

CPS: Medium: Making Every Drop Count: Accounting for Spatiotemporal Variability of Water **Needs for Proactive Scheduling of Variable Rate Irrigation Systems**

Sangmi Lee Pallickara¹, Allan Andales¹, Jeff Niemann¹, Jay Breidt², and Shrideep Pallickara¹ Colorado State University¹ and NORC at the University of Chicago²

Project Overview

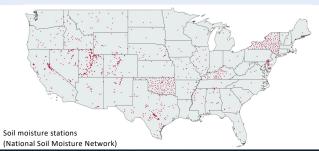
HYDRO is a CPS for smart irrigation. We instrument the field with a limited number of in-situ soil moisture content sensors; these in situ observations are complemented with remotely sensed data from radars and satellites. The effort includes design of novel AI (Artificial Intelligence) methods based on deep neural networks (DNN) to generate forecasts of water needs. These DNNs operate on multimodal, high-dimensional data to identify soil moisture deficits and variability in different parts of the field. The generated forecasts account for crop, soil type, precipitation events, and the crop growing phase.

The project closes the loop between the sensing environment and actuation within the Al-guided cyber physical system. These projections are leveraged within a game theory-based algorithm to inform precise actuations of the watering arm with prescription plans that control watering rates at the nozzle and zone level. The algorithm is adaptive and responsive to precipitation events, uncertainty in the forecasts, and actuation overheads.

Generating Soil Moisture Maps

Overview

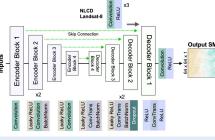
Generating high-precision soil moisture maps at 30m resolutions for the top 5 cm of soil. We integrate deep neural networks with scientific models. topographical data, and environmental conditions. We leverage in situ sensors and remote sensing (satellites) of soil moisture while infusing the model training process with domain science.



	Training Dataset	Inference Dataset
gNATSGO	1.6 GB	8.6 GB
Polaris	2.4 GB	45 GB
Landsat	351 MB	8 GB
NLCD	114 MB	2.3 GB
Köppen Climate	76 MB	1.7 GB
DEM	241 MB	4.2 GB
GridMet	3.3 GB	92 MB
ACD15A3H (Interpolated)	41 GB	13.6 GB
SMAP	1.2 GB	93 MB
Hydroblocks	70 GB	-
In-situ Stations	1.4 GB	-
Total	121.68 GB	83.56 GB

Physics-Guided Loss Function

- Reconcile errors per pixel (Mean-absolute Errors)
- Spatial agreement of soil moisture over smaller patches (Fractional-skill score)

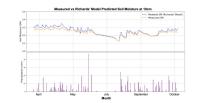


Estimating Root-zone Soil Moisture

Overview

A novel science-guided Graph Neural Network to predict SM in the top 20 cm of soil using deep neural networks (DNNs). By integrating physical equations, such as Richards' equation, into the learning process, our approach ensures scientifically consistent predictions while improving model generalizability. Our empirical results show that the proposed graph-based model outperforms traditional ML approaches by more than 30% in accuracy, while predicting SM with an error of less than 5% compared to ground-truth in-situ measurements.





Experiment Sites

ield experiments will be conducted during 2026 on a 4.8 ha field located at the Agricultural Research Development & Education Center (ARDEC), Fort Collins, CO, USA (40°39'57.4" N. 104°59′53. 1" W). This site corresponds to the south portion of a field under a pivot irrigation system. The soil type is a Kim loam, classified as fine-loamy. mixed, active, mesic Ustic-Torriorthents (Soil Survey Staff, 2000). Based on corresponding soil samples, the texture was classified as sandy clay loam. The slope of the field is 0.9% in a single plane gradient. The field has been under conventional tillage continuous maize cropping system for the past 10 years.

	Model Variations	SM at Depth 5		SM at Depth 10		SM at Depth 20		Avg. Testing
	Stoder variations	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
1	Base model-I (no KGML in loss)	0.065	0.00698	0.071	0.00834	0.079	0.01011	0.07183
2	Base model-II (Dropping NaNs, no KGML in loss)	0.070	0.00835	0.072	0.00874	0.084	0.01119	0.07560
3	Using KGML only in loss	0.067	0.00711	0.070	0.00827	0.078	0.00988	0.07170
4	Previous day hourly SM (10 cm)	0.050	0.00442	0.050	0.00497	0.049	0.00484	0.04994
5	Previous day average daily SM (5cm)	0.043	0.00358	0.066	0.00636	0.066	0.00730	0.05648
6	Previous day average daily SM (10 cm)	0.050	0.00429	0.052	0.00540	0.050	0.00488	0.05118
7	Previous day avg. daily SM (5 and 10 cm)	0.047	0.00399	0.052	0.00530	0.053	0.00531	0.05084
8	Dropping NaN rows, no KGML in loss Previous day hourly SM (10 cm)	0.055	0.00507	0.054	0.00526	0.054	0.00530	0.05363
9 [SubTerra]	Previous day hourly SM (10 cm) and avg. daily SM (5cm)(GNN)	0.042	0.00287	0.048	0.00432	0.048	0.00400	0.04605
10	Previous day hourly SM (10 cm) and avg. daily SM (5cm)(CNN)	0.049	0.00438	0.053	0.00530	0.052	0.00492	0.05134

Neutron probes for sensing soil moisture

5 in-situ soil moisture sensors with historical data. Measuring root zone SM hourly 5cm,10cm, 25cm, 50cm. and 100 cm





https://spatial.colostate.edu/HydroSim/

Variable Rate Irrigation Systems

- Creating virtual sectors and zones
- Applying watering prescriptions
- (direction; degree; watering depth) Bookkeeping and changing prescriptions
- Visualizing soil moisture and crop growth



