A COMPARATIVE ASSESSMENT OF MACHINE LEARNING AND A MULTILAYER PHYSICAL MODEL WITH DATA ASSIMILATION FOR ROOT-ZONE SOIL MOISTURE ESTIMATION

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Introduction

Root-zone soil moisture (RZSM) is central to drought assessment and irrigation management, yet it is difficult to observe directly. We compare two approaches for estimating RZSM in vineyards: a multilayer perceptron (MLP) and a parsimonious physical model with Ensemble Kalman Filter (EnKF) assimilation. Using in-situ data we evaluate how well each method reproduces RZSM. The goal is to quantify the value of ingesting surface soil moisture (SSM) observations and to contrast a data-driven baseline with a physically constrained model.

Area of Study

The study focuses on the Terra Alta vineyard region (Catalonia, NE Spain), an inland Mediterranean area with a more continental climate. Mean annual precipitation is ∼464 mm, and the monitored vineyards are non-irrigated.

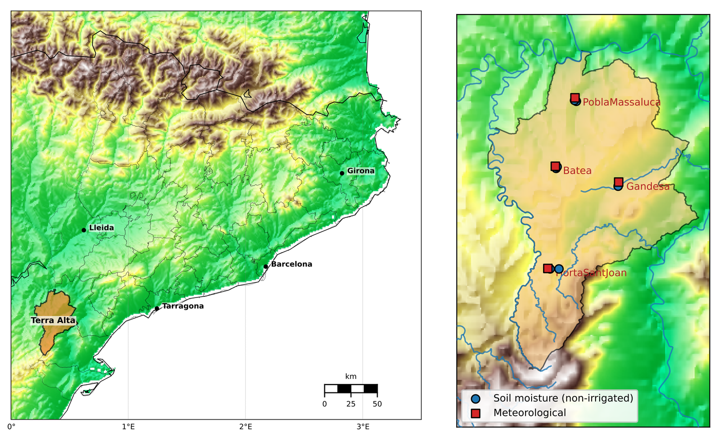

Fig. 1: Study Area: Location of the Terra Alta vineyard region within Catalonia (left) and spatial distribution of the 5 monitored stations (right).

Data

Meteorology is provided by SMC and AEMET. Soil moisture is measured by METER Teros-10 probes at **5, 10, 25, 50, 70 cm**. Observed RZSM is the weighted mean of deep sensors (25–70 cm), representing the 15–75 cm interval. Validation compares this monitored layer against the corresponding model layers (full model profile is 150 cm). We use daily data (2020–2025) from 5 non-irrigated Terra Alta stations for training and validation.

Methodology

We compare two approaches to estimate RZSM from meteorological forcing and SSM:

- (1) A machine-learning (ML) approach based on a **multilayer perceptron** (MLP) [4], ingesting SSM (MLP-SSM) and not ingesting SSM (MLP-NOSSM).
- (2) A physical model based on **FAO-56 dual crop coefficient [1] and a multi-layer soil (DC11L) with optional EnKF assimilation [2].**

The validation metric is the non parametric KGE (KGEnp) [3] and a leave one out cross-validation (LOOCV) method was used.

References

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[3] S. Pool, M. Vis, and J. Seibert. Evaluating model performance: towards a non-parametric variant of the kling-gupta efficiency. *Hydrological Sciences Journal*, 63(13-14):1941–1953, 2018.

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Methodology (continuation)

Machine learning approach

The machine learning baseline uses a multilayer perceptron (MLP) to benchmark the physical model's predictive skill.

- **Inputs**: A 21-day window of P, T, ET_0, plus SSM for MLP-SSM.
- **Target**: Daily RZSM (and SSM) from in-situ observations.
- **No leakage**: SSM inputs are antecedent only ($t-21$ to $t-1$) for predicting day t.

Data assimilation approach

The Ensemble Kalman Filter (EnKF) assimilates SSM into the multilayer physical model to improve RZSM estimates.

- **EnKF strategy**: Ensemble layer states are forced daily; SSM updates use the Kalman gain.
- **Vertical coupling**: Surface–root zone covariance propagates information downward.
- **Variants**: perturbation of precipitation (EnKF-P), transpiration (EnKF-KCB), and EnKF-BOTH.

Results

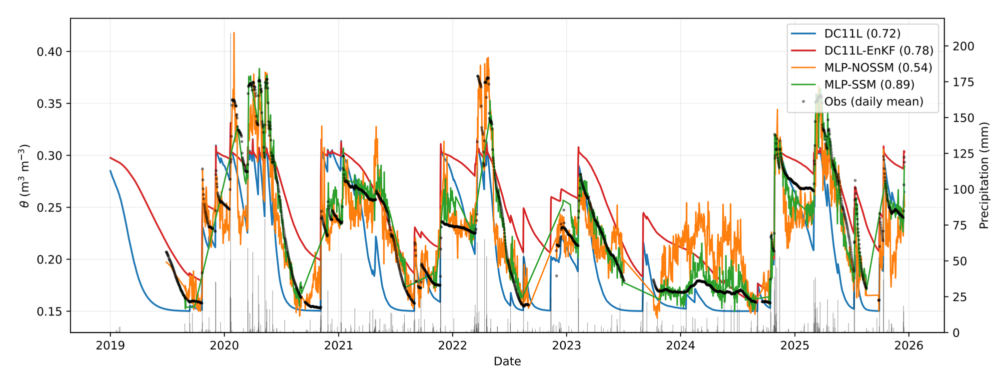

Fig. 2: Daily root-zone soil moisture ($m^3\ m^{-3}$) at HA1 site, showing observed daily means and model simulations with and without SSM assimilation (RZSM is the 15–150 cm mean).

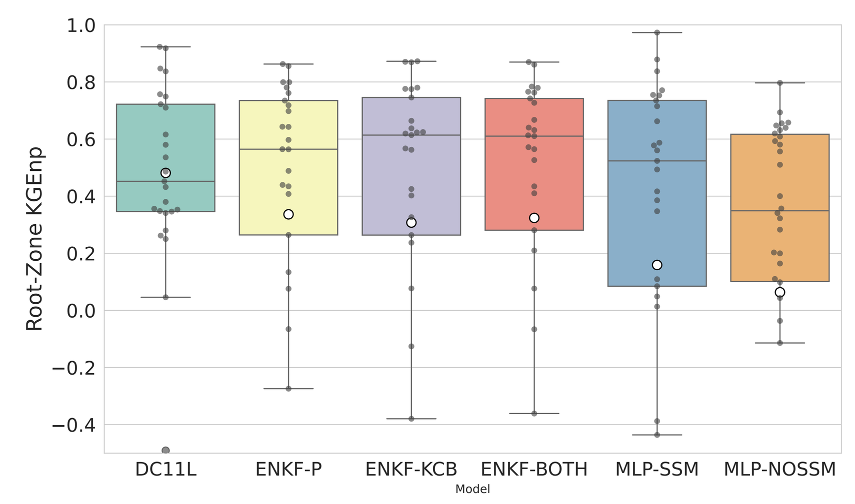

Fig. 3: Daily KGEnp boxplots (N=25 station-years; 5 stations over 2020–2025 with sufficient SSM). Each dot represents one validation year per site (leave-one-out cross-validation).

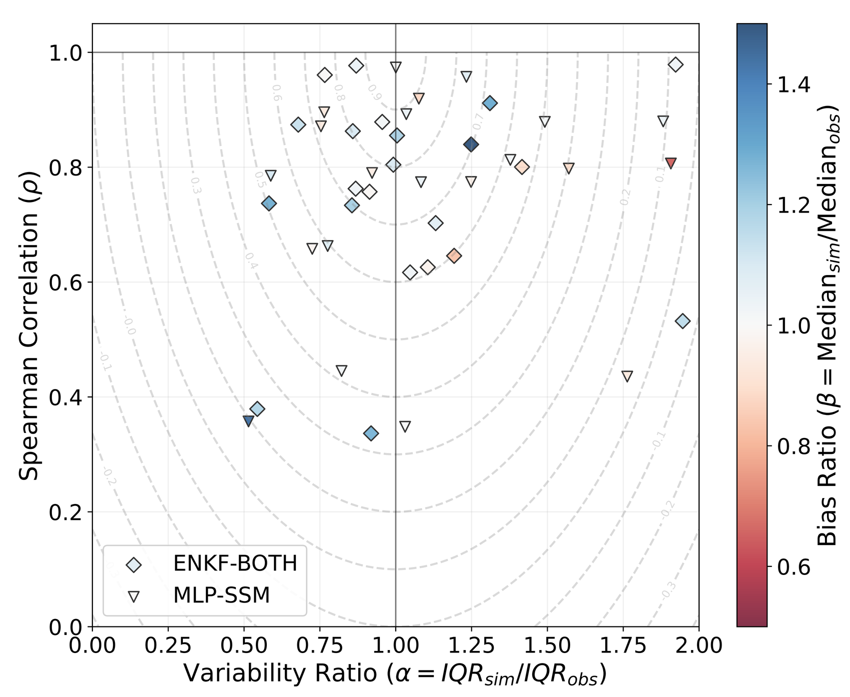

Fig. 4: Daily KGEnp components for the same N=25 station-years (correlation, variability ratio, and bias ratio).

Results (continuation)

Model validation

Figure 2 indicates that reproducing root-zone soil moisture with precision remains challenging, yet overall performance is strong, as reflected by KGEnp scores (legend). KGEnp medians are 0.45 for DC11L and 0.52 for MLP-SSM (IQRs 0.35–0.72 and 0.08–0.74, respectively). The MLP exhibits higher short-term variability (noisier trajectories), whereas the physical model is overly smooth.

SSM data assimilation/ingestion

Boxplots (Fig. 3) show that both models perform relatively well: DC11L has a median KGEnp of 0.45 and MLP-NOSSM 0.35 (medians are pooled across all station-years). Ingesting SSM improves the performance, as expected. The median KGEnp for EnKF-BOTH is 0.61, and 0.52 for MLP-SSM. EnKF variants are the best approaches.
The KGE component plot (Fig. 4) shows generally strong correlations for both ENKF-BOTH and MLP-SSM except for a few station-years. Variability ratios cluster around 1 with a few high-variability cases, and bias ratios are centered near 1 without a consistent shift.

Conclusion

Both approaches provide useful RZSM estimates under Mediterranean vineyard conditions. The physical model is generally more stable and benefits clearly from in-situ SSM assimilation, while the MLP offers a strong data-driven baseline with competitive performance. Together, they provide complementary pathways for operational RZSM monitoring and motivate integrating satellite SSM products and extended validation across additional sites. A next step is to integrate satellite SSM and regionalize model parameters to enable RZSM estimation at any vineyard.

Perspectives

- Iterate on the MLP implementation and check if its performance can be improved.
- Ingest downscaled satellite SSM products.
- Regionalize model parameters to evaluate performance on non-instrumented vineyards.
- Check whether the EnKF can mitigate sparse precipitation observations.
- Assess irrigation recommendation potential across the study area.

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