Delft University of Technology

An improved method of soil moisture meter calibration for satellite data validation at watershed scale

Cheruiyot, Elijah; Mito, Collins; Menenti, Massimo

DOI
10.1007/s12145-023-01170-w

Publication date
2023

Document Version
Final published version

Published in
Earth Science Informatics

Citation (APA)
Cheruiyot, E., Mito, C., & Menenti, M. (2023). An improved method of soil moisture meter calibration for satellite data validation at watershed scale. *Earth Science Informatics*, *17*(1), 117-129. https://doi.org/10.1007/s12145-023-01170-w

Important note
To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright
Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy
Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.

This work is downloaded from Delft University of Technology.
For technical reasons the number of authors shown on this cover page is limited to a maximum of 10.

Green Open Access added to TU Delft Institutional Repository

'You share, we take care!' - Taverne project

https://www.openaccess.nl/en/you-share-we-take-care

Otherwise as indicated in the copyright section: the publisher is the copyright holder of this work and the author uses the Dutch legislation to make this work public.

Earth Science Informatics
https://doi.org/10.1007/s12145-023-01170-w

RESEARCH

An improved method of soil moisture meter calibration for satellite data validation at watershed scale

Elijah Cheruiyot[1] · Collins Mito[1] · Massimo Menenti[2]

Received: 31 July 2023 / Accepted: 18 November 2023
© The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2023

Abstract
This work presents an improved gravimetric algorithm to derive reference soil moisture, with removal of some of the hypothesis on which its original expression was based, and addition of a new corrective term that takes into account the interdependence between temperature and non-unitary water density. The temperature correction term improves reference measurements by up to 0.55% of their values in the temperature range 10–35℃. The temperature-corrected reference measurements were applied to the calibration of a hand-held soil moisture meter (Lutron PMS-714) for three soil texture types: medium, fine, and very fine. Linear regression models were used to calibrate the meter for each soil type, and the resulting calibration equations were validated with field data sampled from Sondu-Miriu watershed in Western Kenya. The validation produced errors (RMSE = 0.022, 0.010, 0.010 m^3/m^3) that are significantly better than the meter's reported factory calibration errors of ± 0.05 m^3/m^3. While calibrations did not improve correlation statistics (R^2 and RMSE), they did significantly reduce biases (+ 0.009, + 0.004, -0.001 m^3/m^3) compared to uncalibrated ones (-0.216, -0.181, -0.184 m^3/m^3). Additionally, the calibrated meter values compared well with Soil Moisture Active Passive (SMAP) surface moisture data, with errors (RMSE = 0.010, 0.007, 0.008 m^3/m^3) well within SMAP recommended value of ± 0.04 m^3/m^3. A spatial scalability test showed that the calibrations are adequately robust (with R^2 = 0.81, RMSE = 0.016 m^3/m^3, and Bias = + 0.005 m^3/m^3), permitting calibration equations derived from one site to be scaled out to other sites of similar soil texture regime.

Keywords Gravimetric soil moisture · Temperature effect · Calibration · Soil texture · Spatial scalability · SMAP

Introduction

While the gravimetric method remains the most accurate way of determining soil water content, it is labour intensive and is not suitable for extensive surveys. Soil moisture meters are portable and rapidly deployable, and are a more practical and cost-effective alternative for sampling soil moisture point measurements at a wider scale (Rowlandson et al. 2013). To allow meaningful application of the data at a wider spatial scale, for example in satellite data validation, the point measurements can be averaged to obtain an area representative value, or interpolated to obtain a spatially continuous distribution of the state variable. The attempt becomes more reliable when location specific calibration of the sensors has been performed (Colliander et al. 2017).

Technological advancement has allowed the development of a wide variety of soil moisture sensors employing different measurement principles (Robinson et al. 2008; Zermeño-González et al. 2012). However, not one sensor or measuring principle perfectly meets all the desired features at the same time: a wide sensitivity range, good accuracy for all soil types and temperatures, reliable, inexpensive, durable, user-friendly, portable, rapidly deployable, etc. (Shock et al. 1998). Factors that affect the measurement accuracy of soil moisture sensors, e.g., soil texture, temperature and terrain, can vary significantly across space. Consequently, using a single soil moisture meter with the same calibration across extensive and inhomogeneous surfaces could lead to measurement errors. Proper soil-specific calibration of the sensors is therefore desirable in order to optimize their

Communicated by: H. Babaie

✉ Elijah Cheruiyot
ekcheru@gmail.com

1 Department of Physics, University of Nairobi, P.O. Box 30197, Nairobi 00100, Kenya

2 Department of Geoscience and Remote Sensing, Delft University of Technology, P.O. Box 5048, Delft, GA 2600, The Netherlands

Published online: 23 November 2023

performance in the environment and conditions for which they are deployed.

A soil moisture meter calibration is presented in the form of a mathematical expression that directly relates the raw data counts of the meter to the known (reference) soil moisture values of the soil as determined by another more accurate method, often gravimetric analysis.

Different types of soil moisture instruments employ a variety of measurement principles to measure a physical parameter that is associated with the quantity of water in the soil medium, and apply a suitable calibration to infer soil moisture content. Neutron probes (neutron scattering principle) measure fast moving neutrons that are slowed (thermalized) principally by an elastic collision with hydrogen (H^+) atoms present in soil, so that a change in neutron counts of successive measurements can be related with an appropriate calibration curve to a change in the moisture content in soil (Bell 1987). Tensiometers measure the pressure (tension) of a partial vacuum in the equipment resulting from a loss of water that is drawn by the contiguous soil matrix (Hensley and Deputy 1999). Porous blocks allow water in the soil to reach an equilibrium with water in a porous block, permitting measurements of different properties of the block which are affected by water tension, most commonly the electrical resistance between electrodes that are embedded in the block (Johnson 1962; Richards and Weaver 1943). Resistive sensors measure the resistivity of a soil medium, which is chiefly influenced by water, as water has significantly higher electrical conductivity than dry soil (Adla et al. 2020). Electromagnetic sensors exploit the high dielectric constant of water (80), compared to that of soil (2 to 5) and that of air (1), to infer the volumetric content of water in the soil matrix. But different electromagnetic sensors determine the dielectric permittivity of the unsaturated soil medium using different physical principles. Time-domain reflectometry (TDR) sensors measure transit time of the voltage impulse wave, determined by the dielectric permittivity of the soil medium through which it travels (Sharma et al. 2018). Capacitance sensors measure capacitance of a soil medium which is related to its dielectric properties, which in turn depends on water content in the medium (Briciu-Burghina et al. 2022; Nagahage et al. 2019). Impedance sensors determine the amplitude difference in voltage due to changes in impedance between the transmission line of the sensor and the rods that are inserted in the soil medium, which is related to the dielectric permittivity of the soil medium (Matula et al. 2016).

Several manufacturers offer soil moisture meters that come with default calibrations. These calibrations estimate soil water content based on the raw sensor counts of the physical parameter being measured by the sensor, in accordance with its measurement principle. Default calibrations provided by manufacturers often do not achieve the desired accuracy levels consistently, as noted by Varble and Chávez (2011). However, these default calibrations may be suitable when the same soil type as that of the manufacturer is being used and when emphasis is given to the relative soil water changes and trends over time rather than over space. However, the default calibrations come short in cases where soil moisture variations over both time and space are measured, and where the space in consideration is extensive enough for significant variations in soil characteristics to occur. For the latter case, many manufacturers recommend soil-specific calibration to adapt the sensor to various soil types while maintaining acceptable level of accuracies.

While some manufacturers provide users with an opportunity to adapt the sensors to various soil types and to optimize their performance by updating calibration parameters in the instrument, some meters come with limited or no access to raw data nor calibration information. In the latter case, the meter operates in a 'black box' that the user has no control of. However, provided the meter is adequately sensitive to the changes in soil water, its usefulness could still be achieved with a proper site-specific calibration. Calibration in this case is presented as a mathematical expression that directly relates the uncalibrated soil moisture meter readings to the known or accurately determined soil moisture values for that soil. This kind of calibration has been shown to have reasonable outcomes (Merlin et al. 2007). Soil-specific calibration allows users of low-cost soil moisture sensors to achieve sensor performances almost similar to those of sophisticated and expensive sensors.

This study presents an improved method for the calibration of a hand-held soil moisture meter, with suggested adjustments to the determination of gravimetric-based reference values. The calibrated meter was applied to the validation of SMAP Level-4 surface soil moisture data at Sondu-Miriu watershed in Western Kenya, a site with currently no network of installed stationary sensors. SMAP L4 soil moisture is a model-derived value-added surface soil moisture product posted on a 9 km Equal-Area Scalable Earth grid version 2 (EASE-2) with three-hourly simulation intervals, and is derived from a combination of SMAP's radiometric measurements, land surface modelling and climate data (Colliander et al. 2017). Soil moisture ground measurements sampled for the purpose of validating a satellite-based retrieval must be gathered within a reasonable temporal proximity to the satellite overpass or product simulation time. An automated network of spatially distributed stationary sensors is usually installed to collect this kind of validation data in a long-term basis. In the absence of such a network, there is need to sample large areas in a short time, and this demands that the sensor must be both portable and rapidly deployable. While soil moisture measurement methods such as cosmic-ray sensing that have minimal dependence on soil type are technically feasible (Rivera

Villarreyes et al. 2013; Zreda et al. 2008), they are not easily portable nor rapidly deployable and hence their applicability to extended surfaces in short periods remains impractical.

Materials and method

Soil moisture meter (Lutron PMS-714)

Lutron PMS-714 (Master Instruments Pty Ltd, Australia) is a hand-held soil moisture meter, with a cylindrical probe 220 mm long and 10 mm in diameter. Its measurement principle is based on electrical resistivity of a material, and is powered by a 1.5 V direct current power supply with about 12 mA of current. An inbuilt microprocessor infers percentage volumetric moisture content of the soil sample using factory calibration settings; the factory calibration parameters are not accessible to the user. The meter has a measurement range of 0–50% with a resolution of 0.1%. It has a sampling time of approximately 0.8 s, and an operating temperature of 0–50℃. The manufacturer's reported accuracy is ± 5% at 23 ± 5℃ ("Lutron PMS714 Soil Moisture Meter," nd).

Sampling design and data collection

Sondu-Miriu watershed in Western Kenya extends over 3500 square kilometres, covering four soil types in terms of soil texture: coarse, medium, fine, and very fine, according to World Soil Information (ISRIC)'s SoilGrids soil map (Hengl et al. 2017). In view of the extensive and inhomogeneous nature of soil in the study area, calibration of the soil moisture meter on the basis of soil type was considered (Holzman et al. 2017). Soil texture is a spatially variable soil physical parameter with the highest effect on the measurement accuracy of moisture meters (Sharma et al. 2017). Three sampling sites were identified based on the SoilGrids soil texture map shown in Fig. 1, each site representing a 9 × 9 km square sampling unit that correspond to SMAP pixel grid with predominantly one of the three major soil texture classes in the watershed: medium (Kuresoi), fine (Sotik), and very fine (Kapsuser). Coarse texture soil was excluded from the study as it is not a predominant soil type in any of the SMAP pixels within the watershed.

Soil samples were collected from approximately the top 5 cm of soil surface using metallic core rings (Kopecky cylinders) of between 4.05–5.10 cm height and volume of 100 cubic centimetres. Although some studies have been successful in reconstructing soils to imitate natural conditions (Ponce-Hernandez et al. 1986; Power et al. 1981), it should be noted that modifying the soil sample will inevitably alter its soil structure, leading to changes in its water retention capacity (Holzman et al. 2017). Thus, a sampling procedure was adopted that guaranteed minimal disturbance to the collected samples which were collected from undisturbed

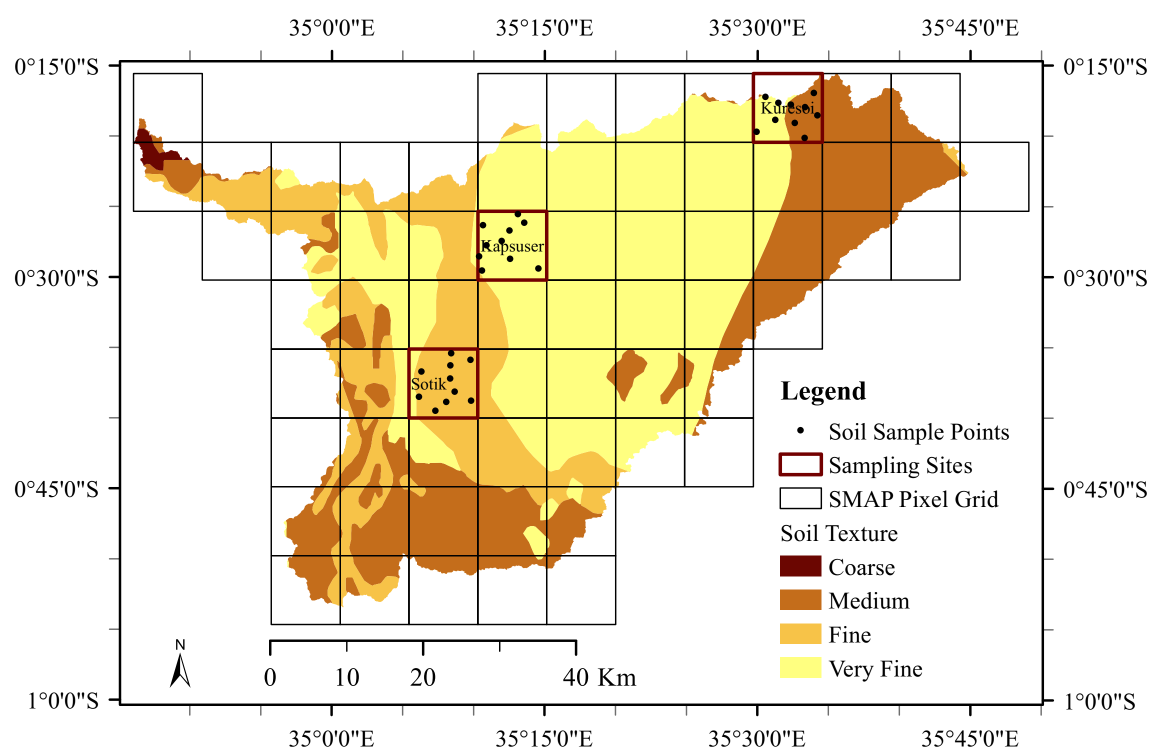

Fig. 1 Soil texture map of Sondu-Miriu watershed, showing the sampling sites and sample points within the sites

terrains away from roads, buildings, and active farmlands. The surface was cleared of any vegetation and other materials on the ground surface, before driving in each core ring until it was just covered by soil. The rings were gently removed by first digging on the sides. Soil was trimmed on both ends of the core ring and sealed off with lids. Ten samples were collected from each sampling site.

Sample preparation and measurement

Lutron PMS-714 was calibrated in the laboratory by tracking the moisture values of field samples (using both the meter and gravimetric method) as the samples gradually dried out from full saturation to the driest possible level under natural conditions. The soil samples were prepared and analyzed at the Soil Science laboratory of the University of Nairobi.

The base of each core ring was wrapped in a filter that allows water to percolate but retains all soil. The samples were saturated by placing them on a pool of water and allowing the soil to soak from the bottom-up for 24 h to allow the soil to attain full saturation. The saturated samples were removed from water and let to dry naturally by evaporation and percolation. As the soil progressively lost water, its soil moisture readings were taken using a moisture meter inserted at the centre of the core ring from the top. For each moisture reading taken, a corresponding weight was measured using a weight scale upon which the soil sample was placed.

Several readings were made until no further change in the moisture meter reading or the weight scale was observed. The soil sample was then oven dried at 105℃ for 24 h, after which the weight of oven-dried soil sample was taken.

Reference soil moisture determination

Reference soil moisture is the moisture value obtained from what is considered the most accurate method of calculating it, based on which all other methods can be assessed. Gravimetric analysis is the standard procedure for determining reference soil moisture ($\theta_{g,i}$) for soil sample (i) in a laboratory process that involves oven-drying the sample at 105℃ for 24 h, and calculating soil moisture as a ratio of masses of water held in the soil sample and that of oven-dried soil sample (Kitić and Crnojević-Bengin 2013):

$$\theta_{g,i} = \frac{m_i - m_{d,i}}{m_{d,i}} \tag{1}$$

where $(m_i - m_{d,i})$ is the weight of water in soil sample i, obtained as the difference between the weight of the sample (m_i) and that of oven-dried sample $(m_{d,i})$.

To allow comparison with some meter measurements and satellite products which are presented in volumetric terms, the gravimetric reference moisture measurements can be converted to volumetric moisture ($\theta_{v,i}$) using laboratory determined bulk density for the respective soil sample, and the density of liquid water. Assuming non-dependence of soil moisture on temperature, the reference soil moisture in volumetric terms can be obtained as:

$$\theta_{v,i} = \theta_{g,i} \times \frac{\rho_{b,i}}{\rho_w} \tag{2}$$

where ρ_w is non-temperature dependent water density, and $\rho_{b,i}$ is the bulk density of soil sample i obtained from the dry weight of the sample $(m_{d,i})$ and the inner volume (v_i) of the core ring used to sample it:

$$\rho_{b,i} = \frac{m_{d,i}}{v_i} \tag{3}$$

Since water density is dependent on its temperature (T), Eq. (2) can be written as:

$$\theta_{v,i}(\rho_w(T)) = \theta_{g,i} \times \frac{\rho_{b,i}}{\rho_w(T)} \tag{4}$$

and the magnitude of error in the computation of soil moisture as a result of the assumptions of Eq. (2) can be evaluated by:

$$\theta_{v,i}\left(\rho_w(T)\right) - \theta_{v,i} = \kappa\theta_{v,i} \tag{5}$$

where

$$\kappa = \frac{\rho_w}{\rho_w(T)} - 1 \tag{6}$$

is a dimensionless temperature-induced error factor in the measurement of sample weight (m_i), resulting from the dependence of water density on temperature. At low temperatures ($T \leq 4$°C), the effect of temperature on water density is minimal ($\rho_w(T) \approx \rho_w$) and Eq. (6) reduces to $\kappa \approx 0$, so that there is no difference between the values of Eqs. (2) and (4).

The temperature dependent volumetric water content can be written by solving Eq. (5) for $\theta_{v,i}\left(\rho_w(T)\right)$:

$$\theta_{v,i}\left(\rho_w(T)\right) = \theta_{v,i}(\kappa + 1) \tag{7}$$

where T is the soil temperature during the measurement of the sample weight (m_i).

Estimation of κ

A plot of κ (Fig. 2) for several sets of temperature and water density values from https://www.internetchemistry.com/chemical-data/water-density-table.php (Andreas 2022) shows that κ increases exponentially with increase in T. Linear regression analysis with least-square sum fitting showed

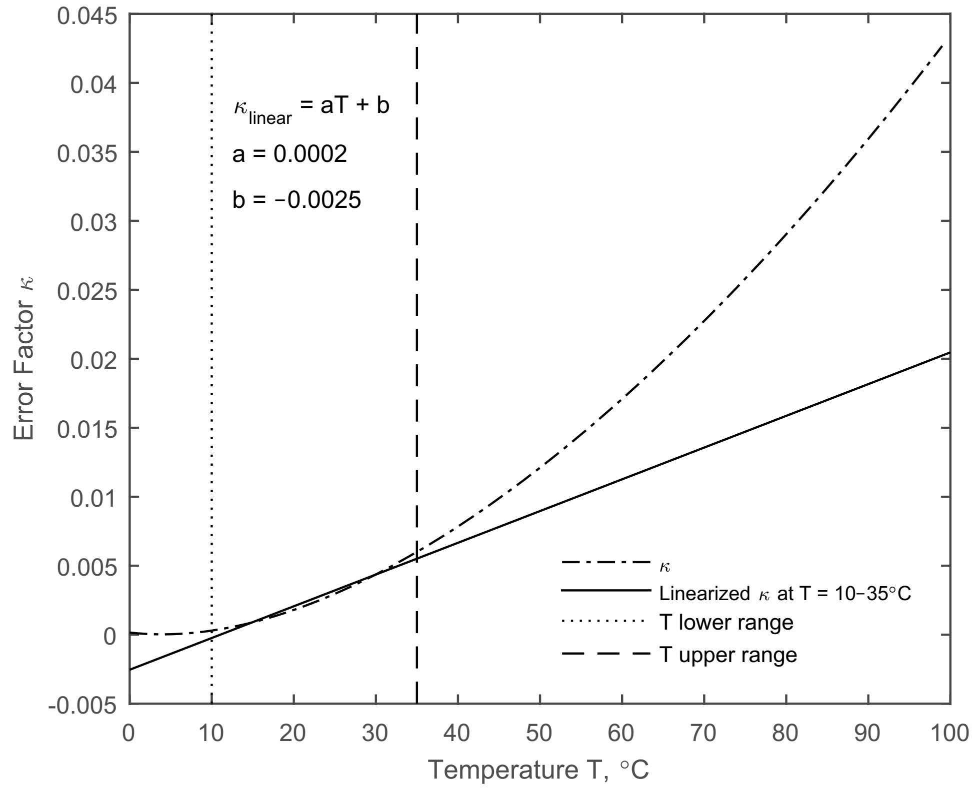

Fig. 2 Relationship between the error factor κ and soil temperature T. The lower and upper bounds of the operational temperature range are indicated

that κ is linearly dependent on T according to Eq. (8) in the temperature range 10–35℃:

$$\kappa \approx aT + b \tag{8}$$

where $a = 0.0002°C^{-1}$, and $b = -0.0025$. 10℃ and 35℃ are respectively the lower and upper bounds of the operational temperature range in this study.

Figure 3 compares soil moisture $\theta_{v,i} = 0.24m^3m^{-3}$ obtained with a unitary water density assumption using Eq. (2), and the corresponding soil moisture with corrected temperature effect obtained using Eq. (7). The temperature factor correction improves soil moisture measurements by up to 0.55% of their values in the temperature range 10–35℃.

Testing spatial scalability of calibrations

Robustness of the calibrations was tested with a view of determining whether calibration equations derived from samples of one site can be scaled out to soils of other sites of similar cluster in terms of their textural properties. In order to ensure all key intrinsic site variabilities were captured in the test, it was necessary to use spatially balanced samples. For this purpose, a sub-basin about 12.5 km^2 was selected in Sotik region – an area adjacent to Sotik sampling site to the South; both areas are generally classified as fine-texture soil type according to SoilGrids texture map. A geostatistically balanced sampling design was constructed to ensure no more sampling cost and effort than is necessary was expended, and to improve the statistical efficiency of derived sample data by maximizing spatial independence among sample locations (Theobald et al. 2007). The design took into account altitude (which partially controls drainage due to local elevation differences), and vegetation cover (which principally controls soil water retention capacity through precipitation interception and evapotranspiration, as well as humous matter deposition), to define an inclusion probabilities criterion necessary for the selection of sampling points. Altitude information was derived from SRTM digital elevation model, while land cover was obtained from Landsat 8 satellite imagery. The resulting sampling design and the validation analysis are presented in Section "Comparison of Calibrated Meter Values with SMAP Data".

Determining the operational moisture range

Each soil type displayed a unique relationship between soil moisture meter readings and the corresponding reference measurements, but they all largely followed a similar pattern shown in Fig. 4. The pattern exhibited by the calibration curves in its full range can best be described by a polynomial expression of order four. The highest point in the curve physically represents the soil saturation point, which is the maximum possible moisture content of the soil, attained when all the soil pores are filled with water molecules. The

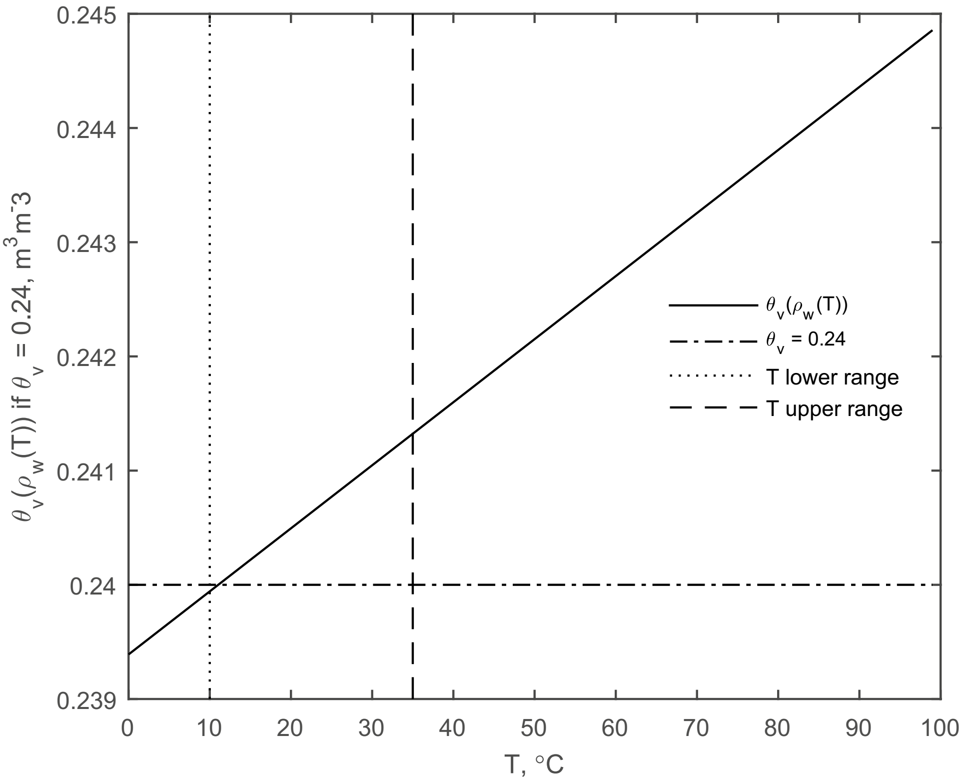

Fig. 3 Comparison of soil moisture $\theta_{v,i} = 0.24m^3m^{-3}$ and temperature-adjusted soil moisture $\theta_{v,i}\left(\rho_w(T)\right)$ across the soil temperature spectrum. The lower and upper bounds of the operational temperature range are indicated

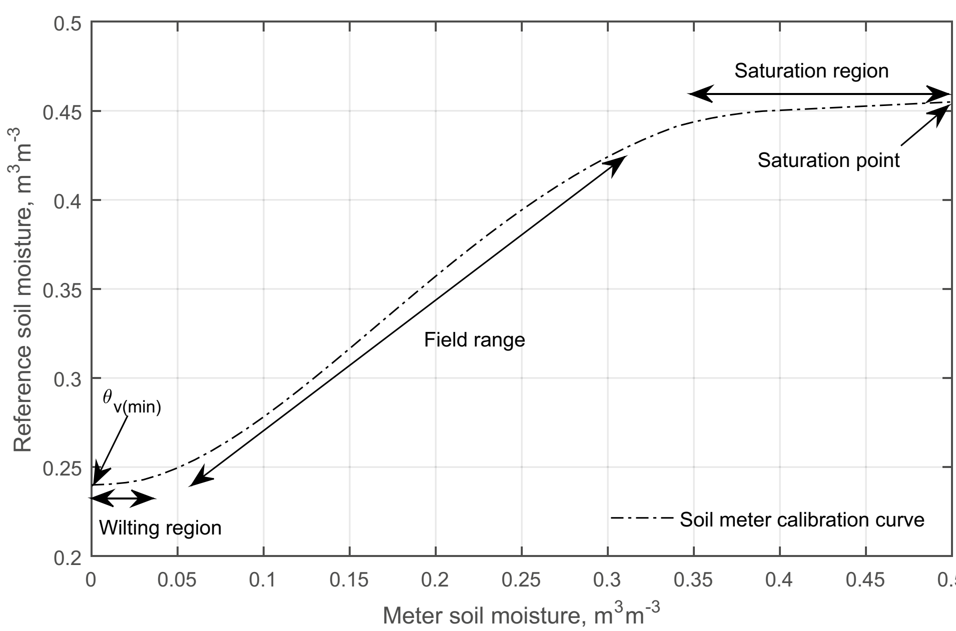

Fig. 4 The pattern exhibited by the calibration curve of a soil moisture meter

y-intercept is the lowest point of the curve ($\theta_{v(min)}$), which physically represents the lowest moisture content the soil retains when it reaches its driest level under natural conditions, attained when the soil holds the water molecules in the micropores so strongly as to inhibit plant water uptake processes (Assi et al. 2018; Garg et al. 2020), and basically shuts down evapotranspiration (Hohenegger and Stevens 2018).

The central portion of the calibration curve displays a near linear relationship between the two sets of soil moisture values, and physically represents the field moisture range of soil – the range between the field capacity and wilting point of soil. Field capacity is the amount of water held by the soil when the rate of gravitational drainage has substantially decreased having drained much of the excess water (Rai et al. 2017; Weiler and McDonnell 2004), and the internal drainage becomes essentially negligible (Zettl et al. 2011). The calibration curve flattens at saturation and wilting regions of the curve—which are on either ends of the field range, with meter showing a disproportionately higher response compared to reference values. In the example shown in Fig. 4, a moisture meter could report a figure between 0.35 and 0.50 (a moisture range of 0.15 m^3/m^3) corresponding to reference moisture values of 0.445–0.455 (a moisture range of 0.01 m^3/m^3). Operating the meter at either of these two regions is therefore considered unreliable. For the practical application in this study, the calibration equations were derived from the field range of the calibration curves, where the meter sensitivity and the calibration equations are adequately reliable, and where most of the field survey values fall.

Results and discussion

Determining the calibration equations

The soil moisture meter was calibrated for each soil type using linear models presented in Fig. 5a–c, obtained by comparing the meter measurements with gravimetric-based

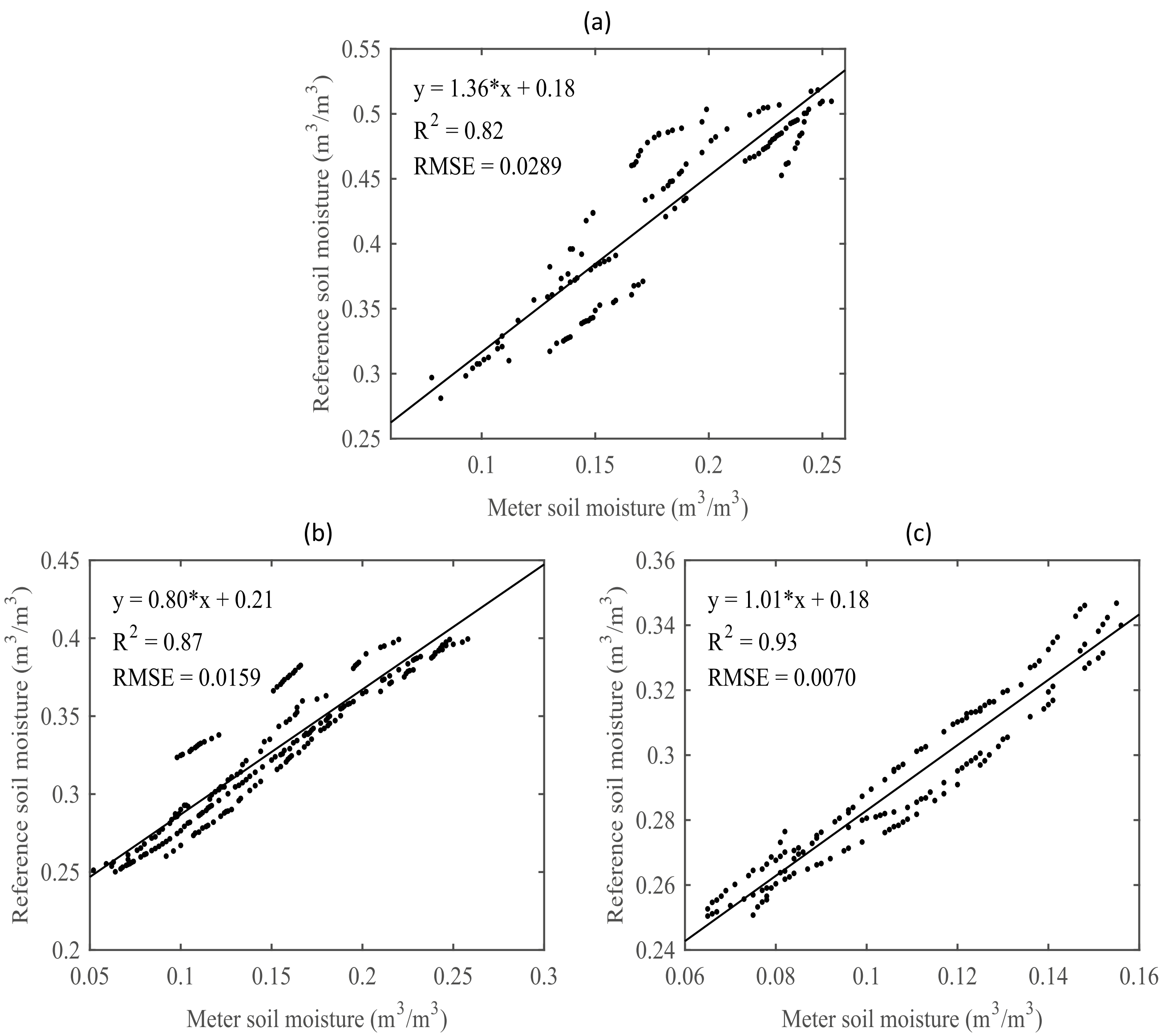

Fig. 5 The field-range portion of the meter calibration curves for medium **a**, fine **b**, and very fine **c** soil samples obtained from Kuresoi, Sotik, and Kapsuser sampling sites, respectively. A linear fit of the datapoints and a calibration equation are indicated for each site

reference measurements. A calibration equation for each soil type and the correlation statistics are indicated in the diagrams. The reference values were computed using temperature-adjusted Eq. (7) at laboratory room temperature of 23℃. Four soil samples were used to calibrate the meter for each soil type.

The calibration curve obtained from four soil samples from Kuresoi sampling site presented in Fig. 5a shows that the calibration data for this site was fitted to R^2 of 0.82 and RMSE of 0.0289 m^3/m^3. The calibration curve for soils from Sotik sampling site presented in Fig. 5b shows that the calibration data for this site was fitted to R^2 of 0.87 and RMSE of 0.0159 m^3/m^3. The calibration curve for soils from Kapsuser sampling site presented in Fig. 5c shows that the calibration data for this site was fitted to R^2 of 0.93 and RMSE of 0.007 m^3/m^3.

Validation of calibration equations

Validation of the calibration equations was achieved by comparing meter values taken in the field (calibrated and uncalibrated) with the corresponding gravimetric-based reference moisture measured in the laboratory using samples collected simultaneously with the meter readings. The calibrated meter values were obtained by applying calibration equations of Fig. 5 to the moisture meter measurements from respective sites.

The validation results are presented in Fig. 6a–c and summarized in Table 1. Values in brackets indicate pre-calibration error statistics. A positive bias indicates an overestimation, while a negative bias indicates an underestimation with respect to the reference moisture values. These results show that the reference moisture values compare well with the calibrated (uncalibrated) meter moisture values with R^2 of 0.80, 0.83, 0.85 (0.80, 0.83, 0.85) and RMSE of 0.022, 0.010, 0.010 m^3/m^3 (0.016, 0.012, 0.010 m^3/m^3), respectively for medium, fine, and very fine soil types. These correlation indicators do not seem to improve with calibration since all field moisture values fall within the near linear portion of the calibration curve (field range). Nonetheless, the reported errors are better than the manufacturer's reported errors of ± 0.05 m^3/m^3 with factory calibrations. Calibrated meter values, however, show significantly reduced bias values (+ 0.009, + 0.004, -0.001 m^3/m^3) compared to the uncalibrated biases (-0.216, -0.181, -0.184 m^3/m^3), respectively for medium, fine, and very fine soil types, indicating that the calibrated values are much closer to the expected (reference) values than the uncalibrated values are.

Calibration of Lutron PMS-714 at field conditions as presented in this study compares with those of other instruments, which have a reported RMSE of 0.016–0.04 m^3/m^3 for TDR (Francesca et al. 2010; Gnatowski et al. 2018), and 0.025–0.036 m^3/m^3 for capacitance sensors (Francesca et al. 2010). These figures are however obtained by calibrating the sensors to specific soil characteristics. Results of soil texture-based calibrations in this study agree with those reported by Rowlandson et al. (2013), with R^2 of 081–0.85 and RMSE of 0.04–0.05 m^3/m^3.

These results demonstrate that a proper calibration can improve the accuracy and reliability of low-cost sensors, and consequently reduce the opportunity cost of choosing them over sophisticated sensors, in agreement with findings of Schwamback et al. (2023).

A study by Louki and Al-Omran (2023) reports that proximal soil moisture sensors are most accurate at temperatures close to 25℃. This is optimal for the sampling of soil moisture at warmer areas like Sondu-Miriu watershed, which is near the equator with temperatures well within 10–35℃ for most parts of the year (Omumbo et al. 2011; Wanjala and Kweka 2016). This study on the other hand shows that gravimetric measurements are most accurate at near freezing temperatures, and measurement errors increase exponentially with temperature. But since during soil moisture meter calibration, both meter and gravimetric measurements must be taken simultaneously at laboratory room temperatures which are typically about 20–23℃, the importance of the temperature correction procedure proposed in this study becomes evident.

Comparison of calibrated meter values with SMAP data

The calibrated meter values for the same data presented in Fig. 6 were compared with SMAP Level-4 surface soil moisture data, whose product simulation time match the ground data sampling time. This comparison is presented in Fig. 7a-c. These results show a good agreement between the calibrated meter values and SMAP soil moisture values, with R^2 of 0.81, 0.83, 0.88, an RMSE of 0.010, 0.007, 0.008 m^3/m^3 and a bias of 0.030, -0.014, -0.002 m^3/m^3, respectively for medium, fine, and very fine soil types, which are within the SMAP mission objective RMSE value of 0.04 m^3/m^3 (O'Neill et al. 2011).

Spatial scalability of calibrations

The sampling design for the scalability test is presented in Fig. 8a, showing locations of 20 spatially balanced sampling points. A set of soil moisture meter measurements collected from the 20 sampling points were compared with gravimetric-based moisture measurements of soil samples collected simultaneously from the same locations. Calibration equation for Sotik site defined in Fig. 5b was applied to the meter measurements. The corrected meter measurements were compared with gravimetric-based reference moisture values in a regression analysis shown in Fig. 8b.

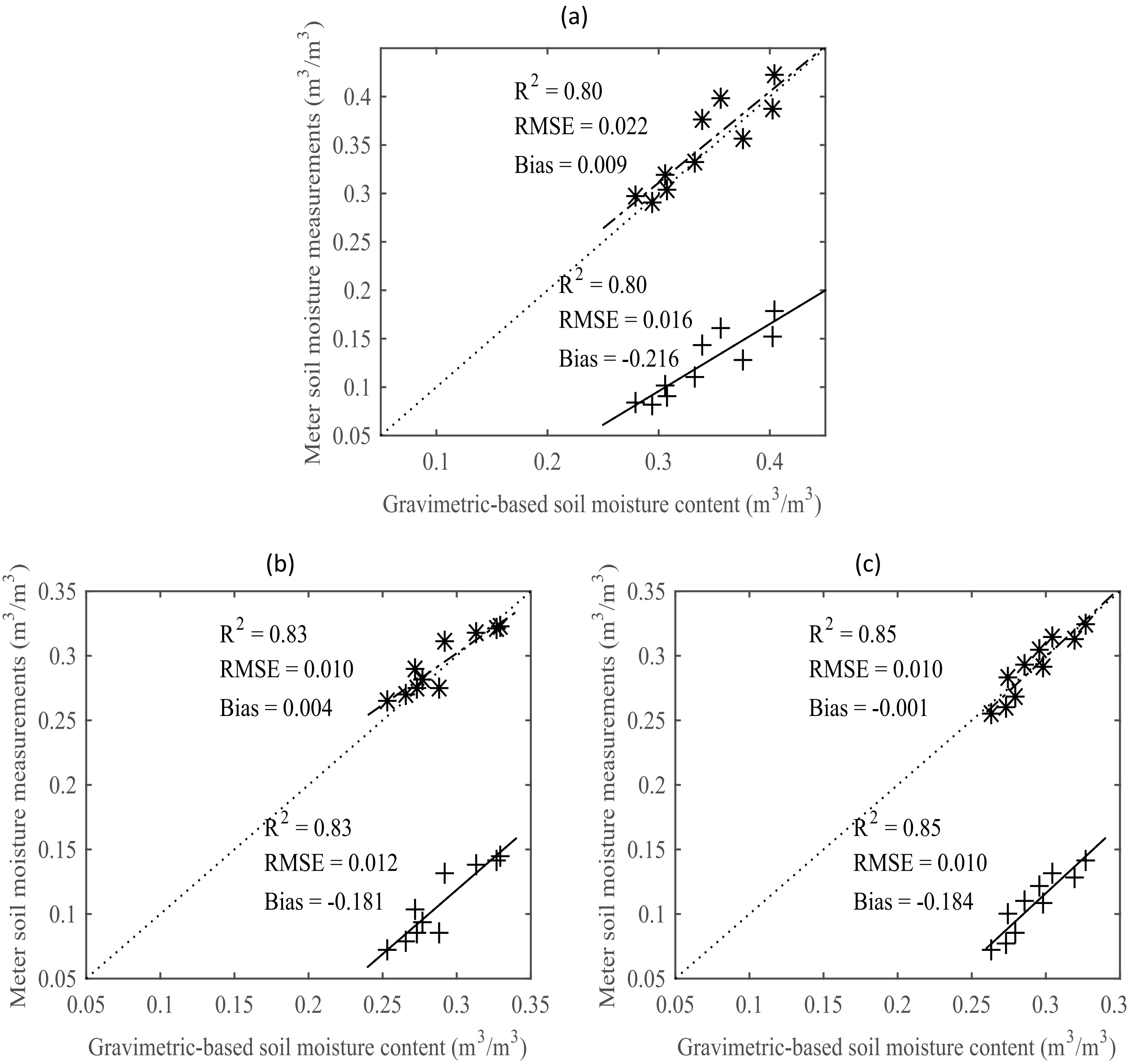

Fig. 6 Graphs of calibrated (*) and uncalibrated (+) moisture meter values vs. gravimetric-based reference values for medium **a**, fine **b**, and very fine **c** soil samples

Table 1 Validation results for the calibration of a soil moisture meter. Values in brackets indicate pre-calibration error values

Sampling site (Soil texture)	Kuresoi (medium)	Sotik (fine)	Kapsuser (very fine)
R^2	0.80 (0.80)	0.83 (0.83)	0.85 (0.85)
RMSE (m^3/m^3)	0.022 (0.016)	0.010 (0.012)	0.010 (0.010)
Bias (m^3/m^3)	+0.009 (-0.216)	+0.004 (-0.181)	-0.001 (-0.184)

With $R^2 = 0.81$, RMSE = 0.016 m^3/m^3, and Bias = +0.005 m^3/m^3, these results show that the corrected moisture values compare well with reference moisture values, indicating that the calibration is adequately robust and can be applied to soils of other sites with similar soil texture regime.

Conclusions

A hand-held soil moisture meter (Lutron PMS-714) was calibrated for three main soil types of Sondu-Miriu watershed as classified according to texture: medium, fine, and very fine,

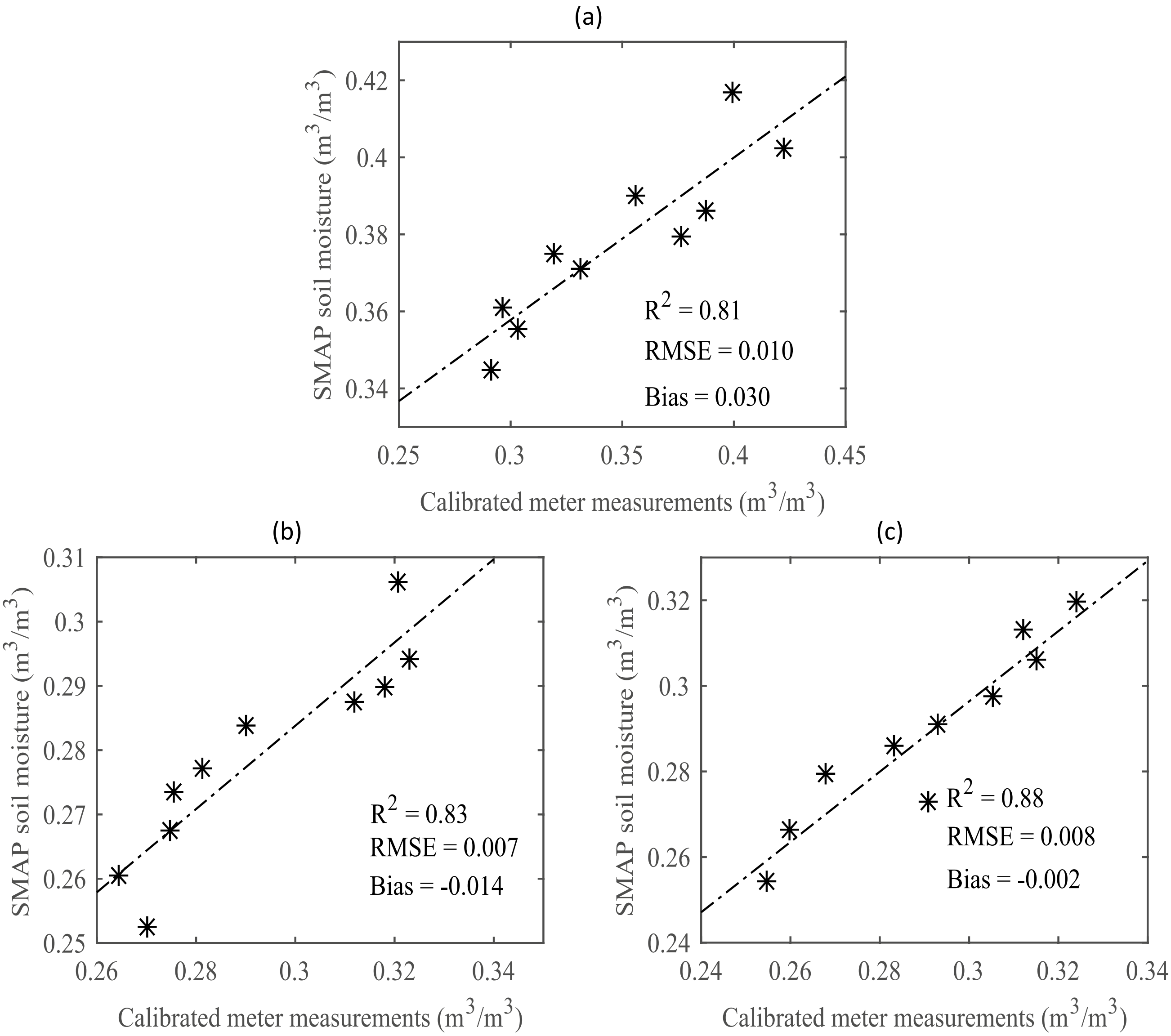

Fig. 7 Comparison of calibrated moisture meter values vs. SMAP surface moisture values for medium **a**, fine **b**, and very fine **c** soil samples

with the objective of adapting the instrument to the specific soil types to permit gathering of reliable in-situ soil moisture measurements. Instrument calibration was carried out using data from the field determined based on gravimetric method. The equation for deriving gravimetric-based reference soil moisture was improved by introducing a temperature correction term, which takes away the assumption of unitary water density and introduces a relationship for the dependence of derived soil moisture on the temperature of soil samples. This temperature correction term improves reference moisture by up to 0.55% of its value in the temperature range 10–35℃.

A fourth order polynomial curve was found to best describe the relationship between the meter and the reference moisture values, but generation of calibration equations was restricted to the field moisture range of the curve, which is nearly linear. Therefore, a linear model was used to calibrate the meter in a laboratory process in which soil moisture of field samples were monitored using both the meter and gravimetric method as the samples gradually dried out. This produced two sets of moisture data that was fitted to within R^2 of 0.82–0.93 and RMSE of 0.0070–0.0289 m^3/m^3. The resulting meter calibration equations were validated with field data to within R^2 of 0.80–0.85 and RMSE of 0.010–0.022 m^3/m^3, a significant improvement from manufacturer's reported errors of $\pm$ 0.05 m^3/m^3. Though the reported field validation errors are larger than those of lab-based errors, it is generally established that application of laboratory-developed calibration equations to correct field measurements

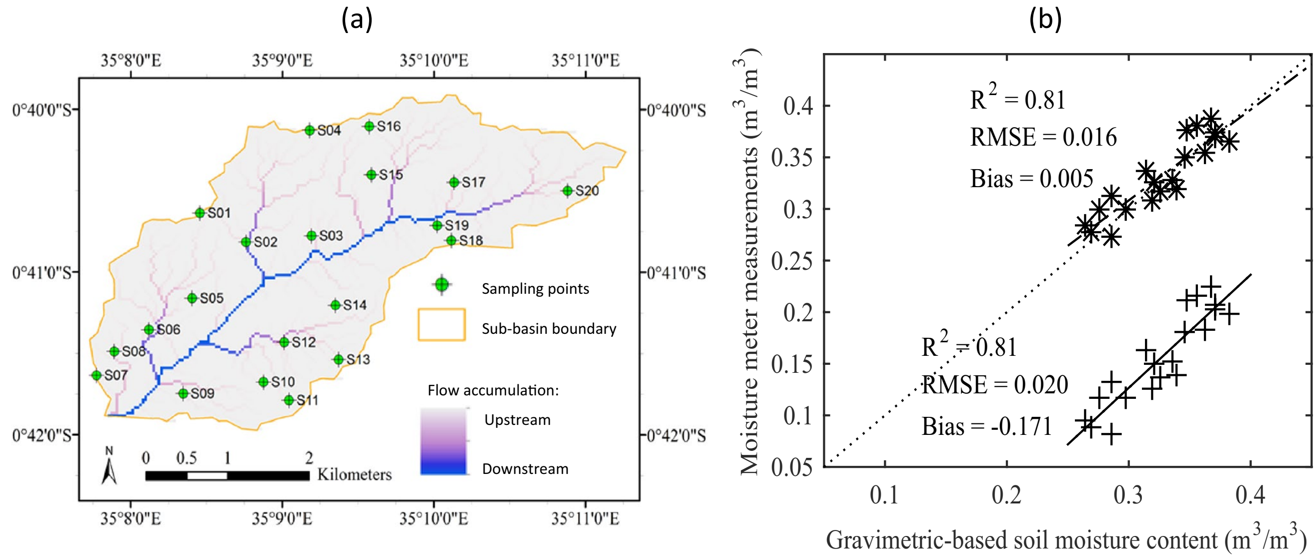

Fig. 8 A sampling design for collecting spatially balanced soil moisture data for the scalability test at Sotik sub-basin **a**, and the results of a scalability test **b**, showing calibrated (*) and uncalibrated (+) moisture meter values vs. gravimetric-based reference values

may not consistently yield the expected laboratory-based accuracies, but they often produce better results than factory calibrations (Varble and Chávez 2011). Additionally, validation results show that calibrations do not improve significantly the correlation statistics of meter values with respect to reference moisture values, but significantly reduce biases (+0.009, +0.004, -0.001 m^3/m^3) compared to uncalibrated ones (-0.216, -0.181, -0.184 m^3/m^3), respectively for medium, fine, and very fine soil types, indicating that calibrations correct for major underestimations by the meter. Comparison of calibrated meter values with SMAP surface soil moisture data produced errors (RMSE of 0.010, 0.007, 0.008 m^3/m^3) that are well within the SMAP mission objective value of 0.04 m^3/m^3. Tests carried out at Sotik region showed that the calibrations are adequately robust, permitting application of the calibration equations to sites of similar soil texture regime.

Author contributions All authors contributed to the conceptual design, methodology, investigation, and validation. C.M. and M.M. provided supervision. E.C. drafted the manuscript, and all authors reviewed the manuscript.

Funding This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests The authors declare no competing interests.

References

Adla S, Rai NK, Karumanchi SH, Tripathi S, Disse M, Pande S (2020) Laboratory calibration and performance evaluation of low-cost capacitive and very low-cost resistive soil moisture sensors. Sensors 20:363. https://doi.org/10.3390/s20020363

Andreas J (2022) Water density table [WWW Document]. Internetchemistry. URL https://www.internetchemistry.com/chemical-data/water-density-table.php (accessed 3.7.23)

Assi AT, Mohtar RH, Braudeau E (2018) Soil pedostructure-based method for calculating the soil-water holding properties. MethodsX 5:950–958. https://doi.org/10.1016/j.mex.2018.08.006

Bell JP (1987) Neutron probe practice. 3rd edition. (Publication - Report No. 19). Institute of Hydrology, Wallingford

Briciu-Burghina C, Zhou J, Ali MI, Regan F (2022) Demonstrating the potential of a low-cost soil moisture sensor network. Sensors 22:987. https://doi.org/10.3390/s22030987

Colliander A, Jackson TJ, Bindlish R, Chan S, Das N, Kim SB, Cosh MH, Dunbar RS, Dang L, Pashaian L, Asanuma J, Aida K, Berg A, Rowlandson T, Bosch D, Caldwell T, Caylor K, Goodrich D, Jassar H, Lopez-Baeza E, Martínez-Fernández J, González-Zamora A, Livingston S, McNairn H, Pacheco A, Moghaddam M, Montzka C, Notarnicola C, Niedrist G, Pellarin T, Prueger J, Pulliainen J, Rautiainen K, Ramos J, Seyfried M, Starks P, Su Z, Zeng Y, van der Velde R, Thibeault M, Dorigo W, Vreugdenhil M, Walker JP, Wu X, Monerris A, O'Neill PE, Entekhabi D, Njoku EG, Yueh S (2017) Validation of SMAP surface soil moisture products with core validation sites. Remote Sens Environ 191:215–231. https://doi.org/10.1016/j.rse.2017.01.021

Francesca V, Osvaldo F, Stefano P, Paola RP (2010) Soil moisture measurements: comparison of instrumentation performances. J Irrig Drain Eng 136:81–89. https://doi.org/10.1061/(ASCE)0733-9437(2010)136:2(81)

Garg A, Bordoloi S, Ganesan SP, Sekharan S, Sahoo L (2020) A relook into plant wilting: observational evidence based on unsaturated soil–plant-photosynthesis interaction. Sci Rep 10:22064. https://doi.org/10.1038/s41598-020-78893-z

Gnatowski T, Szatyłowicz J, Pawluśkiewicz B, Oleszczuk R, Janicka M, Papierowska E, Szejba D (2018) Field calibration of TDR to assess the soil moisture of drained peatland surface layers. Water 10:1842. https://doi.org/10.3390/w10121842

Hengl T, de Jesus JM, Heuvelink GBM, Gonzalez MR, Kilibarda M, Blagotić A, Shangguan W, Wright MN, Geng X, Bauer-Marschallinger B, Guevara MA, Vargas R, MacMillan RA, Batjes NH, Leenaars JGB, Ribeiro E, Wheeler I, Mantel S, Kempen B (2017) SoilGrids250m: Global gridded soil information based on machine learning. PLoS ONE 12:e0169748. https://doi.org/10.1371/journal.pone.0169748

Hensley DL, Deputy JC (1999) Using tensiometers for measuring soil water and scheduling irrigation (CTAHR No. L–10), Landscape. Cooperative Extension Service, College of Tropical Agriculture & Human Resources, University of Hawaii at Manoa, Manoa, Hawaii

Hohenegger C, Stevens B (2018) The role of the permanent wilting point in controlling the spatial distribution of precipitation. Proc Natl Acad Sci 115:5692–5697. https://doi.org/10.1073/pnas.1718842115

Holzman M, Rivas R, Carmona F, Niclòs R (2017) A method for soil moisture probes calibration and validation of satellite estimates. MethodsX 4:243–249. https://doi.org/10.1016/j.mex.2017.07.004

Johnson AI (1962) Methods of measuring soil moisture in the field (USGS Numbered Series No. 1619- U), Methods of measuring soil moisture in the field, Water Supply Paper. U.S. G.P.O., Washington. https://doi.org/10.3133/wsp1619U

Kitić G, Crnojević-Bengin V (2013) A sensor for the measurement of the moisture of undisturbed soil samples. Sensors 13:1692–1705. https://doi.org/10.3390/s130201692

Louki II, Al-Omran AM (2023) Calibration of soil moisture sensors (ECH2O-5TE) in hot and saline soils with new empirical equation. Agronomy 13:51. https://doi.org/10.3390/agronomy13010051

Lutron PMS714 Soil Moisture Meter [WWW Document], n.d. URL https://www.master-instruments.com.au/products/59341/PMS714.html (accessed 10.22.23).

Matula S, Báťková K, Legese WL (2016) Laboratory performance of five selected soil moisture sensors applying factory and own calibration equations for two soil media of different bulk density and salinity levels. Sensors 16:1912. https://doi.org/10.3390/s16111912

Merlin O, Walker J, Panciera R, Young R, Kalma J, Kim JE (2007) Soil moisture measurement in heterogeneous terrain. In: Oxley, L., Kulasiri, D. (Eds.), Land, Water and Environmental Management: Integrated Systems for Sustainability. Presented at the MODSIM 2007 International Congress on Modelling and Simulation, Modelling and Simulation Society of Australia and New Zealand, Christchurch, New Zealand, pp. 2604–2610

Nagahage EAAD, Nagahage ISP, Fujino T (2019) Calibration and validation of a low-cost capacitive moisture sensor to integrate the automated soil moisture monitoring system. Agriculture 9:141. https://doi.org/10.3390/agriculture9070141

O'Neill P, Entekhabi D, Njoku E, Kellogg K (2011) The NASA Soil Moisture Active Passive (SMAP) mission: Overview. In: 2010 IEEE International Geoscience and Remote Sensing Symposium. Presented at the 2010 IEEE International Geoscience and Remote Sensing Symposium, Institute of Electrical and Electronics Engineers, Honolulu, HI, pp. 3236–3239. https://doi.org/10.1109/IGARSS.2010.5652291

Omumbo JA, Lyon B, Waweru SM, Connor SJ, Thomson MC (2011) Raised temperatures over the Kericho tea estates: revisiting the climate in the East African highlands malaria debate. Malar J 10:1–16. https://doi.org/10.1186/1475-2875-10-12

Ponce-Hernandez R, Marriott FHC, Beckett PHT (1986) An improved method for reconstructing a soil profile from analyses of a small number of samples. J Soil Sci 37:455–467. https://doi.org/10.1111/j.1365-2389.1986.tb00377.x

Power JF, Sandoval FM, Ries RE, Merrill SD (1981) Effects of topsoil and subsoil thickness on soil water content and crop production on a disturbed soil. Soil Sci Soc Am J 45:124–129. https://doi.org/10.2136/sssaj1981.03615995004500010027x

Rai RK, Singh VP, Upadhyay A (2017) Chapter 17 - Soil Analysis. In: Rai, R.K., Singh, V.P., Upadhyay, A. (Eds.), Planning and Evaluation of Irrigation Projects. Academic Press, pp. 505–523. https://doi.org/10.1016/B978-0-12-811748-4.00017-0

Richards L, Weaver L (1943) The sorption-block soil moisture meter and hysteresis effects related to its operation. J Am Soc Agron 35:1002–1011

Rivera Villarreyes CA, Baroni G, Oswald SE (2013) Calibration approaches of cosmic-ray neutron sensing for soil moisture measurement in cropped fields. Hydrol Earth Syst Sci Discuss 10:4237–4274. https://doi.org/10.5194/hessd-10-4237-2013

Robinson DA, Campbell CS, Hopmans JW, Hornbuckle BK, Jones SB, Knight R, Ogden F, Selker J, Wendroth O (2008) Soil moisture measurement for ecological and hydrological watershed-scale observatories: a review. Vadose Zone 7:358–389. https://doi.org/10.2136/vzj2007.0143

Rowlandson TL, Berg AA, Bullock PR, Ojo ER, McNairn H, Wiseman G, Cosh MH (2013) Evaluation of several calibration procedures for a portable soil moisture sensor. J Hydrol 498:335–344. https://doi.org/10.1016/j.jhydrol.2013.05.021

Schwamback D, Persson M, Berndtsson R, Bertotto LE, Kobayashi ANA, Wendland EC (2023) Automated low-cost soil moisture sensors: trade-off between cost and accuracy. Sensors 23:2451. https://doi.org/10.3390/s23052451

Sharma H, Shukla MK, Bosland PW, Steiner R (2017) Soil moisture sensor calibration, actual evapotranspiration, and crop coefficients for drip irrigated greenhouse chile peppers. Agric. Water Manag. Special Issue on Improving Agricultural Water Productivity to Ensure Food Security under Changing Environments Overseen by: Brent Clothier 179:81–91. https://doi.org/10.1016/j.agwat.2016.07.001

Sharma PK, Kumar D, Srivastava HS, Patel P (2018) Assessment of different methods for soil moisture estimation: a review. J Remote Sens GIS 9:57–73

Shock CC, Barnum JM, Seddigh M (1998) Calibration of watermark soil moisture sensors for irrigation management. Presented at the International Irrigation Show, San Diego, pp. 139–146

Theobald DM, Stevens DL, White D, Urquhart NS, Olsen AR, Norman JB (2007) Using GIS to generate spatially balanced random survey designs for natural resource applications. Environ Manage 40:134–146

Varble JL, Chávez JL (2011) Performance evaluation and calibration of soil water content and potential sensors for agricultural soils in eastern Colorado. Agric Water Manag 101:93–106. https://doi.org/10.1016/j.agwat.2011.09.007

Wanjala CL, Kweka EJ (2016) Impact of highland topography changes on exposure to Malaria Vectors and Immunity in Western Kenya. Front Public Health 4:208917. https://doi.org/10.3389/fpubh.2016.00227

Weiler M, McDonnell JJ (2004) Soil development and properties | water storage and movement. In: Burley, J. (Ed.), Encyclopedia of Forest Sciences. Elsevier, Oxford, pp. 1253–1260. https://doi.org/10.1016/B0-12-145160-7/00249-0

Zermeño-González A, Munguia-López J, Cadena-Zapata M, Campos-Magaña SG, Ibarra-Jiménez L, Rodríguez-García R (2012) Critical evaluation of different techniques for determining soil water content, In: Kumar, M. (Ed.), Problems, Perspectives and Challenges of Agricultural Water Management. InTech, Rijeka, Croatia, pp. 199–216

Zettl J, Lee Barbour S, Huang M, Si B, Leskiw LA (2011) Influence of textural layering on field capacity of coarse soils. Can J Soil Sci 91:133–147. https://doi.org/10.4141/cjss09117

Zreda M, Desilets D, Ferré TPA, Scott RL (2008) Measuring soil moisture content non-invasively at intermediate spatial scale using cosmic-ray neutrons. Geophys Res Lett 35:L21402. https://doi.org/10.1029/2008GL035655

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.