MultiTaskNet: Multi-Task Deep Learning for IoT Soil Moisture Calibration & Forecasting

① IoT Platform & Dataset

21,312

raw sensor readings

2 farms · 110 days · 15-min intervals

Input Features

| ADC Count | Supply Voltage |
| Temperature | Pressure |

+ 22 engineered features

Capacitive Soil Moisture Sensors

② MultiTaskNet Architecture

Shared BiLSTM-Attention Encoder
shared latent representation
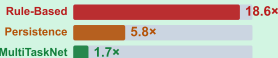
Calibration
$R^2=0.912$
RMSE = 2.1%

Forecasting
1.7× degrad.
vs 18.6× rule-based

Ablation: A2 (BiLSTM+Attn) = optimal

③ Performance Results

Forecasting Degradation
(lower = better)

Rule-Based — 18.6×
Persistence — 5.8×
MultiTaskNet — 1.7×

10.9×

better than
rule-based baseline

✓ Cross-farm generalisation ($R^2 > 0.91$)

✓ No retraining needed

Calibration: $R^2=0.912$ · RMSE=2.1%

21,312 readings · 2 farms · 110 days

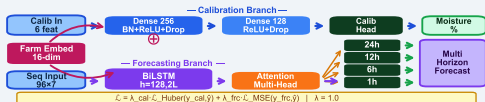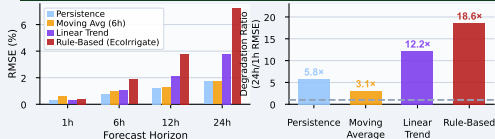### Fig. 1 — MultiTaskNet Architecture (Calibration + Forecasting)

Calib In 6 feat
Farm Embed 16-dim
Seq Input 96×7

— Calibration Branch —
Dense 256 BN+ReLU+Drop
Dense 128 ReLU+Drop
Calib Head → Moisture %

— Forecasting Branch —
BiLSTM h=128,2L
Attention Multi-Head
24h 12h 6h 1h
Multi Horizon Forecast

$\mathcal{L} = \lambda\_cal \cdot \mathcal{L}\_Huber(y\_cal, \hat{y}) + \lambda\_frc \cdot \mathcal{L}\_MSE(y\_frc, \hat{y}) \quad | \quad \lambda = 1.0$

Fig. 2 — RMSE by Forecast Horizon & Degradation Ratio (24h / 1h)

Persistence
Moving Avg (6h)
Linear Trend
Rule-Based (EcoIrrigate)

RMSE (%) — Forecast Horizon: 1h, 6h, 12h, 24h

Degradation Ratio (24h/1h RMSE):
Persistence 5.8×
Moving Average 3.1×
Linear Trend 12.2×
Rule-Based 18.6×

Conclusion

Multi-task learning enables simultaneous calibration ($R^2=0.912$) and IoT sensor forecasting, outperforming rule-based baselines by 10.9× and generalising across farms— scalable precision irrigation.