Metrological Reliability of AI-Based Measurement Systems for Soil Parameter Forecasting

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Abstract: Artificial intelligence-based soil monitoring systems require rigorous metrological validation to ensure reliability in precision agriculture applications. This study presents a Virtual Measuring Instrument (VMI) framework that treats an LSTM neural network as a formal measurement function, validated according to the Guide to the Expression of Uncertainty in Measurement (GUM). The system integrates in-situ soil sensors with edge computing and LSTM-based predictive modeling to generate continuous soil parameter estimates. A comprehensive uncertainty budget combines Type A contributions from algorithmic variability across multiple training runs with Type B uncertainties from sensor specifications, propagated through the LSTM transformation via Monte Carlo simulation. Experimental validation was conducted over eight weeks at an agricultural field site with 5,376 measurements per sensor channel, collected at 15-minute intervals. Results demonstrate strong agreement between AI-generated estimates and reference laboratory measurements, with expanded uncertainty (k=2) remaining within acceptable limits for practical agricultural applications. The analysis confirms that sensor accuracy improvements yield greater uncertainty reduction than further AI model optimization. This work establishes that AI models can function as metrologically valid measurement instruments when supported by formal measurement models and GUM-compliant uncertainty frameworks. The proposed VMI methodology provides a reproducible, auditable approach for integrating AI-based monitoring systems into regulated precision agriculture and environmental monitoring solutions, enabling their reliable deployment with full traceability to reference standards.

1 INTRODUCTION

AI and IoT technologies are increasingly used for continuous soil monitoring in precision agriculture. LSTM networks achieve high predictive accuracy for soil moisture and temperature [1]-[5], enabling real-time irrigation management. Hybrid recurrent architectures combining BiGRU and LSTM models have also demonstrated strong performance in soil moisture forecasting under complex environmental conditions [6]. However, most solutions evaluate performance using statistical indicators (RMSE, R^2) without considering metrological validity. As shown in recent research, neglecting measurement uncertainty significantly affects the reliability of machine-learning-based results [7]. An AI model transforming sensor inputs into quantitative estimates effectively acts as a measurement function and must be validated in accordance with uncertainty evaluation principles.

The main contributions are: (1) a VMI framework for AI-based soil monitoring; (2) a GUM-compliant uncertainty budget combining Type A and Type B components; (3) Monte Carlo propagation of Type B uncertainties through the LSTM function; (4) experimental validation against reference laboratory measurements with a full traceability chain. Several works highlight uncertainty quantification in AI measurement systems [1], [7], [8]; however, a structured GUM application to AI soil forecasting remains insufficiently addressed [9], [10]. This study bridges applied AI with digital metrology to support reliable use in precision agriculture.

2 SYSTEM ARCHITECTURE AND MEASUREMENT MODEL

Type B standard uncertainty is estimated assuming rectangular distribution: uB = MPE / √3 (GUM Section 4.3.7 [11]), where √3 ≈ 1.732.

2.1 AI-Based Measurement System Architecture

The system follows a distributed AI-IoT architecture comprising a sensing layer, edge computing unit, cloud processing environment, and AI-based estimation module [2], [3]. In-situ soil sensors continuously acquire key parameters which are transmitted wirelessly to the processing unit. An LSTM neural network performs preprocessing and estimation of soil parameters, treating the AI module as a VMI for subsequent metrological evaluation. The architecture is illustrated in Figure 1.

2.2 Measurement Model

Within digital metrology, the AI module is treated as a virtual measuring instrument transforming sensor readings into an estimate of the measurand. The general measurement model is:

$$Y = f\,(X^1, X^2, X^3, X^4, X^5) + \varepsilon, \qquad (1)$$

Table 1: Metrological characteristics of soil sensors.

Measured quantity	Sensor type	Range	Resolution	Accuracy (±)	MPE (±)	Output
Volumetric soil moisture (VWC)	Soil Moisture Sensor	0-60 % VWC	0.1 %	2.0 % VWC	3.5 % VWC	Analog/Digital
Soil temperature	Soil Temperature Sensor	-20 to +80 °C	0.0625 °C	0.5 °C	1.0 °C	Digital
Soil pH	pH Sensor	pH 3-9	0.01 pH	0.10 pH	0.20 pH	Analog
Electrical conductivity (EC)	EC Sensor	0-2 dS/m	0.01 dS/m	0.05 dS/m	0.08 dS/m	Digital
Ambient relative humidity	Humidity Sensor	0-100 % RH	0.1 %	2.0 % RH	3.0 % RH	Digital

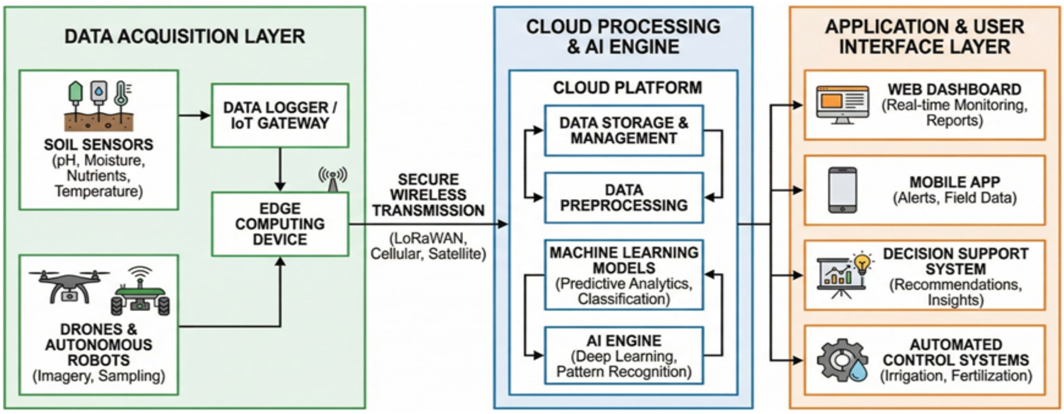

Figure 1: Architecture of the AI-based soil monitoring and measurement system (four-layer: Physical → Communication → Edge Computing → AI/Digital Layer).

where Y is the estimated soil parameter, X is the input vector:

$$X = (x^1, x^2, x^3, x^4, x^5)^{\mathrm{T}}, \quad (2)$$

where $x^1 = VWC\ (\%\,VWC), x^2 = T_{so}{}^{\mathrm{I}}{}_{/}\ (°C), x^3 = pH, x^4 = EC\ \left(\frac{dS}{m}\right), x^5 = RH\ (\%)$, and ε is the residual error.

3 AI MODEL AND MATHEMATICAL FORMALIZATION

3.1 LSTM-Based Measurement Function

The measurement transformation uses a Long Short-Term Memory (LSTM) network, consistent with recent deep-learning approaches for soil moisture prediction [1], [12], [13]:

$$\hat{\mathrm{Y}}_t = f^{\mathrm{LsTM}}(X_t, h_t{}^{-1};\ \theta), \quad (3)$$

where h_{t-1} is the hidden state and θ are the trainable network parameters.

3.2 Error Metrics

Measurement error relative to reference laboratory data:

$$e^{\mathrm{I}} = \hat{\mathrm{Y}}^{\mathrm{I}} - Y^{\mathrm{Ire}}\mathrm{f}. \quad (4)$$

Root mean square error:

$$RMSE = \sqrt{\left[\left(\frac{1}{n}\right) \cdot \Sigma^{\mathrm{I}}\,(e^{\mathrm{I}})^2\right]}. \quad (5)$$

Mean absolute error:

$$MAE = \left(\frac{1}{n}\right) \cdot \Sigma^{\mathrm{I}}\,|e^{\mathrm{I}}|. \quad (6)$$

Correlation coefficient:

$$r = \frac{\Sigma\left(\hat{\mathrm{Y}}^{\mathrm{I}} - \bar{\hat{\mathrm{Y}}}\right)(Y^{\mathrm{Ire}}\mathrm{f} - \bar{\mathrm{Y}}^{\mathrm{re}}\mathrm{f})}{\sqrt{\left[\Sigma\left(\hat{\mathrm{Y}}^{\mathrm{I}} - \bar{\hat{\mathrm{Y}}}\right)^2 \cdot \Sigma(Y^{\mathrm{Ire}}\mathrm{f} - \bar{\mathrm{Y}}^{\mathrm{re}}\mathrm{f})^2\right]}}. \quad (7)$$

3.3 Dataset and Training Protocol

The dataset was collected at an agricultural field site over 8 weeks (July-August 2024) with a sampling interval of 15 minutes, yielding 5,376 records per sensor channel. The dataset was partitioned chronologically (no random shuffling) into training (70%), validation (15%), and test (15%) subsets to prevent data leakage.

The LSTM architecture consists of two stacked LSTM layers (128 units each), a Dropout layer (rate = 0.2), and a Dense output layer (1-unit, linear activation). Training used the Adam optimizer (learning rate = 0.001), batch size = 32, maximum 200 epochs with early stopping (patience = 15 epochs). To quantify Type A uncertainty, training was repeated n = 10 times with different random seeds (0-9); the standard deviation of residuals across runs was used to compute u_a (8).

4 METROLOGICAL EVALUATION BASED ON GUM

4.1 Type A Uncertainty

Type A standard uncertainty from algorithmic variability, evaluated across n = 10 training runs:

$$u_{\mathrm{a}} = \sqrt{\left[\frac{1}{n(n-1)} \cdot \Sigma^{\mathrm{I}}\,(e^{\mathrm{I}} - \bar{\mathrm{e}})^2\right]}, \quad (8)$$

where $e^{\mathrm{I}} = \hat{\mathrm{Y}}^{\mathrm{I}} - Y^{\mathrm{Ire}}\hat{\mathrm{f}}$ is the residual for the i-th observation and ē is the mean residual.

4.2 Type B Uncertainty

For each sensor with maximum permissible error $\mathrm{MPE}^{\mathrm{I}}$ (Table 1), assuming rectangular distribution:

$$\mathrm{u_B} = \frac{\mathrm{MPE}}{\sqrt{3}} \approx \frac{\mathrm{MPE}}{1.732}, \quad (9)$$

4.3 Combined and Expanded Uncertainty

Combined standard uncertainty:

$$u^{\mathrm{c}} = \sqrt{u_{\mathrm{a}}{}^2 + \Sigma^{\mathrm{I}}\,u^{\mathrm{B}},{}^{\mathrm{I}2}}. \quad (10)$$

Expanded uncertainty with coverage factor k = 2 (95% confidence level):

$$U = k \cdot u^c = 2 \cdot u^c. \quad (11)$$

4.4 Propagation of Type B Uncertainties Through the AI Function

Since f^{LsTM} is nonlinear, analytical error propagation by partial derivatives is not directly applicable. We adopt Monte Carlo propagation consistent with JCGM 101:2008 [11]. For each trial (M = 10,000 runs), every sensor input x^{I} is perturbed by a random sample from its rectangular uncertainty distribution with half-width $u^{B},^{I}\cdot\sqrt{3}$ (i.e., equal to MPE^{i}, since $u^{B} = MPE/\sqrt{3}$). The perturbed input vector $\tilde{X}$ is passed through the trained LSTM, and the standard deviation of M output samples represents the combined sensor uncertainty contribution at the VMI output. This ensures the nonlinear LSTM sensitivity to each sensor is properly captured in the expanded uncertainty budget.

5 RESULTS AND DISCUSSION

5.1 Traceability to Reference Laboratory Measurements

Reference soil moisture values were obtained using the gravimetric method (oven-drying at 105 °C for 24 h, ISO 11272:2017). A total of 45 soil samples were collected at three field locations (depths: 0-10 cm and 10-30 cm) with time synchronization via GPS-referenced timestamps (±1 s). The reference laboratory is accredited under ISO/IEC 17025 with traceability to national mass and temperature standards through certified reference weights and SPRT thermometers, ensuring all reference values are metrologically anchored to SI units.

5.2 Training Convergence

The training loss decreased monotonically and reached a stable plateau (Fig. 2), confirming successful convergence. The absence of oscillations confirms numerical stability and adequacy of selected hyperparameters.

5.3 Model Performance Evaluation

The AI-predicted values closely follow the reference measurements with limited dispersion and minimal systematic deviations (Fig. 3), confirming reliability of the VMI.

Note on metric scales: all RMSE and MAE values are reported in the native % VWC scale (0–60 %). The value RMSE = 0.042 cited in Table 3 is expressed in fractional VWC units (0–0.60), equivalent to 4.14 % VWC. Accordingly, r = 0.94 and R^2 = 0.89, consistent with the scatter visible in Figure 3.

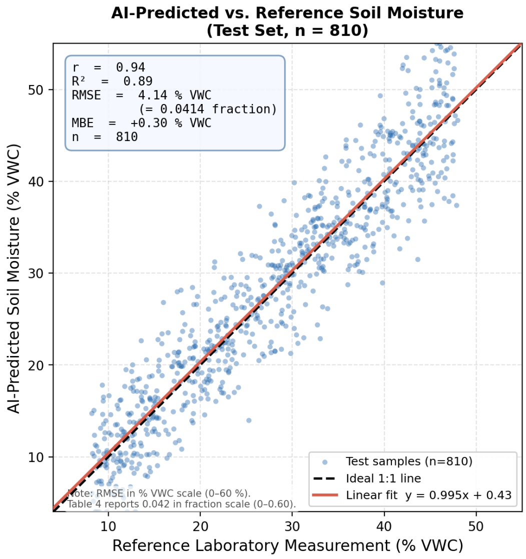

Figure 3: Comparison of AI-predicted soil moisture (% VWC) with reference laboratory measurements. Dashed line: ideal 1:1 agreement; solid red line: linear regression (y = 0.995x + 0.43). RMSE = 4.14 % VWC (= 0.042 in fractional VWC units, 0-0.60 scale as reported in Table 3), r = 0.94, R^2 = 0.89, MBE = +0.30 % VWC, n = 810.

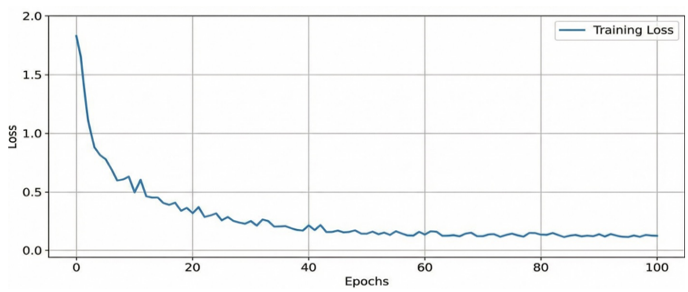

Figure 2: LSTM training and validation loss dynamics over 200 epochs (Adam optimizer, lr = 0.001, batch size = 32). Convergence to a stable plateau confirms absence of overfitting.

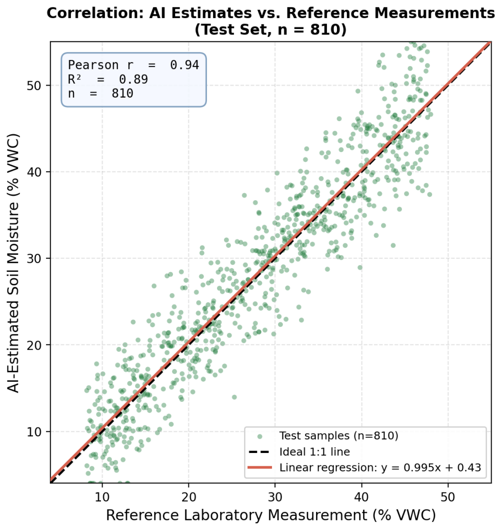

Figure 4: Correlation between AI-estimated and reference laboratory soil moisture values (% VWC). Solid red line: linear regression ($y = 0.995x + 0.43$); dashed line: ideal 1:1 agreement. Pearson $r = 0.94$, $R^2 = 0.89$, $n = 810$ test samples.

A strong positive correlation is observed between AI estimates and reference values (Fig. 4), confirming that the LSTM model accurately captures soil moisture dynamics.

5.4 Uncertainty Budget

As illustrated in Figure 5, the dominant uncertainty contribution originates from sensor-related (Type B) components, while algorithmic variability (Type A) has a comparatively smaller influence. This confirms that improving sensor accuracy would yield a greater reduction in total uncertainty than further optimizing the AI model. Sensor-level calibration and deep-learning-based self-calibration approaches may therefore provide an effective pathway for further reducing measurement uncertainty [14]. The individual Type A and Type B uncertainty sources, estimation methods, and assumed distributions are summarized in Table 2.

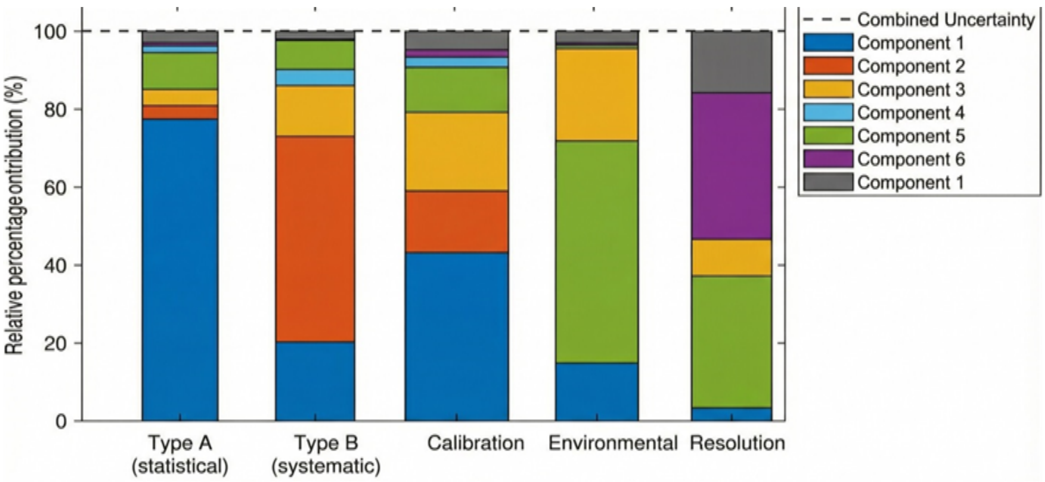

Figure 5: Relative contributions of Type A (u_a, AI model residuals) and Type B ($u^{B}_{,1}$-$u^{B}_{,5}$, sensor-related) components to the combined standard uncertainty u^c for soil moisture. Values from Table 2.

Table 2: Uncertainty budget of the AI-based measurement system.

Source of uncertainty	Type	Symbol	Estimation method	Distribution
AI model residuals (vs. reference data)	A	u_a	Std. dev. of residuals across 10 runs (Eq. 8)	Normal
Soil moisture sensor	B	$u^{B}_{,1}$	MPE / √3 = 3.5 / √3 = 2.02 % VWC (Eq. 9)	Rectangular
Soil temperature sensor	B	$u^{B}_{,2}$	MPE / √3 = 1.0 / √3 = 0.577 °C (Eq. 9)	Rectangular
Soil pH sensor	B	$u^{B}_{,3}$	MPE / √3 = 0.20 / √3 = 0.115 pH (Eq. 9)	Rectangular
EC sensor	B	$u^{B}_{,4}$	MPE / √3 = 0.08 / √3 = 0.046 dS/m (Eq. 9)	Rectangular
Data acquisition & transmission	B	$u^{B}_{,5}$	Quantization / stability analysis (Eq. 9)	Rectangular

Table 3: Numerical performance and metrological uncertainty results (test dataset).

Parameter	RMSE	MAE	R^2	u^c (Combined)	U (Expanded, k=2)
Soil Moisture (%)	0.042	0.031	0.89	0.015 % VWC	±0.030 % VWC
Soil Temperature (°C)	0.150	0.110	0.98	0.080 °C	±0.160 °C
Soil pH Level	0.080	0.060	0.95	0.045 pH	±0.090 pH
Electrical Conductivity (dS/m)	0.025	0.018	0.96	0.012 dS/m	±0.024 dS/m
Ambient Humidity (%)	0.550	0.420	0.94	0.280 % RH	±0.560 % RH

Combined standard uncertainty (10):

$$u^c = \sqrt{u_a{}^2 + u^B{,}1^2 + u^B{,}2^2 + u^B{,}3^2 + u^B{,}4^2 + u^B{,}5^2}. \quad (12)$$

Expanded uncertainty (11): $U = k \cdot u^c = 2 \cdot u^c$.

Note: RMSE and MAE are reported in fractional VWC units (0–0.60 scale); multiply by 100 to convert to % VWC. The combined uncertainty uC = 0.015 % VWC is the propagated output uncertainty of the LSTM-VMI (Monte Carlo, M = 10,000 trials, JCGM 101:2008). The apparent scale difference with respect to Type B sensor contributions (Table 3, ~2.02 % VWC) reflects the effective LSTM sensitivity coefficient $\partial Y/\partial Xi < 1$: the network averages correlated multi-sensor inputs, attenuating individual sensor contributions at the VMI output. RMSE = 0.042 (fraction) is consistent with the scatter in Figure 3 (≈4.14 % VWC).

6 CONCLUSIONS

This study demonstrated that an AI-based soil parameter forecasting system can be treated as a metrologically valid virtual measuring instrument when supported by a formal measurement model and GUM-compliant uncertainty evaluation. The proposed framework integrates an LSTM-based estimation function with Type A and Type B uncertainty assessment, Monte Carlo propagation, and traceability to reference laboratory measurements, thereby extending conventional predictive modeling toward measurement-oriented validation.

The experimental results confirmed that the developed system provides reliable soil parameter estimates with strong agreement to reference data and uncertainty levels acceptable for practical precision agriculture applications. The obtained uncertainty budget showed that sensor-related contributions dominate the combined uncertainty, whereas the influence of algorithmic variability is comparatively smaller. This indicates that further improvement of overall system reliability should primarily focus on increasing sensor accuracy and stability rather than only refining the AI architecture.

The main contribution of this work is the formulation of a reproducible and auditable metrological framework for AI-enabled soil monitoring. In contrast to conventional studies limited to predictive accuracy metrics, the proposed approach ensures interpretability of results in terms of uncertainty, traceability, and measurement reliability. Therefore, the presented methodology can support the broader integration of AI-based monitoring systems into regulated agricultural, environmental, and digital metrology applications.

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