

Comparative Analysis of Moving Average and Exponential Moving Average in a Soil Moisture Monitoring System

Muhammad Wahyu Ardiansyah¹, Farid Baskoro², Rifqi Firmansyah³ Lilik Anifah⁴, and Lusia Rakhmawati⁵

Universitas Negeri Surabaya, Surabaya, Indonesia^{1,2,3,4,5}

E-mail Corresponding: muhammadwahyu.23026@mhs.unesa.ac.id

Received: 18 March 2026

Revised: August 6, 2026

Accepted: September 19, 2026

Abstract

Low-cost capacitive soil moisture sensors can produce short-term fluctuations that reduce the readability of monitoring displays. This study evaluated the internal signal behavior of Moving Average (MA) and Exponential Moving Average (EMA) filters in an Arduino-based soil moisture monitoring system; it did not assess calibrated soil-moisture accuracy. Three repeated acquisition runs were conducted using fresh 2 kg Regosol samples, a capacitive sensor v1.2, and one-second sampling during staged water addition. The primary comparison aligned Raw ADC, MA5, and EMA with $\alpha = 0.2$ over samples 5–300, yielding 888 observations. Parameter sensitivity was examined using MA windows of 3, 5, 7, and 10 and EMA coefficients of 0.1, 0.2, 0.3, and 0.5 over 873 aligned observations. MA5 produced lower internal deviation than EMA with $\alpha = 0.2$, with MAD values of 2.141 versus 3.851 ADC and RMSD values of 6.754 versus 9.367 ADC. MA5 also showed a shorter lag and empirical T50, whereas EMA with $\alpha = 0.2$ produced slightly smaller point-to-point changes. Sensitivity analysis confirmed systematic trade-offs between smoothing strength, tracking fidelity, and response delay. Therefore, filter selection should be based on the operational objective, while calibration remains necessary before Raw ADC values are interpreted as physical soil-water content.

Keywords: capacitive sensor; Arduino Uno; Raw ADC; signal smoothing; parameter sensitivity

INTRODUCTION

Soil moisture is a critical variable in plant cultivation because it governs water availability in the root zone, affects irrigation efficiency, and influences plant growth stability. In precision agriculture, timely soil moisture information supports decisions concerning when irrigation should be applied, how much water is required, and how water use can be optimized. Recent reviews show that continuous soil moisture monitoring has become an important foundation for adaptive irrigation and water management, although the suitability of a monitoring technique remains dependent on measurement scale, soil conditions, and the intended application (Zhang et al., 2024).

The increasing availability of low-cost electronics, microcontrollers, and Internet of Things (IoT) architectures has made environmental monitoring systems more accessible for small-scale experiments, greenhouse applications, household cultivation, and educational laboratories. Microcontroller-based smart agriculture systems can integrate soil and atmospheric sensors with local or cloud-based displays to provide near-real-time observations and support automated control (Kenali et al., 2026). Within this context, an Arduino Uno connected to a low-cost capacitive soil moisture sensor offers a practical platform for observing changes in raw analog output while introducing users to embedded measurement and data processing.

Such low-cost prototypes are also relevant to science education because they allow learners to interact with physical measurements, collect time-ordered data, and evaluate evidence generated by a real device. Inquiry-based science education emphasizes engagement

with scientific questions, procedures, evidence, and interpretation rather than the passive reception of results (Strat et al., 2024). Recent meta-analytic evidence further indicates that virtual laboratories can support learning and engagement but should complement rather than fully replace hands-on laboratory experience (Li & Liang, 2024). An Arduino-based soil moisture prototype can therefore serve both as a monitoring device and as a learning medium for examining how raw sensor output is acquired, processed, interpreted, and critically evaluated.

The affordability of low-cost sensors does not automatically ensure measurement validity. Their outputs may be affected by sensor-to-sensor variation, environmental disturbance, drift, installation conditions, and calibration procedures. Nalakurthi et al. (2024) emphasize that low-cost environmental sensors require appropriate calibration and validation when their readings are intended to represent physical quantities accurately. For dielectric soil moisture sensors, measurement response is also influenced by soil texture, bulk density, salinity, sensor contact, and the selected calibration model (Mane et al., 2024). These factors are particularly relevant to capacitive sensors because the recorded analog value is an indirect response to the dielectric properties of the surrounding medium rather than a direct measurement of volumetric water content.

Recent soil moisture studies reinforce the need to separate signal processing from calibration. Adla et al. (2024) demonstrated that calibration of a low-cost capacitance-based sensor can materially affect irrigation-model performance, while Abdelmoneim et al. (2025) showed that calibration functions and sensor variability influence the reliability of low-cost capacitive sensors across different moisture levels. More recent field evidence indicates that laboratory-derived calibration may not transfer directly to field conditions and that soil-specific field calibration can substantially improve performance (Strypsteen et al., 2026). Accordingly, smoothing a sensor signal may improve its stability and readability, but it does not establish correspondence between raw analog output and true soil water content.

Apart from calibration-related limitations, analog sensor streams may contain short-term fluctuations that make a displayed value unstable and obscure the direction of change. Digital filtering is therefore commonly used to reduce local variation and improve signal readability in embedded monitoring systems. Studies in other real-time sensing contexts have shown that moving-average-based processing can stabilize fluctuating measurements and improve the reliability of sensor outputs (Liu et al., 2024; Ranjan et al., 2024). Embedded implementations are especially relevant because the selected filter must balance computational simplicity, noise reduction, and response delay under limited hardware resources.

Moving Average (MA) and Exponential Moving Average (EMA) are computationally simple filters, but their behavior depends on parameter selection. MA assigns equal weight to a finite window of recent observations; increasing the window generally strengthens smoothing while increasing lag and deviation from rapid changes. EMA recursively assigns greater weight to recent observations, and its behavior is controlled by the smoothing factor α . A smaller α generally suppresses short-term variation more strongly but tracks changes more slowly, whereas a larger α follows new observations more closely. Recent work on embedded adaptive filtering demonstrates that EMA performance is sensitive to parameter tuning and that an automatically or empirically selected coefficient can substantially affect the balance between noise reduction and signal tracking (Simić et al., 2025). Consequently, MA and EMA should not be compared solely through visual inspection or through one arbitrarily selected window and α value.

The reviewed literature reveals two largely separate strands. Soil moisture studies predominantly examine calibration, sensor validity, and field transferability (Adla et al., 2024; Abdelmoneim et al., 2025; Mane et al., 2024; Strypsteen et al., 2026), whereas filtering studies commonly evaluate signal stabilization in positioning, biomedical, or other sensing domains (Liu et al., 2024; Ranjan et al., 2024; Simić et al., 2025). Although these strands establish why capacitive-sensor outputs require careful interpretation and why lightweight filtering can improve signal readability, they do not yet explain how MA and EMA compare when applied to

the same low-cost soil moisture signal under repeated acquisition, aligned sample ranges, and varied parameter settings. This gap is important because filter selection in a resource-limited Arduino system cannot be justified from visual smoothness alone: stronger fluctuation suppression may be accompanied by greater internal deviation and slower response. Moreover, reliance on one predefined MA window or EMA alpha makes it difficult to distinguish the inherent behavior of the method from the effect of parameter choice.

Based on this research gap, the methodological novelty of the present study lies in a controlled, multi-metric comparison of MA and EMA using three repeated acquisition runs with fresh 2 kg Regosol samples under a consistent hardware and sensor-placement configuration. The study differs from previous applications in three respects. First, MA and EMA are applied to the same raw ADC sequences and compared over identical sample ranges. Second, parameter sensitivity is examined through MA windows of 3, 5, 7, and 10 samples and EMA alpha values of 0.1, 0.2, 0.3, and 0.5, rather than relying on a single arbitrary setting. Third, performance is evaluated jointly through internal absolute deviation, root mean square deviation, first-difference-based smoothness, correlation with the raw signal, estimated lag, empirical signal-transition T50, and between-run variability. Therefore, this study aims to identify the operational trade-offs between signal stability, tracking fidelity, and response delay in an Arduino-based soil moisture monitoring system. The findings are expected to contribute a reproducible basis for selecting lightweight smoothing parameters in low-cost embedded monitoring and science-learning prototypes. This contribution is intentionally limited to internal signal behavior and does not constitute evidence of absolute soil moisture accuracy because no gravimetric water-content reference or reference-grade sensor was used.

METHODS

Research design

This study used a controlled repeated-run signal-processing experiment to compare Moving Average (MA) and Exponential Moving Average (EMA) in a low-cost soil-moisture monitoring system. The experimental input was an ordered sequence of Raw analog-to-digital converter (ADC) readings obtained during staged water addition. The processing factors were the MA window length and EMA smoothing coefficient. Three acquisition runs were conducted. The sensor model, Arduino board, pot geometry, soil type and mass, probe depth and orientation, water-application point, sampling interval, and acquisition sequence were kept the same, while a new 2 kg portion of Regosol was used in each run.

The analysis was intentionally limited to internal signal behavior. No gravimetric water-content measurement or reference-grade soil-moisture sensor was available; therefore, the study did not evaluate absolute volumetric water content, calibration accuracy, or measurement error against a true moisture reference. Differences between filtered output and the corresponding Raw ADC series were defined only as internal deviation, signal shift, tracking difference, or response delay. Soil-moisture-specific calibration research shows that low-cost dielectric and capacitance sensors require valid reference measurements and soil-specific calibration before their output can be interpreted as water content (Adla et al., 2024; Mane et al., 2024), while broader low-cost-sensor literature similarly distinguishes signal processing from calibration and validation (Nalakurthi et al., 2024).

The analysis did not include dry-normal-wet threshold classification or fuzzy classification. Although the firmware contained an ADC-to-percentage display function, its endpoints were not validated against gravimetric water content for Regosol, and no defensible threshold boundaries, membership functions, or inference rules were available for the three-run dataset. Accordingly, classification agreement was not included because the available data did not support a calibrated soil-moisture decision.

Hardware and firmware configuration

The monitoring system consisted of an Arduino Uno microcontroller, a capacitive soil moisture sensor v1.2, jumper wires, and a 16 x 2 liquid-crystal display connected through an I2C interface.

The display was initialized at I2C address 0x27. The sensor analog output was connected to Arduino analog input A0. No alternative analog reference was configured in the source code; consequently, the Arduino Uno default analog-reference setting was used. The 10-bit ADC returned integer values from 0 to 1023. The board was powered through a USB connection to a laptop.

Serial communication operated at 9600 baud. The firmware remained in standby until the operator entered the S command to start or continue recording. The P command paused recording, the R command reset the sample counter and filter states for a new run, and the H command reprinted the serial-data header. Sampling was controlled with the Arduino `millis()` function at a nominal interval of 1000 ms. Each serial record contained elapsed active-recording time, sample number, Raw ADC, the MA5 output when a complete window was available, and the EMA output. The EMA state and MA buffer were reset before a new run.

The firmware also converted ADC values to a displayed percentage using operational endpoints of 378 and 143. Those endpoints were retained only in the original LCD display code and were not treated as a Regosol calibration. Percentage values and LCD moisture categories were not used in any statistical analysis. All comparisons were performed in ADC units using the Raw serial records and full-precision recalculated filter outputs.

Table 1. Experimental, acquisition, firmware, and processing settings.

Setting	Specification used in the analysis
Microcontroller	Arduino Uno
Sensor	Capacitive soil moisture sensor v1.2
Sensor input	Analog pin A0
ADC setting	Arduino Uno default 10-bit conversion, 0-1023; no alternative analog reference configured
Display	16 x 2 LCD with I2C interface, address 0x27
Power and communication	USB laptop power; Serial communication at 9600 baud
Sampling control	<code>millis()</code> -based interval of 1000 ms; manual S/P/R/H commands
Soil	Regosol; new 2 kg portion for each run
Container	Plastic pot, upper diameter 15.5 cm and height 11 cm
Probe placement	Nearly vertical; insertion depth 7 cm
Water-application point	Fixed point approximately 5 cm from the probe
Acquisition sequence	60-s baseline, followed by six nominal 25 mL additions and 40-s observation stages; 300 samples per run
Primary filters	MA window $N = 5$ and EMA $\alpha = 0.2$, matching the firmware
Sensitivity settings	MA $N = 3, 5, 7, 10$; EMA $\alpha = 0.1, 0.2, 0.3, 0.5$
Analysis unit	Raw ADC; displayed percentage and classification outputs excluded

Figure 1 documents the physical configuration used during acquisition, including the Regosol-filled pot, inserted capacitive probe, Arduino Uno, and LCD. The image is included as configuration evidence; numerical analysis was based on the serially recorded Raw ADC sequences.



Figure 1. Experimental configuration of the Arduino-based soil moisture monitoring system using Regosol. Source: research documentation, 2026.

Experimental material and acquisition protocol

Each run used a new 2 kg portion of Regosol in the same plastic pot, which had an upper diameter of 15.5 cm and a height of 11 cm. The capacitive probe was inserted in a nearly vertical orientation to a depth of 7 cm. Water was applied repeatedly at the same point, approximately 5 cm from the probe. Probe depth, probe orientation, water-application position, soil mass, pot, and data-acquisition settings were maintained across the three runs. Using a new soil portion prevented direct carry-over of the previous run's wetting history.

No separate gravimetric preconditioning, oven-drying treatment, compaction measurement, bulk-density measurement, salinity measurement, or initial water-content measurement was documented. These variables were therefore not presented as controlled numerical conditions. The firmware entered a standby state after power-up and waited for the S command. The exact elapsed warm-up time before the operator started each run was not recorded. The warm-up duration could therefore not be included as a controlled experimental condition. The first 60 one-second observations after recording began were retained and explicitly treated as the recorded pre-wetting baseline, not as proof of a calibrated dry condition.

Water was added in nominal 25 mL increments immediately before samples 61, 101, 141, 181, 221, and 261. These events produced cumulative additions of 25, 50, 75, 100, 125, and 150 mL. Samples 1-60 formed the baseline segment, and each subsequent stage contained 40 observations collected over approximately 40 s. The standardized analytical endpoint was sample 300. Because recording was stopped manually, the source logs contained additional post-endpoint readings, including a longer continuation in Run 1. All observations after sample 300 were excluded before analysis, using the same rule for every run. No post-endpoint value was used to choose filter parameters or calculate reported performance.

Moving Average processing and window sensitivity

The firmware baseline used a five-sample trailing Moving Average. At each valid observation, the current Raw ADC reading and the four immediately preceding readings were assigned equal weight. At the one-second sampling interval, $N = 5$ represents a five-second rolling observation window. The serial output displayed MA as unavailable for samples 1-4 because a complete five-sample window had not yet been formed; those four observations were excluded from the primary MA5 comparison. The filter was defined as follows (NIST/SEMATECH, 2012a; Oppenheim & Schafer, 2010):

$$MA_t = \frac{1}{N} \sum_{i=0}^{N-1} x_{t-i} \quad (1)$$

where MA_t is the trailing Moving Average at observation t , N is the window length, and $x_{(t-i)}$ is a Raw ADC observation within the current window. $N = 5$ was retained as the primary

operational baseline because it was the setting implemented in the original Arduino firmware, not because it was assumed to be universally optimal. Sensitivity analysis therefore evaluated $N = 3, 5, 7$, and 10 using the same Raw ADC sequences. At the one-second sampling interval, these settings correspond to trailing windows of $3, 5, 7$, and 10 s. This range was selected to compare short embedded-system windows around the firmware baseline and to quantify the expected trade-off between local smoothing and response delay. The use of multiple MA windows is consistent with sensor-processing research showing that filter behavior depends materially on selected window length (Liu et al., 2024).

Exponential Moving Average processing and coefficient sensitivity

The firmware baseline used an EMA smoothing coefficient of $\alpha = 0.2$. The first EMA state was initialized with the first Raw ADC reading, avoiding an externally assigned starting value. Each subsequent output combined the current Raw reading with the previous EMA state according to the following recursive expression (NIST/SEMATECH, 2012b):

$$\text{EMA}_t = \alpha x_t + (1 - \alpha)\text{EMA}_{t-1} \quad (2)$$

where EMA_t is the current EMA output, x_t is the current Raw ADC reading, $\text{EMA}_{(t-1)}$ is the previous output, and α is the smoothing coefficient. $\alpha = 0.2$ was retained only as the primary operational baseline because it was implemented in the original firmware; it was not assumed to be the optimum coefficient. Sensitivity analysis therefore evaluated $\alpha = 0.1, 0.2, 0.3$, and 0.5 on the same Raw ADC sequences. The selected values span stronger smoothing and longer memory at $\alpha = 0.1$ through progressively faster tracking at $\alpha = 0.5$, while including the firmware setting and adjacent intermediate settings. All sensitivity outputs were recalculated with full numerical precision rather than from rounded LCD or serial-display percentages.

Data selection, alignment, and integrity

The primary comparison aligned Raw ADC, MA5, and EMA $\alpha = 0.2$ over samples 5-300. This interval was chosen because sample 5 was the first observation with a complete MA5 window. It yielded 296 aligned observations per run and 888 aligned observations across three runs. Sensitivity analysis aligned every MA and EMA setting over samples 10-300 because sample 10 was the first observation with a complete MA10 window. This yielded 291 aligned observations per run and 873 aligned observations in total. Identical start and end samples were used within each comparison so that differences could not be attributed to unequal sample counts.

Raw ADC sequences were taken from the recorded serial logs. The MA and EMA outputs used in the analysis were recalculated from those Raw sequences, including the primary firmware settings, and checked against the recorded outputs. Calculations retained full-precision values; rounding was applied only when tables and figures were prepared. The Arduino source code, source logs, and aligned analysis workbook were retained as reproducibility materials for this study. Individual one-second observations were treated as temporally ordered measurements and were not interpreted as independent experimental replicates.

Quantitative analysis

Raw and filtered series were summarized using the number of aligned observations, mean, minimum, maximum, and sample standard deviation. Filter-to-Raw differences were evaluated only as internal signal differences. At observation t , internal absolute deviation was defined as:

$$d_t = |x_t - y_t| \quad (3)$$

where x_t is the aligned Raw ADC value and y_t is the corresponding MA or EMA output. Mean absolute deviation (MAD), root mean square deviation (RMSD), and maximum absolute deviation were then calculated:

$$\text{MAD} = \frac{1}{n} \sum_{t=1}^n |x_t - y_t| \quad (4)$$

$$\text{RMSD} = \sqrt{\frac{1}{n} \sum_{t=1}^n (x_t - y_t)^2} \quad (5)$$

$$D_{\max} = \max_{1 \leq t \leq n} |x_t - y_t| \quad (6)$$

MAD, RMSD, and maximum deviation describe the magnitude of the filter-induced shift relative to Raw ADC. They were not interpreted as accuracy metrics or as error against true soil water content.

Signal smoothness was evaluated within each run using the mean absolute first difference and the sample standard deviation of signed first differences. For a processed series y , the mean absolute first difference and the sample standard deviation of signed first differences were defined as:

$$\text{MAS} = \frac{1}{n-1} \sum_{t=2}^n |y_t - y_{t-1}| \quad (7)$$

$$\text{SD}_{\Delta y} = \sqrt{\frac{1}{n-2} \sum_{t=2}^n (y_t - y_{t-1} - \overline{\Delta y})^2} \quad (8)$$

In Equation (8), the overbar denotes the mean of the signed first differences within the relevant run. Lower first-difference values indicate smaller observation-to-observation movement and therefore stronger smoothing. First differences were calculated separately within Run 1, Run 2, and Run 3. The final observation of one run was never subtracted from the first observation of the next run, preventing artificial discontinuities from entering the smoothness metric.

Tracking similarity was summarized using Pearson correlation between each processed series and its aligned Raw ADC series. Correlation was treated as a shape-tracking indicator and not as evidence of measurement validity. Operational response delay was estimated separately for each run by testing integer shifts from 0 to 12 s and selecting the shift that produced the minimum RMSD between the shifted processed series and Raw ADC. The selected shift was reported as estimated signal-tracking lag; it did not represent electronic latency of the Arduino or physical time constant of the sensor.

An empirical signal-transition T50 was calculated for each water-addition stage. The pre-event level was the mean of the ten observations immediately preceding the relevant water addition. The stage-end level was the mean of the final ten observations in the following 40-s stage. The 50% target was located halfway between those levels, and T50 was the first elapsed second at which the relevant series crossed the target in the direction of the stage transition. Transitions with an absolute pre-to-stage-end change below 10 ADC were excluded because a stable halfway crossing could not be defined. T50 was interpreted only as an empirical transition indicator under the stated pot, soil, placement, watering, and sampling protocol.

Between-run variation was described at each cumulative-water stage. Raw ADC, MA5, and EMA $\alpha = 0.2$ were first averaged within each stage separately for each run. The mean and sample standard deviation of the three run-level stage means were then reported. Because there were only three experimental runs and the one-second observations were temporally dependent, no inferential hypothesis test treated the 888 or 873 observations as independent replications. The analysis was descriptive and comparative, with the three runs retained as the experimental repetition level.

Reproducibility boundary

The method is reproducible for the documented hardware, firmware, Regosol mass, pot geometry, sensor placement, water-addition sequence, sampling interval, data-alignment rules, filter settings, and analysis definitions. Variables not documented in the source record - including exact pre-run warm-up duration, gravimetric initial water content, compaction force, bulk

density, salinity, ambient temperature, water-pouring duration, and the instrument used to dispense each nominal 25 mL increment - were not included as controlled numerical conditions. Their absence limits physical generalization but does not alter the reported internal comparison of filters applied to the same recorded Raw ADC sequences.

RESULT AND DISCUSSION

Results

This section presents the findings from the aligned three-run dataset. The results are organized into descriptive characteristics, the primary MA-EMA comparison, operational response indicators, parameter-sensitivity analysis, and between-run variability.

Characteristics of the aligned data

Table 2 presents the descriptive statistics of the aligned Raw ADC, MA5, and EMA $\alpha = 0.2$ series.

These values provide the starting point for the primary comparison.

Table 2. Descriptive statistics of the aligned Raw ADC, MA5, and EMA $\alpha = 0.2$ series.

Series	n	Mean	Minimum	Maximum	SD
Raw ADC	888	333.180	146.000	436.000	109.406
MA5	888	335.005	147.000	435.800	108.683
EMA $\alpha = 0.2$	888	336.833	147.087	435.774	107.657

Based on Table 2, the Raw ADC series had a mean of 333.180 and a standard deviation of 109.406. The corresponding means for MA5 and EMA $\alpha = 0.2$ were 335.005 and 336.833. The closeness of these mean values indicates that both filters preserved the general level of the original signal, so the key differences needed to be examined through deviation and response indicators.

Figures 2-4 complement Table 2 by showing the time-course pattern of the three series in each run.

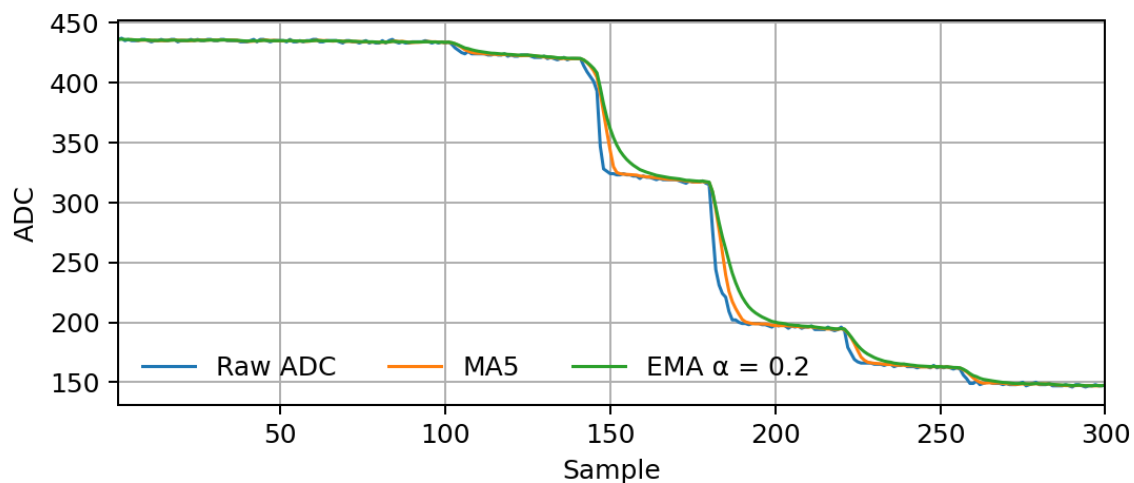
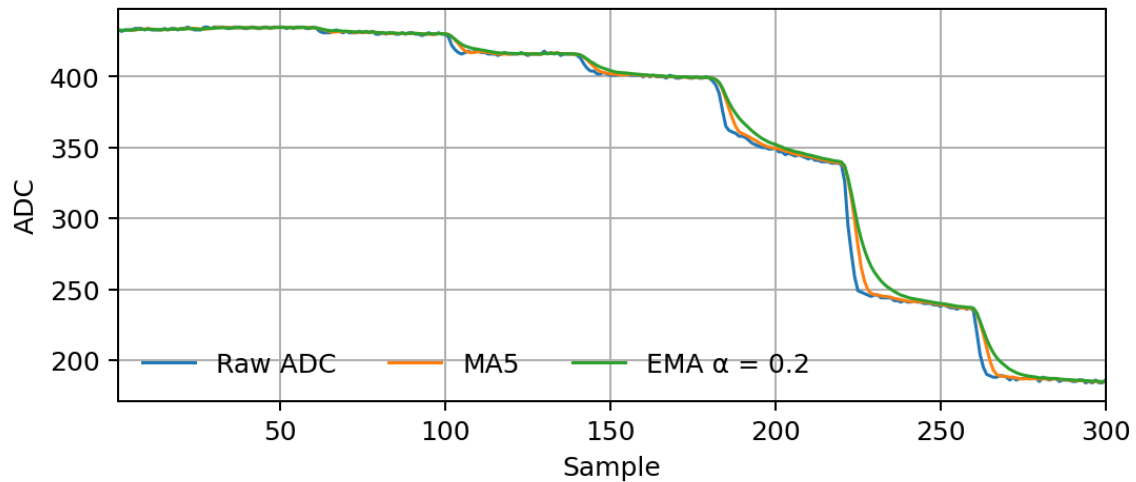
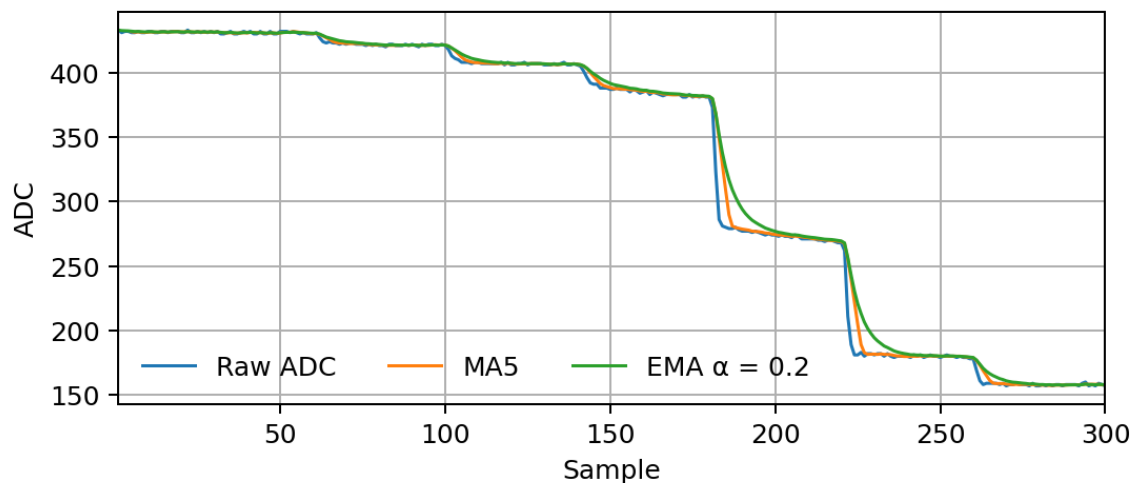


Figure 2. Comparison of Raw ADC, MA5, and EMA $\alpha = 0.2$ in Run 1.**Figure 3.** Comparison of Raw ADC, MA5, and EMA $\alpha = 0.2$ in Run 2.**Figure 4.** Comparison of Raw ADC, MA5, and EMA $\alpha = 0.2$ in Run 3.

Across the three runs, the same directional pattern can be observed. The Raw ADC values decreased as water addition progressed, while MA5 and EMA $\alpha = 0.2$ followed the same trend. The visual separation between the filtered and unfiltered series became clearer around the sharper transitions, which justifies the more formal numerical comparison presented next.

Primary comparison of MA5 and EMA $\alpha = 0.2$

Table 3 summarizes the main indicators used to compare the two primary filtering methods.

Table 3. Internal deviation and smoothness indicators for MA5 and EMA $\alpha = 0.2$.

Method	n	MAD	RMSD	Maximum deviation	Mean abs. step	SD first diff.	Pearson r
MA5	888	2.141	6.754	62.800	0.989	2.872	0.99824
EMA $\alpha = 0.2$	888	3.851	9.367	66.022	0.966	2.161	0.99697

Table 3 shows that MA5 produced a MAD of 2.141 ADC and an RMSD of 6.754 ADC, whereas EMA $\alpha = 0.2$ produced a MAD of 3.851 ADC and an RMSD of 9.367 ADC. Thus, MA5 remained closer to the aligned Raw ADC series. However, EMA $\alpha = 0.2$ showed a slightly lower mean absolute step (0.966) than MA5 (0.989), which means that EMA $\alpha = 0.2$ generated a marginally smoother point-to-point sequence.

The same comparison is shown again in Figure 5 using a simple line diagram.

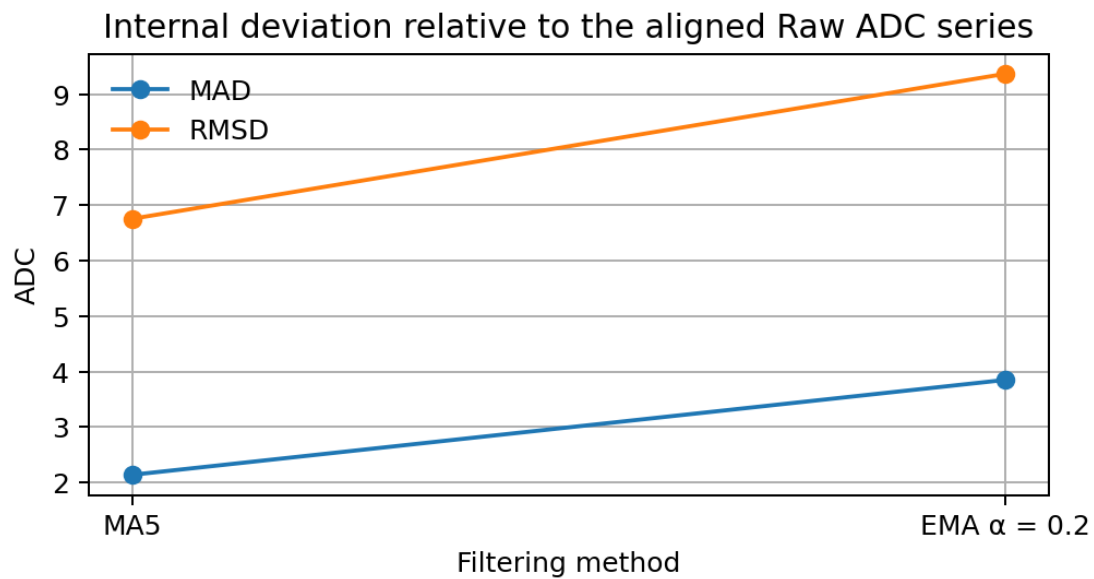


Figure 5. Comparison of MAD and RMSD for MA5 and EMA $\alpha = 0.2$.

Figure 5 confirms the pattern already visible in Table 3. For both MAD and RMSD, the EMA $\alpha = 0.2$ line remains above the MA5 line, indicating greater internal deviation from the Raw ADC series.

Operational response indicators

Because filter behavior also involves response delay, Table 4 reports the operational lag and the empirical signal-transition T50.

Table 4. Operational lag and empirical signal-transition T50.

Series	Lag (s)	Valid transitions	Mean T50 (s)	SD	Median	Range
Raw ADC	0	15	2.000	1.604	1.000	0-6
MA5	2	15	4.067	1.944	4.000	0-8
EMA $\alpha = 0.2$	3	15	5.200	2.210	5.000	1-9

As reported in Table 4, the lag was 2 s for MA5 and 3 s for EMA $\alpha = 0.2$. The mean empirical T50 was 4.067 s for MA5 and 5.200 s for EMA $\alpha = 0.2$. These results indicate that MA5 responded more quickly under the current acquisition protocol.

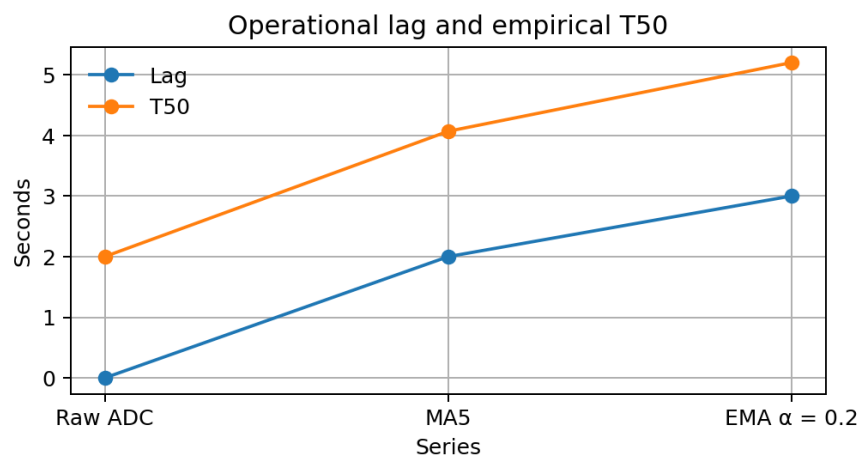


Figure 6. Operational lag and empirical T50 for the compared series.

Figure 6 presents the same trade-off in visual form. Compared with EMA $\alpha = 0.2$, the MA5 line remains lower for both lag and T50, reinforcing the conclusion that MA5 provided the faster operational response.

Parameter-sensitivity analysis

Parameter-sensitivity analysis was performed to determine how the selected MA window and EMA coefficient affected internal deviation, smoothness, and response delay.

Table 5. Sensitivity results for the Moving Average window size.

Window	n	MAD	RMSD	Mean abs. step	SD first diff.	Pearson r	Lag (s)
3	873	1.278	3.976	1.077	3.425	0.99938	1
5	873	2.168	6.811	1.003	2.894	0.99822	2
7	873	3.066	9.117	0.978	2.547	0.99687	3
10	873	4.421	12.003	0.955	2.180	0.99476	4

Table 5 shows that increasing the MA window from 3 to 10 samples caused MAD to rise from 1.278 to 4.421 ADC and RMSD to rise from 3.976 to 12.003 ADC. Over the same range, the mean absolute step decreased from 1.077 to 0.955, while lag increased from 1 to 4 s. This means that larger MA windows enhanced smoothing but also increased deviation and delay.

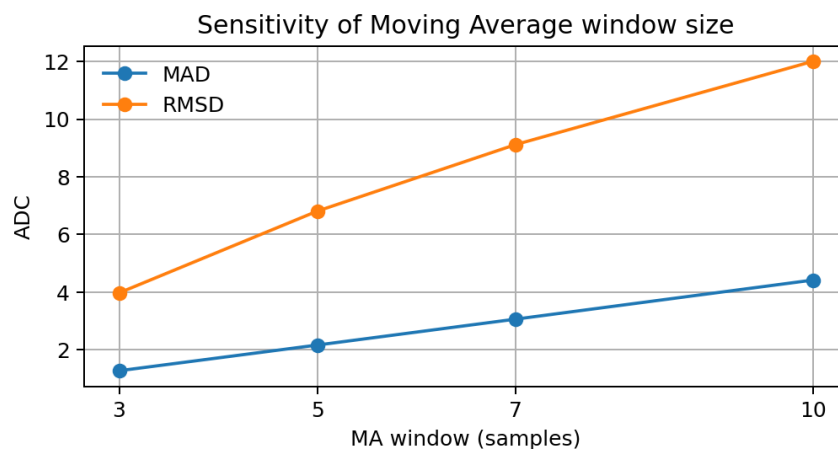
**Figure 7.** Sensitivity of MAD and RMSD to the Moving Average window size.

Figure 7 visualizes the same progression, with both lines increasing as the MA window becomes larger.

Table 6. Sensitivity results for the Exponential Moving Average coefficient.

Alpha	n	MAD	RMSD	Mean abs. step	SD first diff.	Pearson r	Lag (s)
0.1	873	8.468	16.265	0.944	1.554	0.99232	7
0.2	873	3.908	9.447	0.980	2.176	0.99693	3
0.3	873	2.390	6.468	1.027	2.617	0.99848	2
0.5	873	1.145	3.373	1.147	3.250	0.99957	1

By contrast, Table 6 shows that as α increased from 0.1 to 0.5, MAD decreased from 8.468 to 1.145 ADC and RMSD decreased from 16.265 to 3.373 ADC. At the same time, the mean absolute step increased from 0.944 to 1.147, while lag decreased from 7 to 1 s. Thus, smaller α values favored stronger smoothing, whereas larger α values favored closer tracking and faster response.

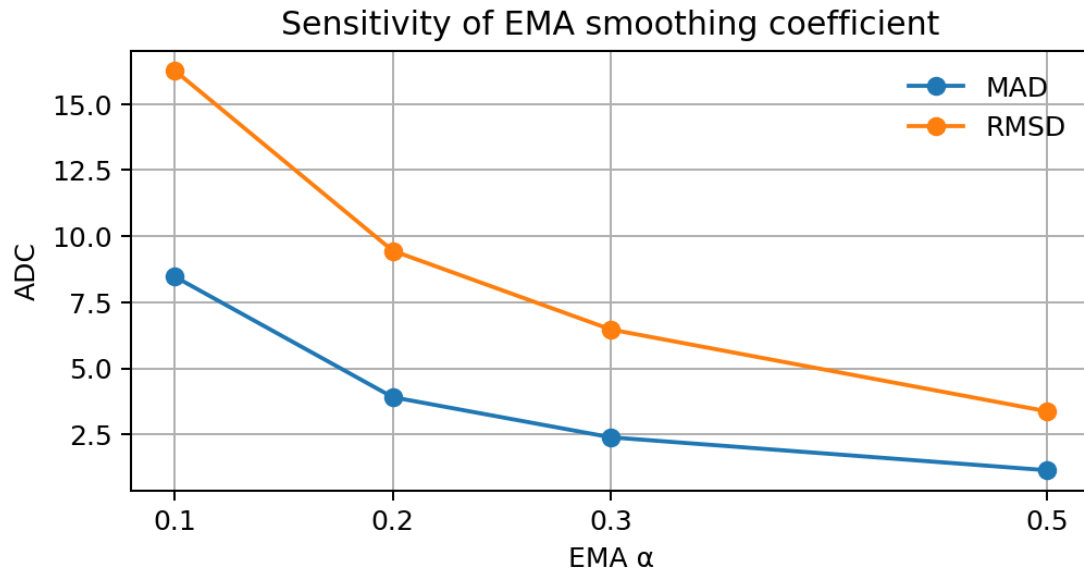


Figure 8. Sensitivity of MAD and RMSD to the EMA coefficient.

Taken together, Tables 5 and 6 and Figures 7 and 8 show that the MA and EMA parameters should be interpreted as trade-off settings rather than as universally fixed values.

Between-run variability

Table 7 summarizes the Raw ADC stage means across the three runs to show the degree of repeatability at each cumulative water level.

Table 7. Between-run Raw ADC stage means across cumulative water additions.

Water (mL)	Sample range	Run 1	Run 2	Run 3	Mean $\pm$ SD
0	5-60	435.089	434.214	431.161	433.488 $\pm$ 2.063
25	61-100	434.050	430.925	422.175	429.050 $\pm$ 6.156
50	101-140	423.050	416.850	407.550	415.817 $\pm$ 7.801
75	141-180	333.950	401.325	386.025	373.767 $\pm$ 35.321
100	181-220	202.525	352.075	277.800	277.467 $\pm$ 74.776
125	221-260	164.000	245.925	183.275	197.733 $\pm$ 42.834
150	261-300	148.100	188.000	158.350	164.817 $\pm$ 20.721

As shown in Table 7, the mean Raw ADC value decreased from 433.488 $\pm$ 2.063 at baseline to 164.817 $\pm$ 20.721 after cumulative water addition reached 150 mL. The largest between-run standard deviation occurred at 100 mL (74.776 ADC), followed by 125 mL (42.834 ADC) and 75 mL (35.321 ADC). Therefore, the direction of change was consistent across runs, but the intermediate wetting stages showed the greatest variability.

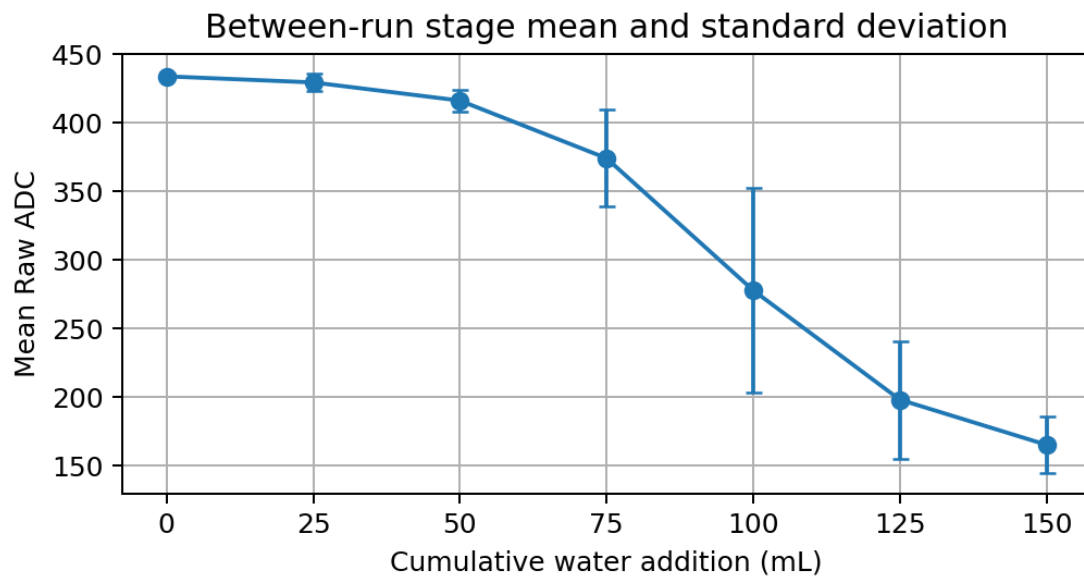


Figure 9. Mean Raw ADC value and standard deviation at each cumulative water stage.

Figure 9 confirms this result visually. The overall mean declined with additional water, but the spread between runs widened most clearly in the middle part of the sequence.

Overall, the results show that MA5 remained closer to the aligned Raw ADC series and responded more quickly than EMA $\alpha = 0.2$, whereas EMA $\alpha = 0.2$ produced slightly smaller local point-to-point changes. The sensitivity analysis further demonstrates that these characteristics varied systematically with the chosen MA window and EMA coefficient.

Discussion

The main finding of this study is that the relative performance of MA and EMA depended on the operational objective rather than on the filter name alone. Under the primary settings, MA5 remained closer to the aligned Raw ADC series than EMA with $\alpha = 0.2$, as indicated by its lower MAD (2.141 versus 3.851 ADC) and RMSD (6.754 versus 9.367 ADC). MA5 also showed a shorter lag and a lower empirical T50, whereas EMA $\alpha = 0.2$ produced slightly smaller point-to-point changes. These results reveal a clear trade-off. MA5 was more suitable when preserving signal transitions and limiting response delay were prioritized, while EMA $\alpha = 0.2$ provided a marginally steadier local trajectory. Consequently, the present data do not support a universal claim that one method is always smoother or more responsive; the preferred filter depends on whether tracking fidelity, display stability, or response speed is the main requirement.

The parameter-sensitivity analysis explains why the original MA5 and EMA $\alpha = 0.2$ settings should be regarded as operational baselines rather than universally optimal values. Increasing the MA window from 3 to 10 samples progressively reduced short-term variation, but it also increased internal deviation and extended the estimated lag from 1 to 4 s. This pattern is consistent with the behavior of trailing moving averages, in which a longer window produces stronger smoothing at the cost of slower tracking (Liu et al., 2024; NIST/SEMATECH, 2012a). The EMA results showed the complementary pattern. Increasing α from 0.1 to 0.5 reduced internal deviation and shortened the lag, but allowed larger observation-to-observation changes. Thus, small α values favored stronger smoothing, whereas large α values followed the Raw ADC signal more closely. The broader embedded-filtering literature similarly emphasizes that parameter selection must be matched to the characteristics of the signal and the intended use of the device (Simić et al., 2025).

The repeated-run results strengthen the analysis by showing that the direction of the sensor response was reproducible, although its magnitude was not equally stable at every wetting stage. Across the three runs, the mean Raw ADC value decreased from 433.488 ± 2.063 at baseline to 164.817 ± 20.721 after the cumulative addition reached 150 mL. The between-run

dispersion was relatively small during the early stages but widened substantially at 75–125 mL, with the largest standard deviation occurring at 100 mL. This pattern suggests that the sensor consistently responded to progressive wetting, while the intermediate response remained sensitive to the physical conditions surrounding the probe. Differences in water distribution, infiltration, sensor–soil contact, packing density, and the initial condition of each fresh Regosol portion are plausible explanations. Previous studies have likewise shown that dielectric soil-moisture sensor responses depend on soil properties, installation conditions, and calibration procedures (Mane et al., 2024; Abdelmoneim et al., 2025; Strypsteen et al., 2026). Because these factors were not measured separately in the present study, they are interpreted as possible sources of variability rather than demonstrated causal effects.

The decline in Raw ADC values after staged water addition was consistent with the expected operational response of the tested capacitive sensor, but it cannot be interpreted as evidence of absolute soil-moisture accuracy. No gravimetric reference or reference-grade sensor was used, and the ADC-to-percentage endpoints included in the original firmware were not validated for Regosol. Accordingly, MAD and RMSD represent internal differences between the filtered and Raw ADC sequences; they do not represent errors relative to true volumetric water content. This distinction is essential because low-cost capacitive sensors require sensor- and soil-specific calibration before their analog output can be translated reliably into physical water-content values (Adla et al., 2024; Mane et al., 2024; Abdelmoneim et al., 2025). Evidence from field studies further shows that calibration developed under one condition may not transfer directly to another without additional adjustment (Strypsteen et al., 2026). Therefore, filtering in this study should be understood as a means of improving signal readability and operational stability, not as a substitute for calibration or validation.

The contribution of this study lies in the way the two lightweight filters were evaluated under a common experimental and analytical framework. MA and EMA were applied to the same Raw ADC sequences, compared over identical sample ranges, examined across three acquisition runs, and evaluated using multiple parameter settings and complementary indicators of deviation, smoothness, and response. The use of identical aligned sample ranges controls for differences in data availability and provides a consistent basis for parameter selection. For the tested Arduino configuration, MA5 is a reasonable baseline when closer tracking and shorter delay are required, whereas $\text{EMA } \alpha = 0.2$ may be selected when a slightly steadier displayed value is preferred. The sensitivity results also make clear that different settings can change this balance. In a science-learning context, the prototype offers a practical way to demonstrate that raw measurement, filtering, response delay, repeatability, and calibration are distinct stages of evidence interpretation rather than interchangeable indicators of measurement quality.

Several limitations define the scope of these conclusions. The experiment used one capacitive sensor model, one Arduino board, one pot geometry, and one soil type, which limits generalization to other devices, textures, and installation conditions. Only three independent runs were available, while the one-second observations within each run were serial measurements rather than independent experimental replicates. Initial gravimetric moisture, bulk density, compaction, salinity, temperature, and the exact stabilization period were not recorded. Water was also applied manually, so the empirical T50 reflects the combined effects of filtering, pouring, infiltration, and sensor–soil interaction rather than an isolated electronic response time. Future studies should include gravimetric calibration, several soil types and sensor units, controlled packing and salinity, automated water dosing, documented warm-up periods, and a larger number of independent runs. Such a design would permit stronger uncertainty estimates and repeated-measures analysis while testing whether the trade-offs identified here remain stable across devices and soil conditions.

CONCLUSION

This study concludes that the relative performance of the Moving Average and Exponential Moving Average filters was determined by the operational objective and the selected parameter

setting. Under the primary configuration, MA5 remained closer to the aligned Raw ADC series and produced a shorter response delay than EMA with $\alpha = 0.2$, as reflected by its lower internal deviation, shorter operational lag, and lower empirical T50. In contrast, EMA with $\alpha = 0.2$ produced slightly smaller point-to-point changes, indicating a marginally steadier local signal. The parameter-sensitivity analysis further demonstrated that increasing the MA window strengthened smoothing but also increased deviation and response delay, whereas increasing the EMA coefficient improved tracking and shortened the lag while allowing larger local fluctuations. Therefore, neither method nor parameter setting can be regarded as universally superior. For the tested Arduino-based system, MA5 provides a reasonable operational baseline when closer tracking and faster response are prioritized, while EMA with $\alpha = 0.2$ may be considered when a slightly steadier displayed value is preferred. The study contributes a more defensible comparative framework by applying both filters to identical sample ranges, repeated acquisition runs, multiple parameter settings, and complementary indicators of deviation, smoothness, and response. Nevertheless, the findings are limited to internal Raw ADC behavior for one capacitive sensor, one Regosol condition, and three runs; they do not establish absolute soil-moisture accuracy. Future studies should incorporate gravimetric calibration, additional soil types and sensor units, controlled water dosing, documented stabilization periods, and more independent runs to evaluate whether the identified trade-offs remain stable under broader experimental conditions.

ACKNOWLEDGMENT

The author acknowledges the academic supervisor, laboratory support, and all parties who contributed to the development and documentation of the Arduino-based soil moisture monitoring prototype used in this study.

REFERENCE

- Abdelmoneim, A. A., Al Kalaany, C. M., Khadra, R., Derardja, B., & Dragonetti, G. (2025). Calibration of low-cost capacitive soil moisture sensors for irrigation management applications. *Sensors*, 25(2), Article 343. <https://doi.org/10.3390/s25020343>
- Adla, S., Bruckmaier, F., Arias-Rodriguez, L. F., Tripathi, S., Pande, S., & Disse, M. (2024). Impact of calibrating a low-cost capacitance-based soil moisture sensor on AquaCrop model performance. *Journal of Environmental Management*, 353, Article 120248. <https://doi.org/10.1016/j.jenvman.2024.120248>
- Kenali, E. W., Rofianto, D., Amaliah, K., Fitra, J., Fathoni, H., Khoerunnisa, T. K., & Sari, H. P. (2026). IoT-based smart irrigation and fertilization system with realtime cloud integration. *Jurnal Nasional Teknik Elektro dan Teknologi Informasi*, 15(1), 34–43. <https://doi.org/10.22146/jnteti.v15i1.23124>
- Li, J., & Liang, W. (2024). Effectiveness of virtual laboratory in engineering education: A meta-analysis. *PLOS ONE*, 19(12), Article e0316269. <https://doi.org/10.1371/journal.pone.0316269>
- Liu, J., Gao, Z., Li, Y., Lv, S., Liu, J., & Yang, C. (2024). Ranging offset calibration and moving average filter enhanced reliable UWB positioning in classic user environments. *Remote Sensing*, 16(14), Article 2511. <https://doi.org/10.3390/rs16142511>
- Mane, S., Das, N., Singh, G., Cosh, M., & Dong, Y. (2024). Advancements in dielectric soil moisture sensor calibration: A comprehensive review of methods and techniques. *Computers and Electronics in Agriculture*, 218, Article 108686. <https://doi.org/10.1016/j.compag.2024.108686>
- Nalakurthi, N. V. S. R., Abimbola, I., Ahmed, T., Anton, I., Riaz, K., Ibrahim, Q., Banerjee, A., Tiwari, A., & Gharbia, S. (2024). Challenges and opportunities in calibrating low-cost environmental sensors. *Sensors*, 24(11), Article 3650. <https://doi.org/10.3390/s24113650>
- NIST/SEMATECH. (2012a). *What are moving average or smoothing techniques?* In *NIST/SEMATECH e-Handbook of statistical methods*. <https://www.itl.nist.gov/div898/handbook/pmc/section4/pmc42.htm>
- NIST/SEMATECH. (2012b). *What is exponential smoothing?* In *NIST/SEMATECH e-Handbook of statistical methods*. <https://www.itl.nist.gov/div898/handbook/pmc/section4/pmc43.htm>
- Oppenheim, A. V., & Schaffer, R. W. (2010). *Discrete-time signal processing* (3rd ed.). Pearson. <https://siducat.org/index.php/isej/>

- Ranjan, R., Shin, D., Jung, Y., Kim, S., Yun, J.-H., Kim, C.-H., Lee, S., & Kye, J. (2024). Comparative analysis of integrated filtering methods using UWB localization in indoor environment. *Sensors*, 24(4), Article 1052. <https://doi.org/10.3390/s24041052>
- Simić, M., Ouni, C., Ammar, N., Keutel, T., Stojanović, G., & Kanoun, O. (2025). Embedded hardware-based adaptive filtering for noise reduction in bioimpedance data. *Computers in Biology and Medicine*, 197, Article 110850. <https://doi.org/10.1016/j.combiomed.2025.110850>
- Strat, T. T. S., Henriksen, E. K., & Jegstad, K. M. (2024). Inquiry-based science education in science teacher education: A systematic review. *Studies in Science Education*, 60(2), 191–249. <https://doi.org/10.1080/03057267.2023.2207148>
- Strypsteen, G., Persson, M., Miroshnychenko, M., & Rakonjac, N. (2026). Field performance and calibration strategies for low-cost capacitive soil moisture sensors. *Sensors*, 26(11), Article 3291. <https://doi.org/10.3390/s26113291>
- Zhang, X., Feng, G., & Sun, X. (2024). Advanced technologies of soil moisture monitoring in precision agriculture: A review. *Journal of Agriculture and Food Research*, 18, Article 101473. <https://doi.org/10.1016/j.jafr.2024.101473>