Physics-Informed Neural Networks for Predicting Soil Moisture and VGM Parameters

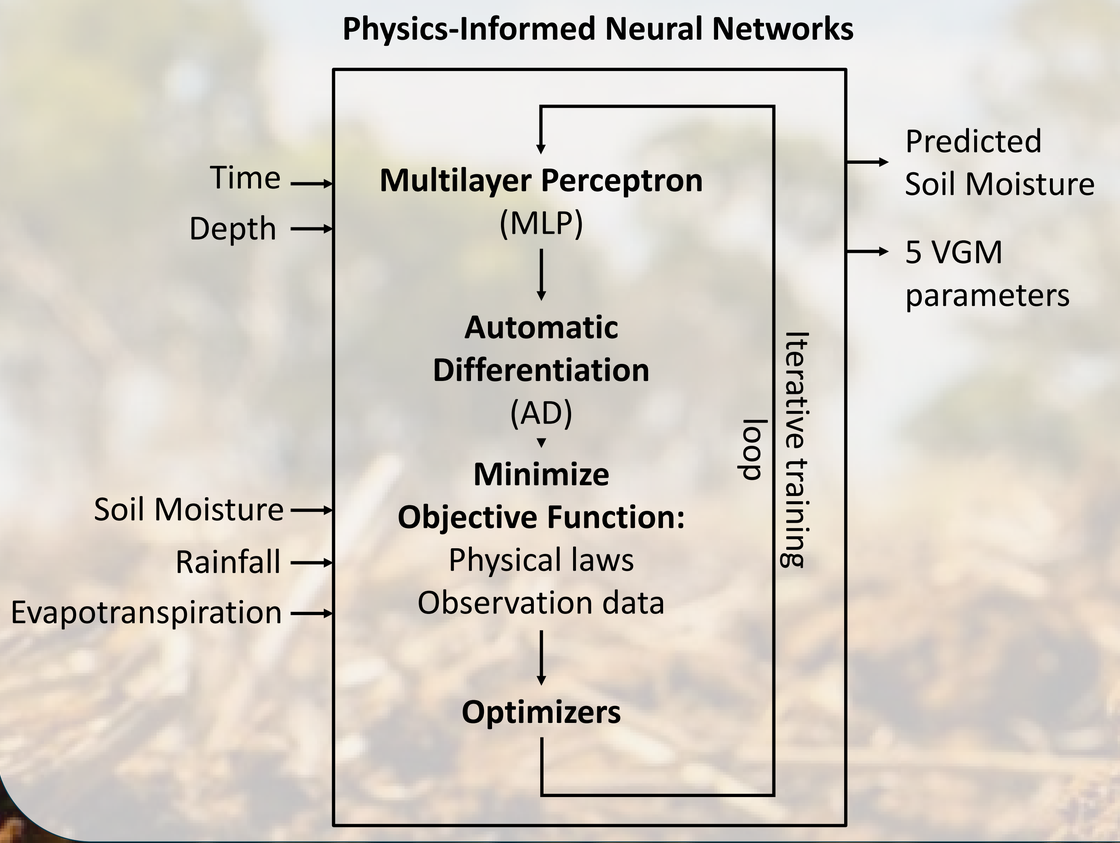
Chenting Jiang

Supervisors: Asst. Prof. Marcus Hardie and Asst. Prof. Quan Bai

Introduction

- The **soil water retention function and van Genuchten-Mualem (VGM) hydraulic parameters** are crucial for understanding soil water behaviours, measuring soil health, and facilitating effective irrigation management
- The challenge of reliable and accurate prediction of soil moisture and hydraulic parameters from **field soil moisture probe data** lies in the inherent **heterogeneity and uncertainty** of real-world soils, which cannot be adequately addressed with existing inverse modelling
- We propose a **Multi-task Physics-Informed Neural Network (PINN) model** that integrates a multilayer perception for predicting soil moisture and VGM parameters, the automatic differentiation method for computing partial differential function (the Richards equation), an objective function for guiding the minimization of errors from physical laws and observational data, and L-BFGS and Adam optimizers

PINN Architecture



- **Multilayer Perceptron (MLP) / multi-task deep neural network:** sequentially predict the VGM hydraulic parameters in a middle-hidden layer and then predict soil moisture at the output layer
- **Automatic Differentiation (AD):** automatically computes derivatives of predicted soil moisture to time and depth, enabling the seamless integration of physical laws l into the neural network
- **Objective Function:** guides the minimization of errors or losses associated with:
  - **Physical Laws** from ensuring the network's predictions comply with the soil moisture dynamics dictated by the Richards equation and the VGM model
  - **Initial Condition** from aligning the model's initial state with observed soil moisture conditions
  - **Boundary Conditions** from Incorporating upper and lower boundary conditions (e.g., free drainage) to reflect real-world constraints
  - **Observational Data** from minimizing the difference between observed and predicted soil moisture data
- **Optimizer:** utilizes L-BFGS and Adam optimizations to update the MLP parameter values iteratively

Results

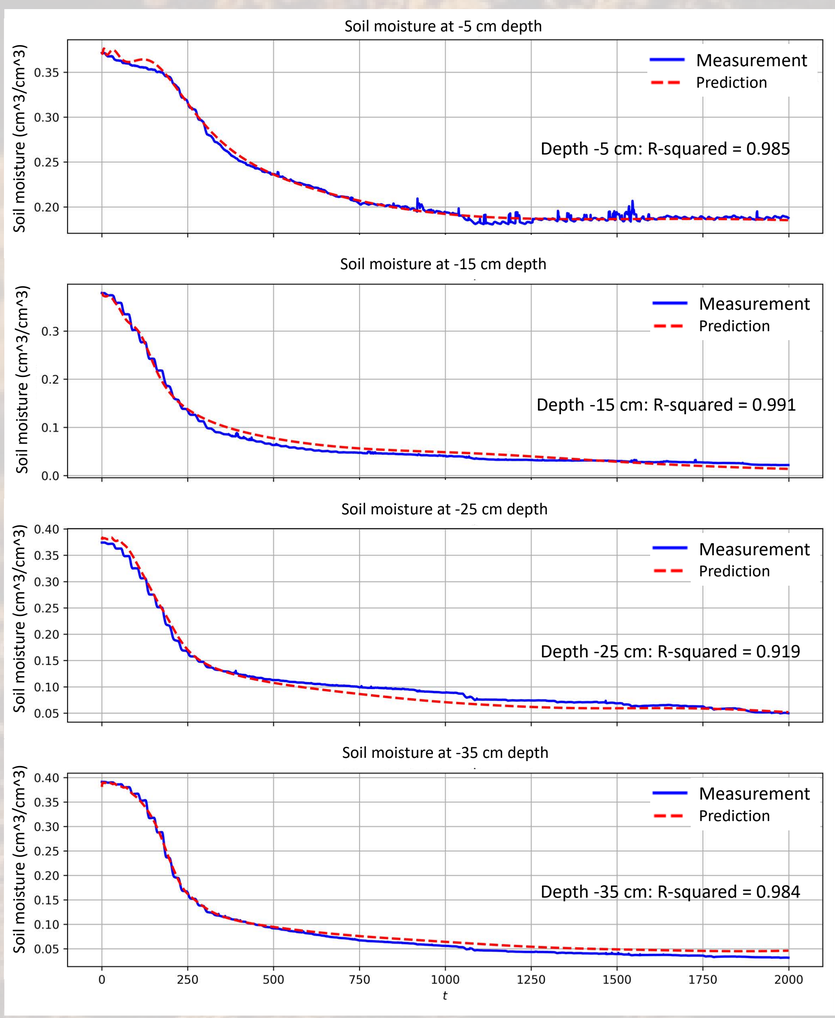
Minimized objectives results –

- Total error/loss: 1.005e-03
- Physical Laws error/loss: 3.818e-08
- Initial condition error/loss: 7.288e-02
- Upper BC error/loss: 8.397e-04
- Lower BC error/loss: 2.337e-07
- Data error/loss: 1.653e-04

The results indicate –

- The multi-task PINN model enhances **the accuracy of soil moisture predictions** across various depths, achieving **strong adherence to physical laws**, which offers a substantial improvement over traditional data-driven machine learning models
- The PINN's effectiveness in **reliably predicting hydraulic parameters** highlights its potential for practical applications in irrigation management and soil health monitoring

Soil moisture prediction



Hydraulic Parameters prediction

VGM Hydraulic Parameters	Lab Measurement	PINN Prediction
Depth: -5 cm		
Saturated soil moisture	0.511	0.495
Residual soil moisture	0.185	0.141
Alpha	0.006	0.245
n	1.576	5.733
Ksat	11.048	0.663
Depth: -15 cm		
Saturated soil moisture	0.479	0.496
Residual soil moisture	0.226	0.162
Alpha	0.003	0.249
n	1.501	5.089
Ksat	0.005	0.716
Depth: -25 cm		
Saturated soil moisture	0.479	0.490
Residual soil moisture	0.226	0.165
Alpha	0.003	0.246
n	1.501	4.922
Ksat	0.005	0.729
Depth: -35 cm		
Saturated soil moisture	0.497	0.489
Residual soil moisture	0.309	0.165
Alpha	0.003	0.245
n	1.724	4.917
Ksat	0.0006	0.725

SOIL CRC
UNIVERSITY of TASMANIA
TIA Tasmanian Institute of Agriculture
UNIVERSITY of TASMANIA
Australian Government
Department of Industry, Science and Resources
Cooperative Research Centres Program