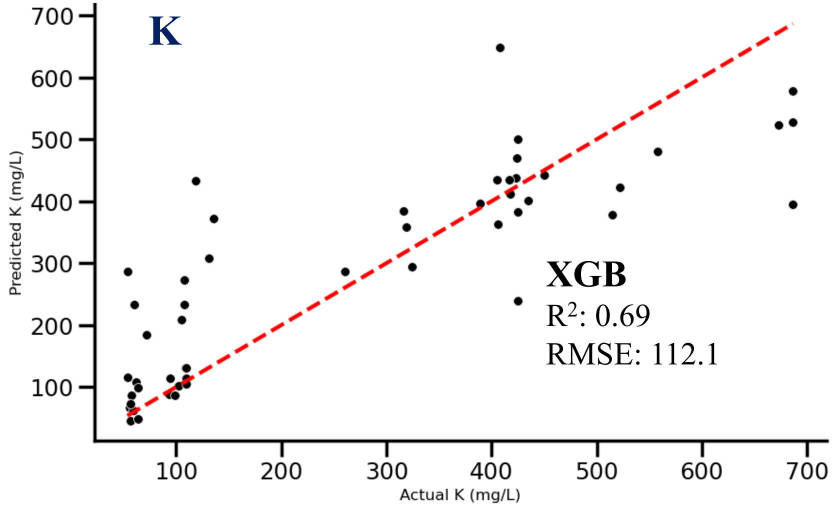
RF
R^2: 0.63
RMSE: 232.9 mg l^{-1}

DT
R^2: 0.56
RMSE: 251.4 mg l^{-1}



RF
R^2: 0.67
RMSE: 1101.8 mg l^{-1}

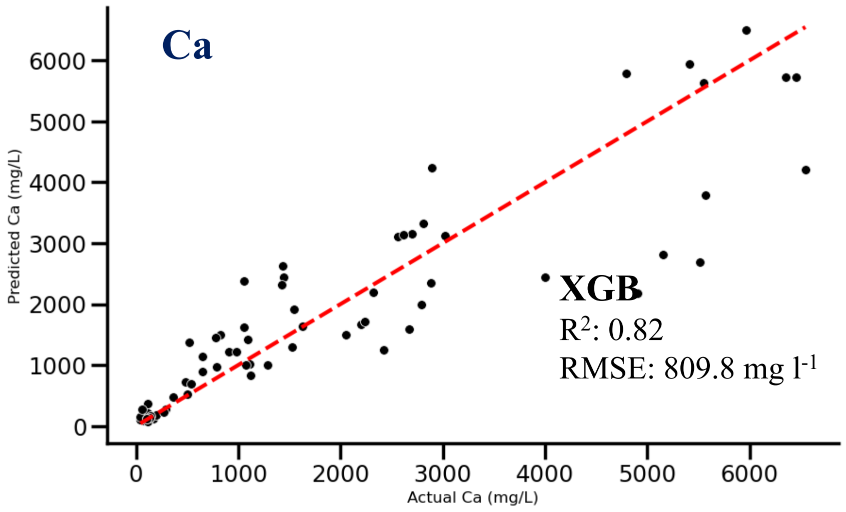
XGB
R^2: 0.64
RMSE: 1145.4 mg l^{-1}



RF
R^2: 0.69
RMSE: 112.6 mg l^{-1}

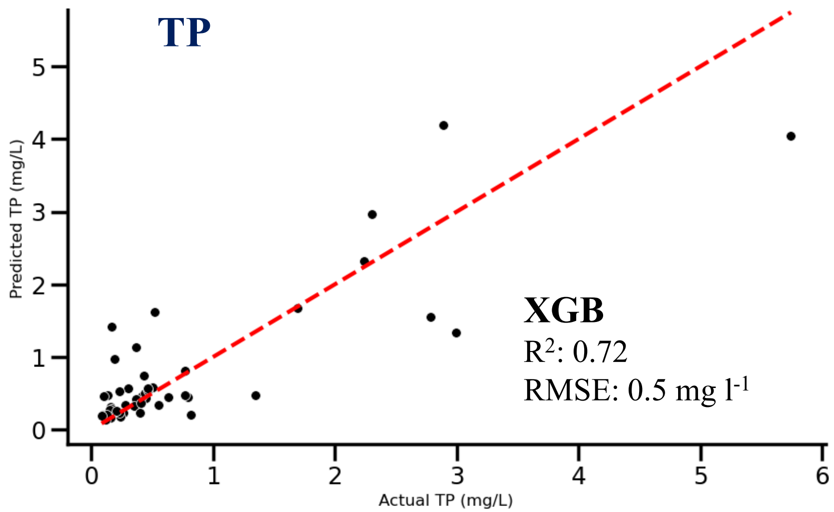
DT
R^2: 0.56
RMSE: 133.9 mg l^{-1}

ML models



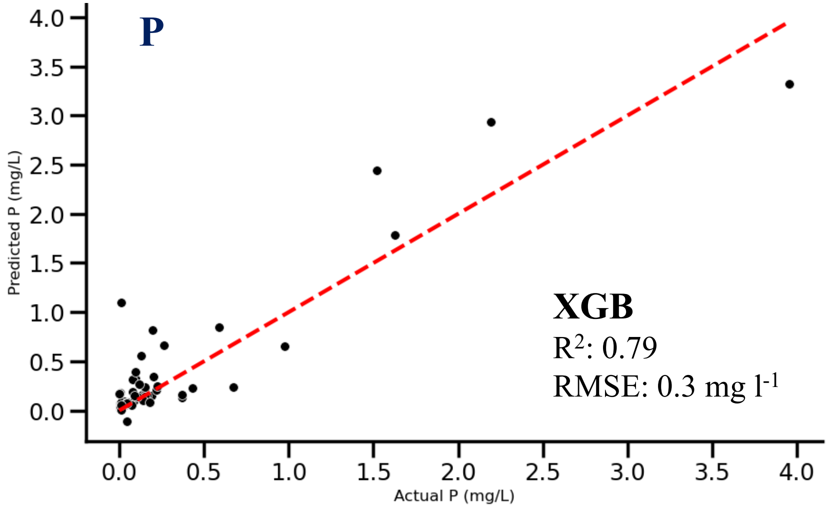
DT
R^2: 0.7
RMSE: 1009.9 mg l^{-1}

RF
R^2: 0.65
RMSE: 1095.1 mg l^{-1}



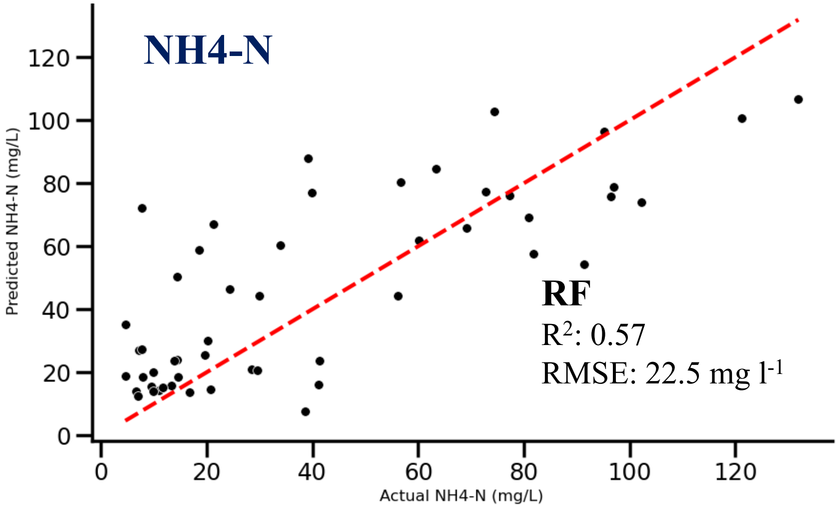
RF
R^2: 0.65
RMSE: 0.6 mg l^{-1}

DT
R^2: 0.56
RMSE: 0.7 mg l^{-1}



RF
R^2: 0.71
RMSE: 0.4 mg l^{-1}

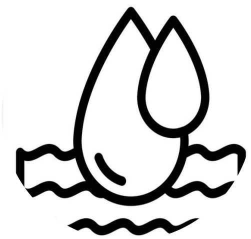
DT
R^2: 0.68
RMSE: 0.4 mg l^{-1}



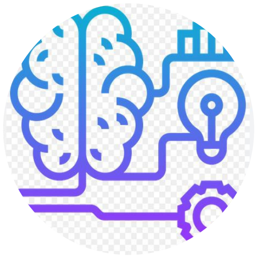
XGB
R^2: 0.53
RMSE: 24.9 mg l^{-1}

DT
R^2: 0.39
RMSE: 26.7 mg l^{-1}

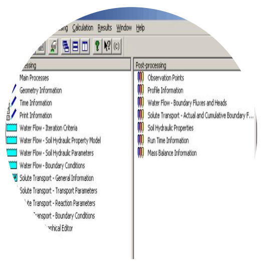
Conclusion



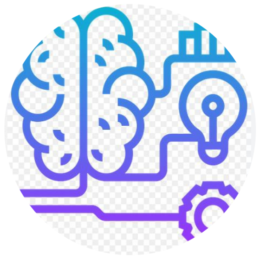
Sea water flooding increased concentrations of Na, Ca, NH_4-N, P, and TP



Machine learning algorithms outperformed Hydrus-1D in simulating all solutes



Hydrus-1D simulated transport of Na and Mg



Machine learning models can be used to understand the transport and fate solutes

Acknowledgements

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Members of the research group

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