Smart Agricultural Technology 12 (2025) 101596

Contents lists available at ScienceDirect

Smart Agricultural Technology

journal homepage: www.journals.elsevier.com/smart-agricultural-technology

Application of low-cost soil moisture sensors for irrigation management in *Brassica oleracea* var. acephala cultivation

Valdemiro Simão João Pitoro [a,b,*], Cleber Alexandre de Amorim [a], José Rafael Franco [a], Rodrigo Máximo Sánchez-Román [a]

[a] Department of Rural Engineering, Faculty of Agronomic Sciences (FCA), São Paulo State University (UNESP), Avenida Universitária, 3780, P.O. Box 18610-034, Botucatu, São Paulo, Brazil

[b] Faculty of Agrarian Sciences (FCA), Department of Rural Engineering, Lúrio University (UniLúrio), Niassa Province, Km 32, Sanga District, Unango, EN 733, Mozambique

ARTICLE INFO

Keywords:
Precision agriculture
Arduino
Irrigation management
Capacitive sensors
Low-cost technology

ABSTRACT

Water scarcity demands efficient irrigation, yet conventional technologies remain inaccessible to low-income farmers. Low-cost, easy-to-use sensors represent a promising alternative. This study develop and evaluate a soil moisture monitoring system using low-cost capacitive sensors (SKU: CE09640) integrated with an Arduino microcontroller, featuring RGB LED alerts to indicate soil water status. Field validation was conducted in kale (*Brassica oleracea* var. *acephala*) cultivation, comparing three irrigation management (IM) strategies: crop evapotranspiration (ETc), tensiometers (IMT), and capacitive sensors (IMC). Sensors were calibrated in the laboratory using the gravimetric method. The experiment followed a randomized block design in a 4 × 3 factorial scheme, with four irrigation levels (50 %, 75 %, 100 %, and 125 % of the irrigation depth estimated by each method). Number of commercial (NCL) and non-commercial leaves (NNCL), fresh weight (FMML), number of mature leaves (NML), and water use productivity (WUP) were evaluated. Calibration results showed a strong inverse correlation ($R < -0.964$), high fit ($R^2 > 0.95$), and acceptable accuracy (RMSE < 0.05) in predicting soil moisture compared to gravimetric method. Field validation revealed no significant interaction between factors and similar performance among IM strategies for most variables. ETc-based IM showed the highest WUP (12.42 g L^{-1}), followed by IMC (10.95 g L^{-1}), and IMT (9.82 g L^{-1}), indicating that the SKU: CE09640 sensors enables greater water savings than conventional devices like tensiometers. The findings support the use of SKU: CE09640 sensors is a viable, accessible solution for IM, promoting efficient water use and benefiting smallholder farmers with limited educational backgrounds or technical training.

1. Introduction

According to United Nations projections, the global population may rise from 8 billion to 9.7 billion by 2050 [1,2]. Meeting the food demand of this constantly growing population will require an estimated 70 % increase in agricultural production over the next 26 years. At the same time, the availability of arable land and water resources has been steadily declining [3], with water scarcity recognized as one of the greatest challenges to agricultural development. In this context, irrigation emerges as a key strategy to secure sustainable food production; however, it is also one of the agricultural practices that most intensively consumes water and exacerbates resource scarcity. Therefore, sustainable solutions must reconcile the essential role of irrigation with the urgent need to optimize water use [4].

Vegetable cultivation is highly dependent on water, making it particularly vulnerable to scarcity. Kale exemplifies this demand, as a nutritionally rich crop whose productivity is strongly affected by irrigation practices. Both water deficit and overirrigation reduce yields and increase costs, highlighting irrigation management (IM) as a central pillar for sustainable vegetable production [5,6].

Fares and Alva (2000); Schlank et al. (2024) [7,8] state that a common problem in any irrigation system is determining the appropriate duration of irrigation and the amount of water to be applied per irrigation event. They also noted that farmers typically rely on visual assessment of crop response to decide when to irrigate; however, in most cases, these visual signs correspond to levels of water stress that

* Corresponding author.
E-mail address: valdemiro.pitoro@unesp.br (V.S.J. Pitoro).

https://doi.org/10.1016/j.atech.2025.101596
Received 23 August 2025; Received in revised form 1 October 2025; Accepted 1 November 2025
Available online 3 November 2025
2772-3755/© 2025 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

negatively affect crop growth and/or yield. Recent studies [9,10] confirm that this practice remains widespread, particularly in developing regions, where limited access of technology and technical training constrains the adoption of more precise IM techniques. This scenario highlights the relevance of exploring accessible and easy-to-use or implement alternatives for IM.

Given the central role of IM in sustaining productivity, recent studies have explored low-cost technologies to support decision-making. In the review by Margiwiyatno et al. (2025) [11], several affordable IM solutions are discussed, including models such as the SKU: CE09640 sensor. However, despite their economic accessibility, many devices remain operationally complex [12–14], which restricts adoption among farmers with limited technical training [15]. Furthermore, most commercially available capacitive soil moisture sensors still require technical expertise and agricultural experience for effective use [11,16]. These constraints underscore the need for research into solutions that combine affordability with operational simplicity [17].

IM aims to determine the optimal amount and appropriate timing of irrigation to meet crop water requirements. It is an essential practice not only to ensure the efficient use of water and the resulting increase in productivity, but also to promote the efficient use of other agricultural inputs and production factors that influence final yield. Proper IM will become even more critical as water access restrictions continue to increase [18], which is a major concern in irrigated agriculture, especially in vegetable cultivation, and requires locally adapted solutions [19]. Various tools have been developed to estimate the correct crop water demand and determine the optimal timing for irrigation in a timely and efficient manner, including weather stations, aerial and satellite-based remote sensing platforms, computer models, plant feedback sensors, and soil moisture sensors [20–22]. Soil moisture sensors have proven to be effective for IM, contributing to increased productivity and water conservation [23,24]. These sensors can detect moisture deficiencies before visual symptoms appear [25].

As a core component of IM, irrigation scheduling can be carried out based on: 1) soil moisture in the plant root zone, 2) the amount of water lost through evapotranspiration, and 3) the plant's response to water stress [24,26]. Soil moisture–based irrigation scheduling has been in use for a longer time compared to the other methods [23,24] in this method, the amount of water to be applied and the timing of irrigation are calculated based on the available soil moisture, which can be determined by weighing and drying soil samples from the area of interest (gravimetric method) [27,28]. However, this process can be time-consuming and labor-intensive, as proper irrigation management may require frequent measurements [12]. The gravimetric method is not able to provide real-time soil moisture measurements, become practically infeasible for large field in situ soil moisture measurements [14].

In recent years, driven by scientific and technological advances and the deepening of soil science studies, several direct and indirect methods and devices for detecting soil moisture have been developed and made commercially available, with the aim of overcoming the limitations of real-time monitoring and spatiotemporal variability. These methods are generally evaluated in terms of cost and accessibility, accuracy and reliability, spatial and temporal resolution, response time, durability and maintenance requirements, and sensitivity to soil-specific factors such as salinity, texture, and temperature. In this context, earlier researchers have employed a wide range of techniques for soil moisture measurement [53], including thermo-gravimetric methods, neutron scattering, soil resistivity, tensiometers, dielectric-based techniques such as time domain reflectometry (TDR), frequency domain reflectometry (FDR), and capacitance sensors, as well as other approaches such as remote sensing [29]. The evaluation of these instruments shows that each technology presents advantages and limitations when examined under these criteria.

The neutron probe is highly accurate but involves health and environmental risks due to its radioactive source, in addition to high acquisition and maintenance costs, low depth resolution, and the need for soil-specific calibration, which restrict its practical use [24,29,30]. Tensiometers, while low-cost and easy to use without complex electronics, perform poorly in fine-textured soils and require frequent maintenance [22,29,30]. Electromagnetic sensors such as TDRs offer safe installation and real-time volumetric moisture readings, but their performance declines in saline soils and their initial cost is high [29,31]. FDR sensors are also accurate but sensitive to soil salinity, temperature, and clay content, and require specific calibration, limiting their applicability in heterogeneous conditions [29,32].

Capacitive sensors emerge as a promising low-cost alternative due to their simplicity, ease of use, and negligible maintenance after installation. When properly calibrated, they can provide useful estimates of soil moisture at various depths, making them particularly suitable for resource-constrained agricultural settings [11,17].

Indurthi; Sarma; Vinod (2024) [25] report that adopting precision technologies for IM can increase yields by 20 % to 30 % compared to traditional methods. Similarly, El-Naggar et al. (2020) [33] observed water savings of 15 % to 51 % when farmers used soil moisture sensors instead of fixed IS. While the benefits of improved IM are well documented, high equipment costs remain a barrier for smallholder farmers in developing regions [11,34]. More recent studies emphasize an additional challenge: even when low-cost devices are available, their operational complexity often makes them inaccessible to users with limited technical training [10,35]. Although various affordable sensing technologies have been proposed, few have been tested under real field conditions or designed with usability by low-literacy farmers in mind, limiting their scalability and adoption.

In this context, most soil moisture monitoring solutions still face limitations related to cost, calibration requirements, or the need for continuous digital data interpretation, which restrict their use by smallholder farmers [14,16,30]. To address these gaps, the present study proposes a low-cost and user-friendly approach that integrates capacitive soil moisture sensors with Arduino-based technology, delivering intuitive visual feedback through RGB LEDs. The specific objectives were to:

- Design and build a soil moisture monitoring prototype using low-cost capacitive sensors integrated with Arduino.
- Implement a simple LED-based alert system to indicate soil moisture levels in an intuitive and interpretable way.
- Evaluate the performance of the prototype in irrigated vegetable cultivation, emphasizing its potential to increase accessibility for low-literacy farmers and enhance irrigation management practices.

2. Materials and methods

2.1. Experimental setup

To address the research objectives, the study was conducted at the experimental area of the Department of Rural Engineering and Socioeconomics, School of Agricultural Sciences (FCA), São Paulo State University "Júlio de Mesquita Filho" (UNESP), Botucatu Campus, São Paulo, Brazil; located at coordinates 22° 50′ 48″ S, 48° 26′ 06″ W and at an altitude of 786 m [36]. The sensors calibration was carried out in the Irrigation Laboratory of the same department.

The region's climate is classified according to the Köppen system as Aw, characterized by a rainy summer and dry winter. The hottest months occur during the summer, with average maximum temperatures around 23.80 °C and peak rainfall reaching approximately 310.37 mm [37]. In winter, average minimum temperatures are recorded around 18.28 °C in July, with minimum rainfall around 38.76 mm in August.

The soil in the area is classified as Dystrophic Red Latosol, according to the Embrapa classification system [38]. Table 1 presents the physical and chemical soil analysis data from the experimental area, conducted at the Soil Laboratory of the Department of Soils and Environmental Resources, FCA – UNESP.

Table 1
Results of the physical and chemical soil analysis from the experimental area.

Sand	Silt	Clay	Porosity	OM	EC	Presin	K	CEC	V
— (g kg^{-1}) —			(%)	g dm^{-3}	μs cm^{-1}	mg dm^{-3}	-(mmol$_c$ dm^{-3})-		(%)
638	66	296	45.42	23.6	147.7	21	3.2	82.6	64.5

OM – organic matter; EC – electrical conductivity; K – potassium; CEC – cation exchange capacity; V – base saturation.

2.2. Sensor specifications and calibration

Most low-cost soil moisture sensors do not come with factory calibration, and there is little information available about their calibration or results regarding their accuracy in estimating soil moisture content [28,39]. Therefore, before field use, it is essential to calibrate the sensors or understand their behavior in estimating actual moisture. In this study, capacitive soil moisture sensors (model SKU: CE09640) were used (Fig. 1a), with specifications presented in Table 2. Prior to installation, the sensor circuitry was protected using 25 mm PVC tubing, 25 mm PVC caps (Fig. 1b), and resin to prevent damage and minimize external interference [40].

For sensor calibration, a data acquisition unit (Fig. 2) was developed to continuously and uninterruptedly record the weight of soil samples and sensor readings, based on the Arduino platform, due to its accessibility, low cost, and ability to perform multiple operations simultaneously. The data acquisition unit was composed of: 12 soil moisture sensors to be calibrated, 1 Arduino Mega 2560 microcontroller, 3 precision scales, 3 amplifier modules for each load cell from the scales, 1 microSD card module, 1 RTC (real-time clock) module, 1 rechargeable battery pack, 1 charge controller, 1 12 V power supply, and various wiring components to connect all parts of the device.

The microcontroller was programmed in *C++* language using the open-source Arduino IDE (version 2.3). The code was designed to collect sensor readings and either display the data on a computer or record it on a memory card, in the latter case also registering the date and time of each reading. The code and additional system details are available in the supplementary materials section.

The calibration was based on the gravimetric method, which is considered a classical and direct approach [29,30,34]. It involved the continuous and uninterrupted weighing of soil samples at room temperature until a constant weight was reached, at which point it is assumed that all soil moisture has been lost through evaporation [30, 41]. The moisture percentage (Eq. (1)) was calculated based on the difference between wet weight and the dry weight of the sample.

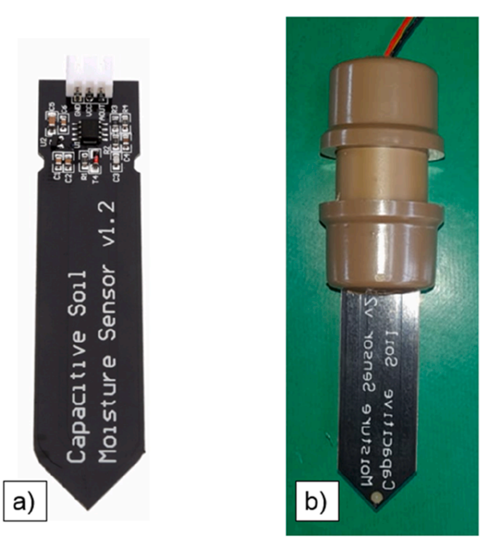

Fig. 1. Capacitive soil moisture sensor and protection procedure.

Table 2
SKU: CE09640 sensor specification.

Parameter	Specification
Operating voltage	3.3 ~ 5.5 VDC
Output voltage	0 ~ 3.0 VDC
Operating current	5 mA
Dimensions	98 mm x 23 mm x 3 mm (length x width x thickness)
Weight	15 g
Pins	3 pins (VCC, GND and Data)
Dimensions	98 mm × 23 mm
Accuracy	±0.3 % for volumetric water content, θ from 0 to 0.50 m^3 m^{-3}
Sensor output	Analog and PWM
Frequency	100 MHz

Source: Abdelmoneim et al. (2025) [16].

$$\mu = \frac{m_w - m_d}{m_d} \tag{1}$$

Where: μ – gravimetric water content (%); m_w – mass of the wet soil (g); m_d – mass of the dry soil (g); 100 – conversion factor to percentage (dimensionless).

The calibration aimed to develop equations describing the sensors' behavior in estimating actual volumetric moisture (Eq. (2)), simulating real field conditions information later used for IM. For this purpose, three undisturbed soil samples were collected from the experimental area at a depth of 0–0.20 m, using PVC cylinders measuring 0.12 m in height and 0.10 m in internal diameter, following the methodology of Gava; Silva; Baio (2016) [42], to ensure samples closely represented field conditions (Fig. 3a). The physical and chemical properties of the soil used for calibration are presented in Table 1.

$$\theta\text{actual} = \mu * \rho b \tag{2}$$

Where: θactual – actual volumetric water content (cm^3 cm^{-3}); μ – gravimetric water content (%); ρb – bulk density (g cm^{-3}).

$$\rho b = \frac{md}{V} \tag{3}$$

Where: ρb – bulk density (g cm^{-3}); m_d – mass of the dry soil (g); V – volume of container used for sample collection (cm^3).

After collection, the samples were properly packaged (Fig. 3b) and sent to the Irrigation Laboratory at FCA – UNESP. In the laboratory, the samples were individually placed in containers filled with irrigation water (the same used in the field) (Fig. 3c) for slow saturation by capillarity over a period of 24 h, following procedures like those described by Fares; Alva (2000) and Gava; Silva; Baio (2016) [7,42]. Subsequently, four sensors were inserted into each cylinder to a depth of 0.06 m.

After saturation, each cylinder was placed on a precision scale (± 1 g) (Fig. 4), connected to the microcontroller of the data acquisition system, and kept there throughout the entire 30-day evaluation period. During these 30 days, the data acquisition unit continuously recorded both the sample weight and the analog readings from the capacitive sensors at one-minute intervals, saving the data to a memory card via an external memory card reader module connected to the microcontroller. Data was collected weekly, at which point the precision scales were recalibrated using a known-weight object, since these scales are prone to calibration drift over time. During the recalibration process, some data

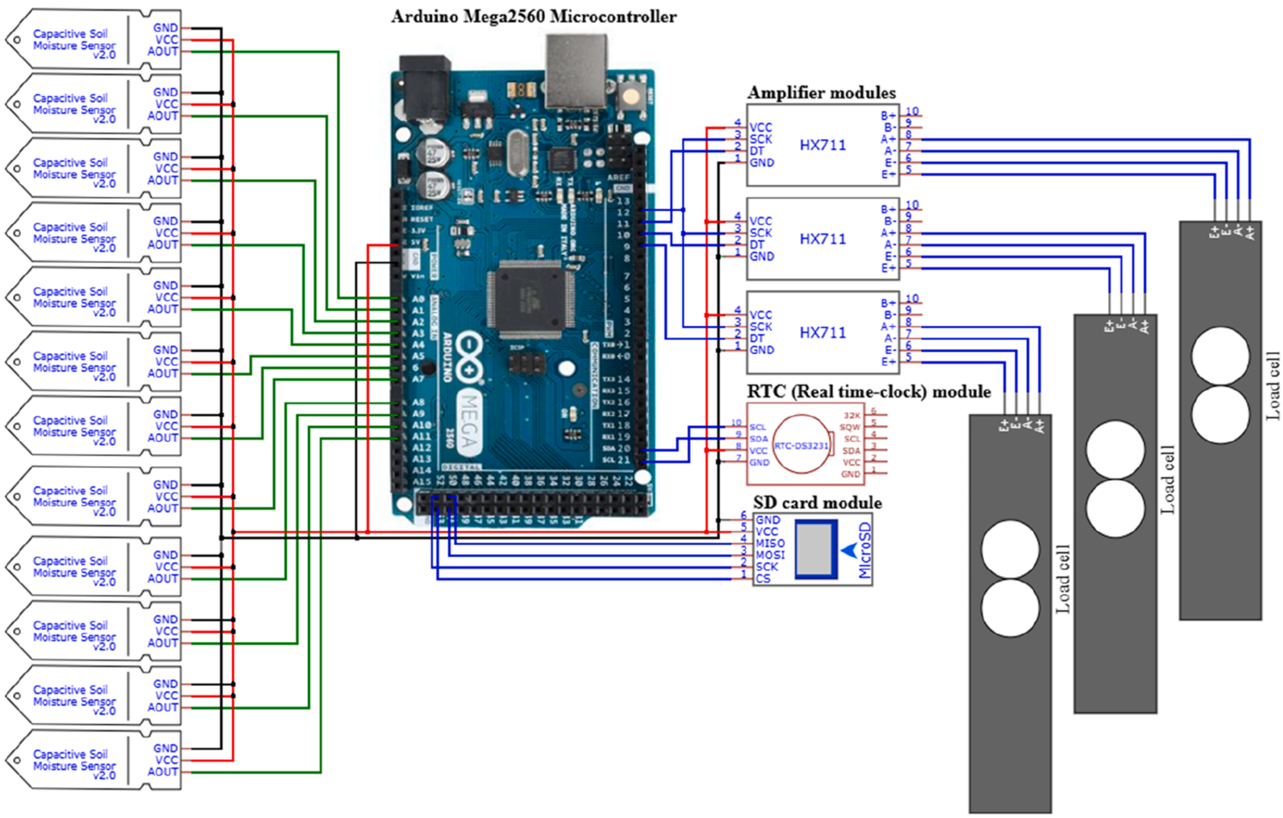

Fig. 2. Data acquisition unit circuit for soil moisture sensor calibration.

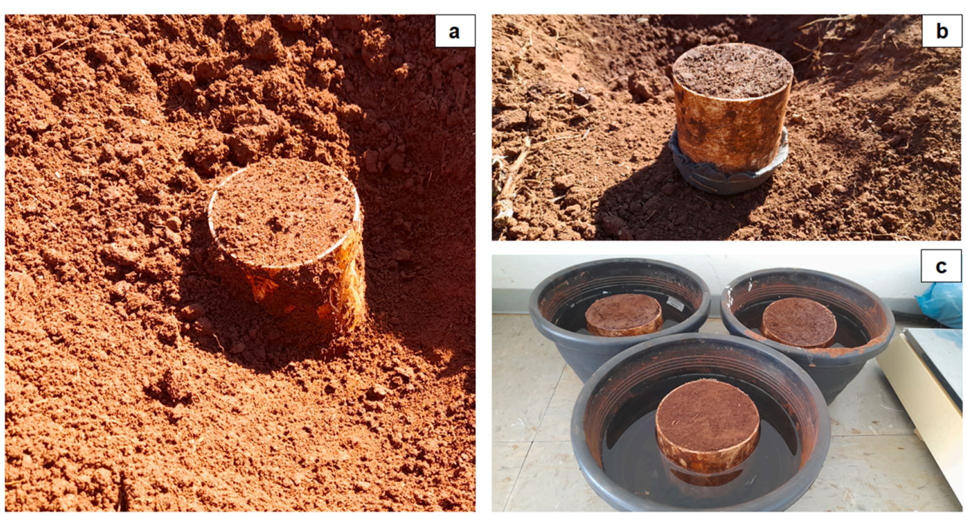

Fig. 3. Handling of soil samples for sensor calibration.

loss occurred due to sample movement, but it was not significant, as each recalibration was completed in less than five minutes per scale.

When little or no variation in the soil sample weight over time was observed, the evaluation was concluded. The sample was then removed from the cylinders, and the residual moisture was eliminated by placing it in a drying oven at 105 °C for 24 h. The resulting dry weight of the undisturbed sample allowed for the calculation of the soil bulk density for each sample (Eq. (3)), which was then used to compute the current volumetric moisture content corresponding to the various sample weight readings recorded throughout the evaluation.

With the calibration equations established, the irrigation depth (θrep) was calculated considering the difference between θ_{fc} (volumetric water content at field capacity) estimated using the calibration equation from sensor readings recorded right after free drainage ceased in the soil sample, which are assumed to correspond to field capacity conditions [7, 29] and θactual (actual volumetric water content), estimated based on sensor readings recorded during the moisture depletion phase beyond field capacity.

2.3. *Description of experimental research*

2.3.1. *Irrigation scheduling protocol*

The experimental research aimed to evaluate the feasibility of a user-friendly soil moisture monitoring system, developed by integrating low-

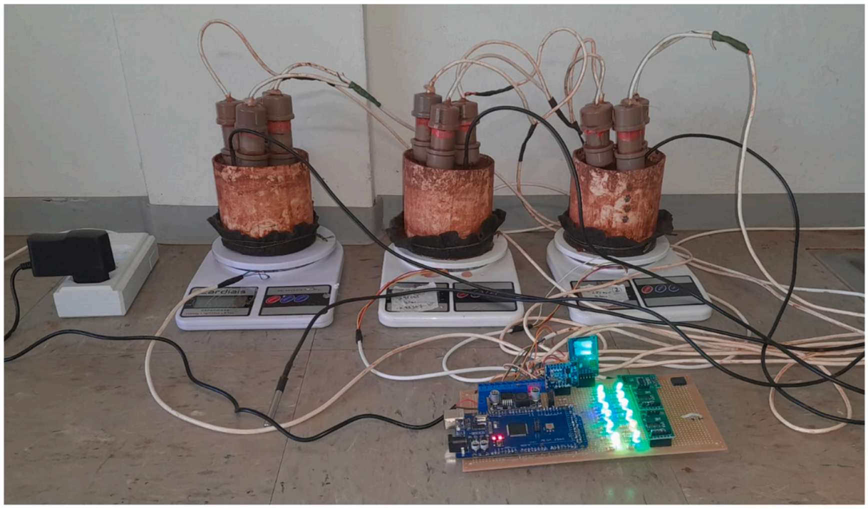

Fig. 4. Data acquisition unit for soil sample weight and raw readings from capacitive sensors.

cost capacitive soil moisture sensors, an Arduino, and RGB LEDs, for the purpose of IM in irrigated vegetable cultivation. To this end, different IM techniques were applied, with the goal of comparing the soil moisture and/or crop water demand results provided by established and widely recognized high-precision methods with those of the system developed in this study, as well as assessing their effect on crop productivity and water use.

Three IM techniques were tested, namely: (i) climate-based management using data from the Meteorological Station of Fazenda Lageado (FCA – UNESP, Botucatu) to determine crop water demand (ETc); and two soil-based methods using (ii) tensiometers (IMT) and (iii) low-cost capacitive soil moisture sensors (IMC). The information obtained from the IM techniques compared was used to determine the irrigation depth or soil moisture replenishment required to meet the crop's water needs. The test crop was kale (cv. Georgia), grown in two cropping cycles between April and November 2024. Drip irrigation was used in the experimental cultivation area.

For climate-based irrigation management, daily reference evapotranspiration (ETo) data were used to determine crop evapotranspiration (ETc) (Eq. (4)), which represents the amount of water that must be replenished in the soil to compensate for the water lost by the plants through transpiration and evaporation from moist surfaces around the plant. The ETo data obtained from the meteorological station are calculated based on the mathematical equation proposed by Penman-Monteith [43], which is the standard method recommended by the Food and Agriculture Organization (FAO).

$$\mathrm{ETc} = \mathrm{ETo} * \mathrm{kc} \tag{4}$$

Where: ETc – crop evapotranspiration (mm day^{-1}), ETo – reference evapotranspiration (mm day^{-1}), kc – crop coefficient (dimensionless).

In the soil-based irrigation management using tensiometers, the soil moisture monitoring devices (in this case, tensiometers) were installed at depths of 15 cm (considered the average effective root depth for most vegetables) and 30 cm. Based on the soil water retention curve constructed for the experimental area (Fig. 5), the irrigation depth was calculated to restore soil moisture to 100 % of field capacity (FC), with irrigation events triggered whenever readings indicated moisture below FC. Two sets of tensiometers were installed to determine the matric potential of soil water, each set consisting of two tensiometers.

The soil water retention curve for the experimental area used in this study was developed based on a soil sample collected at a depth of 0.20 m. The analyses were carried out at the Department of Rural Engineering, FCA – UNESP, using the Richards pressure chamber method [44]. Once the values describing the relationship between soil moisture and matric potential were obtained, the curve (Fig. 1) was fitted using

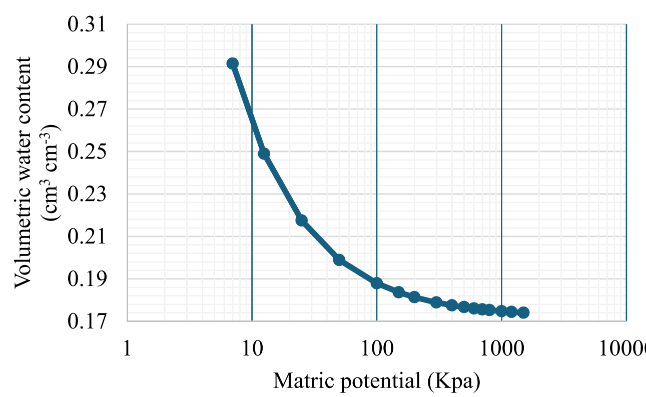

Fig. 5. Soil water retention curve of the experimental area.

the SWRC software [45], applying the model proposed by Van Genuchten (1980), which generated the parameters α, m, n, θr, and θs (Table 3).

With the soil water retention curve data (Table 3) and the daily readings of matric potential, the irrigation time was calculated using the following equations: actual soil moisture (Eq. (5)), moisture to be replenished (Eq. (6)), and net irrigation depth (Eq. (7)).

$$\theta \mathrm{actual} = \theta \mathrm{r} + \left(\frac{\theta \mathrm{s} - \theta \mathrm{r}}{\left[1 + |\alpha * \varphi \mathrm{m}|^{\mathrm{n}}\right]^{\mathrm{m}}}\right) \tag{5}$$

Where: θactual – actual volumetric moisture content ($\mathrm{cm^3\ cm^{-3}}$); θr – residual volumetric moisture content ($\mathrm{cm^3\ cm^{-3}}$); θs – saturation volumetric moisture content ($\mathrm{cm^3\ cm^{-3}}$); φm – soil water matric potential (kPa); α, m, n – empirical parameters of the van Genuchten equation (dimensionless).

Table 3
Parameters of the equation obtained from the model proposed by Van Genuchten (1980).

Layer (m)	α	m	n	θr ($\mathrm{cm^3\ cm^{-3}}$)	θs
0 – 0.20	1.225	0.260	2.918	0.172	0.782

θr – residual volumetric moisture content ($\mathrm{cm^3\ cm^{-3}}$); θs – saturation volumetric moisture content ($\mathrm{cm^3\ cm^{-3}}$); α, m, n – empirical parameters of the van Genuchten equation (dimensionless).

$$\theta rep = \theta fc + \theta actual \quad (6)$$

Where: θrep – volumetric moisture content to be replenished (cm^3 cm^{-3}); θfc – volumetric moisture content at field capacity (cm^3 cm^{-3}) (corresponding to moisture at 7 kPa pressure, 0.29 cm^3 cm^{-3}); θactual – current volumetric moisture (cm^3 cm^{-3}).

$$Ll = \theta rep * z \quad (7)$$

Where: *Ll* – net irrigation depth (mm); *z* – effective rooting depth (mm); *θrep* – volumetric moisture content to be replenished (cm^3 cm^{-3}).

For soil-based irrigation management, low-cost capacitive soil moisture sensors (model SKU: CE09640) were used. Before applying them for IM, the sensors were previously calibrated in the Irrigation Laboratory of the Department of Rural Engineering at FCA-UNESP, since they do not come factory-calibrated, and there is limited information available regarding their performance in estimating soil moisture content [28,39], as described above.

Since drip irrigation was adopted, the irrigation depth calculated for each IM technique was adjusted to account for localization effects (kl), irrigation efficiency (Ei), salt leaching, climate, and advection, resulting in the gross irrigation depth (Gi) (Eq. (8)). An irrigation time was also calculated (Eq. (9)), considering a dripper flow rate of 8 L h^{-1}.

$$Gi = \frac{Ll * kl * ka * kcc}{[1 - (CEi/2*CEe) * (Ei/100)]} \quad (8)$$

Where: Gi – gross irrigation depth (mm); Ll – net irrigation depth (mm); kl – correction coefficient due to localization (for different crop growth stages); ka – correction coefficient due to advection (dimensionless) (0.9); kcc – climatic correction coefficient (dimensionless) (1.15); CEi – irrigation water electrical conductivity (dS cm^{-1}) (0.35 dS m^{-1} based on irrigation water analysis results); CEe – soil electrical conductivity (dS cm^{-1}) (0.591 dS m^{-1} based on soil analysis results); Ei – irrigation efficiency (assumed to be 90 %).

The selection of values for the ka and kcc coefficients followed the guidelines proposed by [46]. To determine kl, the procedure proposed by [47] was adopted. The kl values were calculated for the different crop growth stages, considering the shaded area in each stage, resulting in kl = 0.16 for stage 1, kl = 0.40 for stage 2, kl = 0.91 for stage 3, and kl = 0.66.

$$It = \frac{(Gi - Ep)*Sd * Si}{Nd * Df} \quad (9)$$

Where: It – irrigation time (h); Gi – gross irrigation depth (L m^{-2}); Ep – effective precipitation (mm); Sd – spacing between drippers on the line (m); Si – spacing between irrigation lines (m); Df – dripper flow rate (2 L h^{-1}); Nd – number of drippers per plant (dimensionless) (one dripper per plant was considered).

2.3.2. *Crop establishment and management*

The IM experiment for irrigated kale cultivation began on April 30, 2024, in an area of approximately 88 m^2 (22 *m* × 4 m). The cultivation was arranged in four blocks, each measuring 11 *m* × 1.2 m, and subdivided into 12 plots of 1.2 *m* × 0.8 m. The seedlings were purchased from a local supplier and transplanted 30 days after sowing in 128-cell plastic trays.

A randomized block design (RBD) was adopted, with four replications, in a 4 × 3 factorial arrangement, corresponding to the combination of two factors, namely: (i) Factor 1 – irrigation levels (IL), with four levels (L1 – 50 %, L2 – 75 %, L3 – 100 %, and L4 – 125 %) of soil water replenishment or crop water demand replacement; and Factor 2 – irrigation management techniques (IMT), with three levels (ETc – climate-based management, IMT – soil-based management using tensiometers, and IMC – soil-based management using low-cost capacitive soil moisture sensors), totaling 12 treatments and 48 experimental plots (each measuring 1.2 m in length and 0.8 m in width). The application of treatments began 11 days after transplanting, with the first 10 days of IM based on climate-based crop water demand estimates, during which 100 % of ETc was applied.

In each experimental plot, four plants were placed, with a spacing of 0.6 m between rows and 0.4 m between plants. To supply water to the plants, three blind LDPE (low-density polyethylene) tubes (16 mm, PN 30) were installed in each bed, serving as irrigation lines, with one tube assigned to each irrigation management technique.

The LDPE tubes (Fig. 6) installed in the beds were perforated at 0.8 m

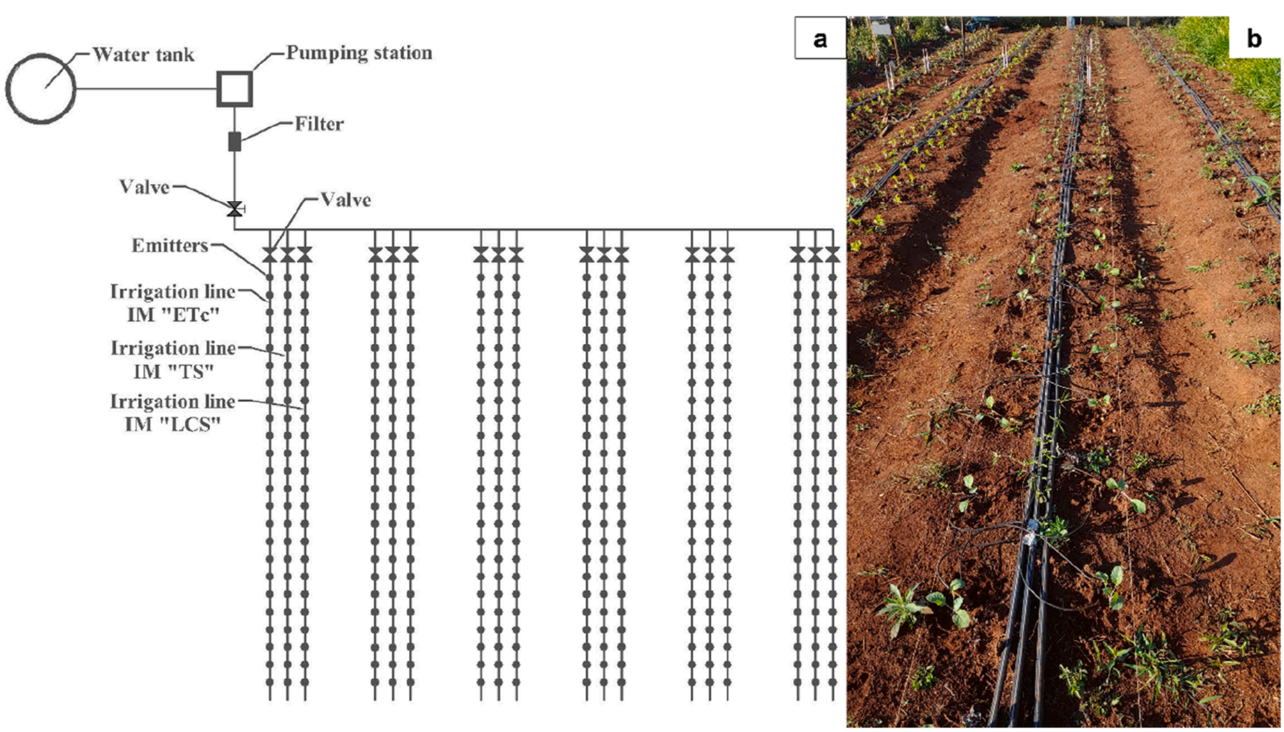

Fig. 6. Irrigation system installation scheme of the experimental cultivation unit of kale (brassica oleracea var. acephala).

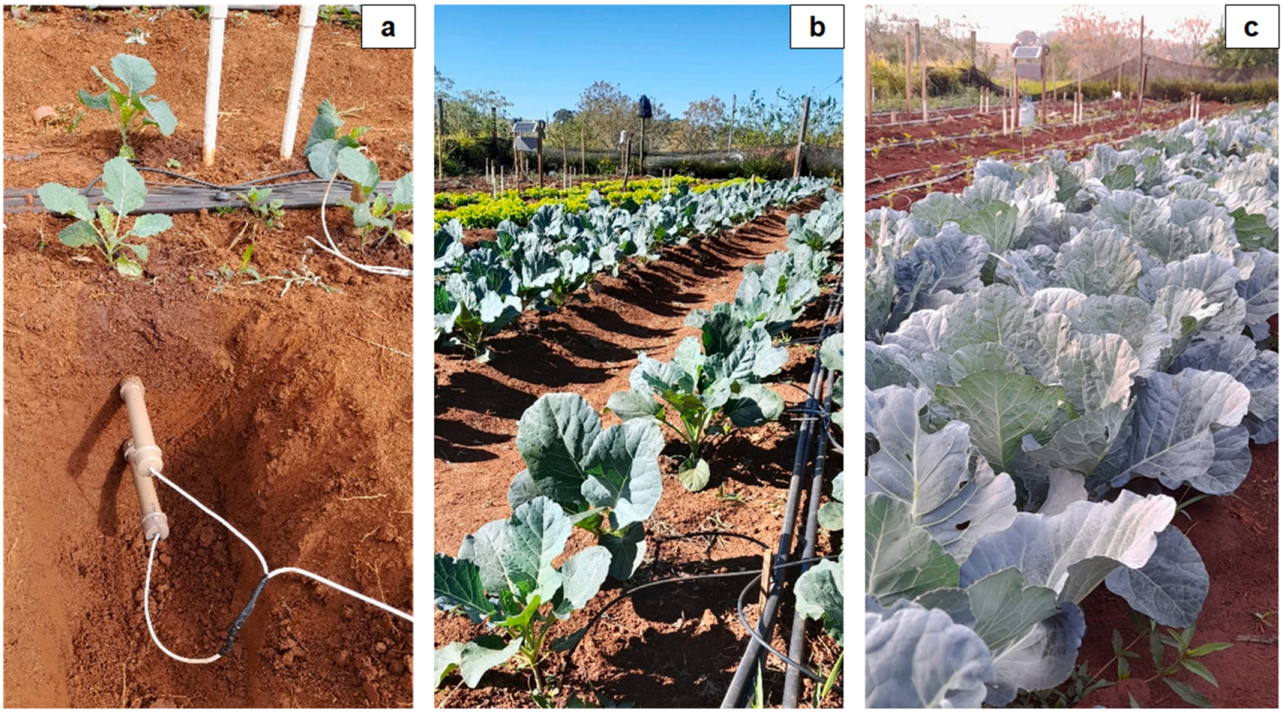

Fig. 7. Installation details of capacitive soil moisture sensors (a), irrigation lines in the experimental unit (b), and plant development (c) of kale (brassica oleracea var. acephala).

intervals along each block to allow for the insertion of drippers with different flow rates: 2 L h^{-1}, 4 L h^{-1}, and 8 L h^{-1}. Using the 8 L h^{-1} dripper as a reference for calculating irrigation time (Eq. (9)), the following water application levels were achieved: 50 % (4 L h^{-1} dripper), 75 % (combination of 2 L h^{-1} + 4 L h^{-1} drippers), 100 % (8 L h^{-1} dripper), and 125 % (combination of 8 L h^{-1} + 2 L h^{-1} drippers) of the crop water demand or required soil moisture replenishment. Each dripper was fitted with a four-outlet adapter, allowing water to be distributed to the four plants in each plot (¼ of the dripper's flow per plant). Additional components of the irrigation system included: a 500-liter plastic water tank, an electric pump, a disc filter, a pressure gauge, a water valve, and various connectors and fittings.

The soil moisture monitoring devices (tensiometers and capacitive sensors) were installed (Fig. 7) in the plots containing 8 L h^{-1} drippers. By monitoring soil moisture in the plots with 8 L h^{-1} drippers, the aim was to ensure that when 100 % of the crop water demand was applied to these plots, the others using 4 L h^{-1}, 6 L h^{-1}, and 10 L h^{-1} drippers would receive the equivalent of 50 %, 75 %, and 125 % of the crop water demand, respectively, for the same irrigation duration.

2.3.3. Crop establishment and irrigation management

For soil moisture monitoring using capacitive sensors, the data acquisition unit developed during the calibration phase was used. RGB LEDs were added to this unit to serve as visual indicators of soil moisture status, and the code was rewritten so that the red LED would activate when sensor readings indicated dry to moderately moist soil, blue for saturated soil, and intermediate values were represented by green and yellow, indicating moist and moderately moist soil, respectively. Each sensor had a customized configuration, programmed according to the relationship between the raw sensor readings and the volumetric moisture content estimated by the calibration equation.

For climate-based irrigation management, irrigation was performed daily, except on days when effective precipitation exceeded the accumulated crop evapotranspiration. In soil-based irrigation management using tensiometers, irrigation was only omitted on days when tensiometer readings indicated that irrigation was not needed (i.e., soil water tension values below 7 kPa).

Using low-cost capacitive soil moisture sensors, irrigation management was guided by the RGB LED colors on the moisture monitoring unit. Therefore, no irrigation was performed on days when the LEDs associated with the sensors installed at 15 cm depth were displaying blue, which indicated saturated soil according to the sensor calibration results (Fig. 8). Irrigation was carried out only on days when the LEDs were green, yellow, or red, indicating different scenarios of soil moisture, respectively, moderately moist, and dry soil.

Taking Fig. 8 as an example, which represents the relationship between readings from sensor SS3 and the observed volumetric moisture, the code was written so that the red RGB LED would activate for sensor readings above approximately 380, and the blue LED for readings below approximately 270. For values between 270 and 330, and between 330 and 380, the green and yellow LEDs were activated, respectively.

On days when the green or yellow RGB LED was activated (Fig. 9), irrigation was carried out assuming that the soil was moist and moderately moist, respectively. To calculate the current volumetric moisture (using the calibration equations in Table 3), an intermediate value of the raw reading from the capacitive sensor within these ranges recorded during the calibration process was considered.

It is important to note that 12 sensors were calibrated; however, only four were used for irrigation management in the kale cultivation experiment, while the remaining eight were kept in reserve in case replacement was needed. The visual interface for indicating soil moisture status consisted of 12 RGB LEDs, with each group of three LEDs assigned to a single sensor. This redundancy was designed to ensure continued field operation and reliable interpretation of sensor readings, even in the event of LED failure.

Taking the calibration results of the SS3 sensor as a reference, the prototype was programmed so that the monitoring interface using RGB LEDs would trigger the blue color whenever the sensor reading was below 270. This value corresponds to a volumetric water content (y) of 0.455 cm^3 cm^{-3}, as determined by the SS3 equation shown in Table 4. As soil moisture decreased, the green color would be activated for readings corresponding to y between 0.455 cm^3 cm^{-3} and 0.343 cm^3 cm^{-3}, yellow

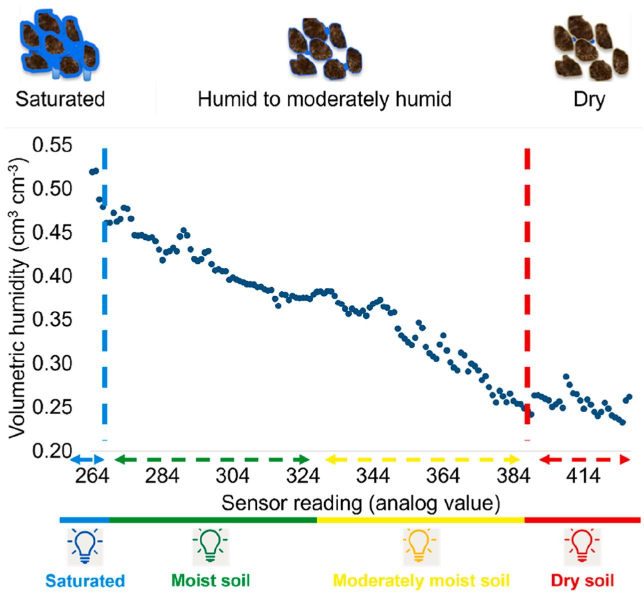

Fig. 8. Logic adopted for visual indication of soil moisture based on the relationship between volumetric water content and readings from the capacitive soil moisture sensor.

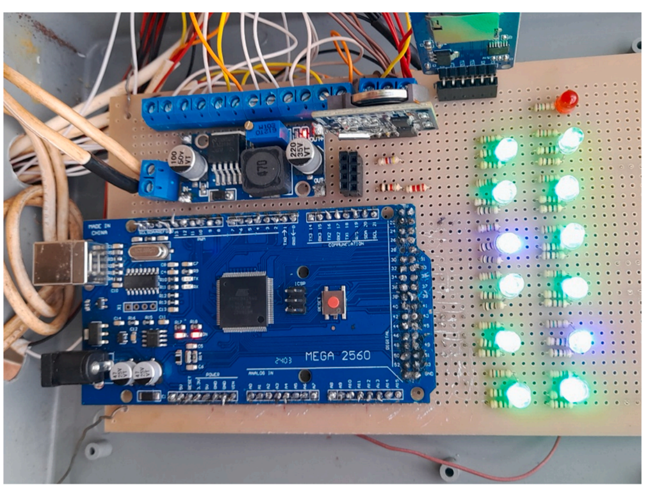

Fig. 9. Interface for visual indication of soil moisture based on RGB LEDs.

for values between 0.343 cm^3 cm^{-3} and 0.271 cm^3 cm^{-3}, and finally, red would be triggered for y values below 0.271 cm^3 cm^{-3} (considered the lower limit of available water).

Irrigation was carried out with the aim of raising the current volumetric water content to values close to 0.455 cm^3 cm^{-3}, which corresponds to the field capacity (FC) estimated for this sensor. The color change of the LEDs occurred based on specific moisture ranges (as

Table 4
Fitted models for estimating current soil volumetric moisture from raw sensor readings.

Sensors	z (cm)	Calibration equations
SS1	15	$y = 3.47E(-6)x2 - 0.004x + 1.13$
SS2	30	$y = 3.43E(-6)x2 - 0.004x + 1.18$
SS3	15	$y = 4.09E(-6)x2 - 0.004x + 1.33$
SS4	30	$y = 3.89E(-6)x2 - 0.004x + 1.29$

z – Sensor installation depth (mm), y – Estimated volumetric water content (cm^3 cm^{-3}), x – Raw sensor reading (analog value), SS1 – capacitive soil moisture sensor 1, …, SS4 – capacitive soil moisture sensor 4.

indicated above), and therefore, for the purpose of estimating water replenishment (θrep), average values were assigned based on the limits of each range: for the green color, the average between 0.455 cm^3 cm^{-3} and 0.343 cm^3 cm^{-3} was considered (resulting in $y = 0.399$ cm^3 cm^{-3}); for the yellow color, the average between 0.343 cm^3 cm^{-3} and 0.271 cm^3 cm^{-3} (resulting in $y = 0.307$ cm^3 cm^{-3}). In the case of the red color, $y = 0.271$ cm^3 cm^{-3} was directly adopted. Thus, for example, when the green color was observed, the water replenishment was estimated at 0.056 cm^3 cm^{-3}, calculated as the difference between field capacity (0.455 cm^3 cm^{-3}) and the average moisture in the green range (0.399 cm^3 cm^{-3}), that is, $\theta rep = 0.455 - 0.399$ cm^3 cm^{-3}.

2.4. Data collection and analysis

2.4.1. Evaluation of sensor performance and calibration model validation

Regression analysis ($p < 0.05$ and $p < 0.01$) and graphical visualizations were used to compare the raw readings from the capacitive soil moisture sensor with the volumetric water content of soil samples obtained through the gravimetric method during calibration. Calibration equations describing the behavior of the capacitive sensor in estimating actual volumetric moisture were developed and adjusted. The correlation coefficient (R), coefficient of determination (R^2), root mean square error (RMSE) (Eq. (10)), mean bias error (MBE) (Eq. (11)), and the index of agreement (d) (Eq. (12)) were used to evaluate the performance and accuracy of the SKU: CE09640 capacitive soil moisture sensors in estimating volumetric water content.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\mathrm{Pi}-\mathrm{Oi})^2}{2}} \tag{10}$$

$$\mathrm{MBE} = \frac{\sum_{i=1}^{n}(\mathrm{Pi}-\mathrm{Oi})}{n} \tag{11}$$

$$d = 1 - \left[\frac{\sum_{i=1}^{n}(\mathrm{Pi}-\mathrm{Oi})^2}{\sum_{i=1}^{n}(|\mathrm{Pi}-\overline{\mathrm{O}}|+|\mathrm{Oi}-\overline{\mathrm{O}}|)^2}\right] \tag{12}$$

Where, P_i – predicted moisture, O_i – observed moisture, $\overline{O}$ – mean observed moisture, RMSE – root mean square error, MBE – mean bias error, d – index of agreement, n – number of observations.

R ranges from −1 to 1 and indicates the strength of the relationship between the predictor variable (sensor reading, in this case) and the response variable (observed volumetric moisture), or how well the sensor reading explains the variability in volumetric water content. R^2 values range from 0 to 1 and represent the proportion of variance between the predicted volumetric moisture values (estimated based on sensor readings) and the actual observed values [48]. For optimal prediction, R and R^2 values should be as close as possible to 1, and when R is negative, it indicates an inverse relationship between variables. RMSE (Root Mean Square Error) is a reasonable indicator of sensor accuracy [49] and was used to evaluate the sensors' ability (based on the calibration equations) to estimate current volumetric moisture. RMSE values closer to zero are desirable and indicate a good fit (RMSE < 0.01), reasonable (0.01 < RMSE < 0.05), poor (0.05 < RMSE < 0.1), and very poor (RMSE > 0.1) [49].

An MBE of zero indicates that the estimated and observed values are unbiased [21], while positive and negative MBE values indicate that the estimated moisture values overestimate and underestimate the actual or observed moisture, respectively [49]. The index of agreement (d) described by Willmott (1981) [50] was used to evaluate the degree to which the observed moisture by the gravimetric method is accurately estimated by the sensor-simulated moisture. The d values range from 0 to 1, where a value of one (1) indicates perfect agreement between observed and predicted moisture, while a value of zero (0) indicates total disagreement [50].

2.4.2. Evaluation of crop production and field sensor performance

To evaluate the effect of the treatments studied, data collection was carried out at the end of the growth cycle, focusing on the number of mature leaves (NML), number of leaves with commercial standards (NCL), number of non-commercial leaves (NNCL), and fresh mass of mature leaves (FMML). ML included the count of leaves with a lamina length (LL) equal to or greater than 10 cm; NCL referred to leaves with LL greater than 20 cm (Melo et al., 2024; Pitoro et al., 2021); and NNCL included leaves with LL equal to or greater than 10 cm and <20 cm (10 cm ≤ LL < 20 cm) (Pitoro et al., 2021).

The measurement of LL was performed using a 50 cm graduated ruler, while the fresh mass of mature leaves (FMML) was determined by weighing all harvested leaves (both commercial-sized and non-commercial-sized) on an analytical balance (±0.1 g). Water use productivity (WUP) was calculated as the ratio between FMML and the total irrigation depth applied (Eq. (13)).

$$\mathrm{WUP} = \frac{\mathrm{FMML}}{\mathrm{Gi}} \tag{13}$$

Where: WUP – water use productivity (g L^{-1}), FMML – fresh mass of mature leaf (g), G_i – total irrigation depth applied (L).

Crop growth and yield data were subjected to analysis of variance (ANOVA) at a 5 % significance level ($p < 0.05$) using the F-test, and a mean comparison test was performed when significant effects were observed. For the variables in which the variation in irrigation depths showed significant effects, regression analysis and model fitting were carried out for each irrigation technique in cases where significant effects of the irrigation level factor were identified.

3. Results and discussion

3.1. Sensor calibration and validation

Fig. 10 shows occasional readings from the capacitive sensor (SC) and the corresponding volumetric water content determined using the gravimetric method. A very strong inverse relationship is observed between volumetric moisture and sensor readings ($-0.977 < R < -0.964$); the wetter the soil, the lower the sensor reading. This behavior is also reported by several other researchers [17,28,51], who note that the wetter the soil, the lower the output voltage, and thus, the lower the digital value returned by the sensor. These results suggest that it is possible to study soil moisture variability using the capacitive sensor SKU: CE09640.

By comparing the volumetric moisture results of soil samples ranging from dry to moderately moist (0.0 – 0.26 cm^3 cm^{-3}), samples at field capacity (0.34 – 0.50 cm^3 cm^{-3}), and saturated samples (0.62 – 0.74 cm^3 cm^{-3}) with sensor readings, Nagahage; Nagahage; Fujino [51] concluded that the SKU: CE09640 sensors are capable of distinguishing different soil moisture conditions, similar to what was observed in the present study, in which the sensor reading increased as the moisture content of the soil sample decreased.

The correlation coefficients between the raw sensor readings and observed volumetric water content recorded in this study (−0.96 for SS1, −0.97 for SS2, −0.98 for SS3, and −0.97 for SS4) are higher than the minimum (R = 0.84) suggested by Draper and Smith (1981) and Veiga and Sáfadi (1999) for calibration model fitting, as cited by Gomes et al. (2013) [52]. Given the observation of a very strong correlation between the observed volumetric moisture and the corresponding raw sensor readings, calibration equations were developed to describe the behavior of the tested capacitive sensors in estimating actual volumetric water content. These equations were subsequently used for the field monitoring interface.

The polynomial model using the raw sensor reading as the predictor variable resulted in $R = 0.98$, $R^2 = 0.95$, RMSE = 1.92×10^{-2}, MBE = 1.66×10^{-7}, and $d = 0.99$ for SS1; $R = 0.98$, $R^2 = 0.95$, RMSE = 1.85×10^{-2}, MBE = 0.99×10^{-7}, and $d = 0.99$ for SS2; $R = 0.99$, $R^2 = 0.97$, RMSE = 1.70×10^{-2}, MBE = 1.55×10^{-7}, and $d = 0.99$ for SS3; and $R = 0.98$, $R^2 = 0.97$, RMSE = 1.80×10^{-2}, MBE = -3.97×10^{-7}, and $d = 0.99$ for SS4. These values indicate strong correlation ($R > 0.98$), high goodness fit ($R^2 > 0.95$), and acceptable predictive accuracy, with RMSE values between 0.017 and 0.019 cm^3 cm-3, within the acceptable range (0.01 < RMSE < 0.05), as defined by Fares et al. (2011) [49]. Additionally, the mean bias error (MBE ≈ 0) indicates minimal systematic error, while the Willmott agreement index ($d = 0.99$) reflets excellent agreement between predicted and observed values [21,49]. These indicators collectively suggest that the sensors evaluated in this study are suitable for effective IM. Details of the models and their performance are presented in Table 5.

In Fig. 11, it can be observed that volumetric soil moisture was estimated accurately within the approximate range of 0.28 cm^3 cm^{-3} to 0.48 cm^3 cm^{-3}, which corresponds to the green and yellow color ranges of the RGB LED. This contrasts with the estimates for moisture levels below 0.28 cm^3 cm^{-3} (red LED color) and above 0.48 cm^3 cm^{-3} (blue LED color), which represent dry and saturated soil, respectively. Although the red and blue ranges are no less important, these results indicate that the sensors were accurate in estimating volumetric moisture within the

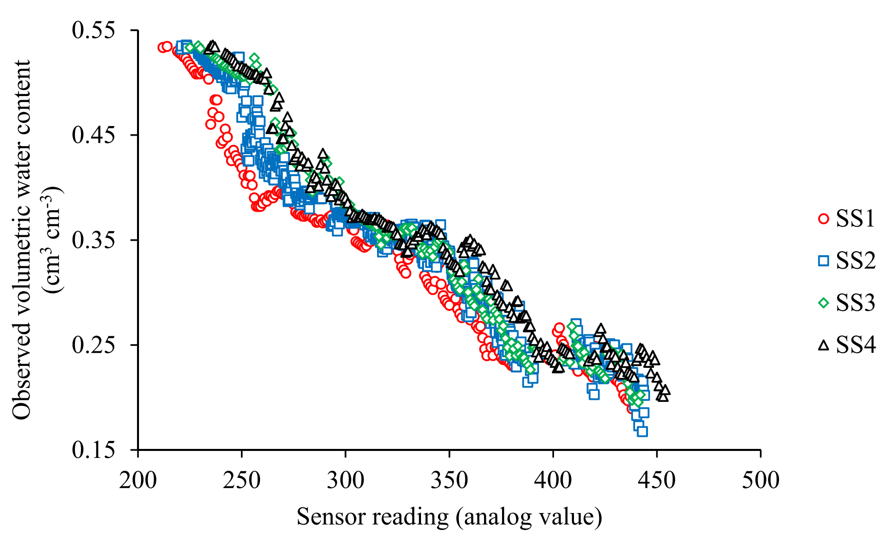

Fig. 10. Relationship between sensor reading values and average volumetric water content (correlation coefficients: SS1 = −0.964, SS2 = −0.968, SS3 = −0.977, SS4 = −0.97).

Table 5
Fitted models for estimating current soil volumetric moisture from raw sensor readings and their performance indicators.

Sensors	Calibration models	R	R^2	RMSE $*10^{-2}$	MBE $*10^{-7}$	d
SS1	$y = 3.47E(-6)x^2$ - 0.004x + 1.13	0.98	0.95	1.92	1.66	0.99
SS2	$y = 3.43E(-6)x^2$ - 0.004x + 1.18	0.98	0.95	1.85	0.99	0.99
SS3	$y = 4.27E(-6)x^2$ - 0.004x + 1.28	0.99	0.97	1.70	1.55	0.99
SS4	$y = 3.89E(-6)x^2$ - 0.004x + 1.29	0.98	0.97	1.80	−3.97	0.99

range of greatest relevance for the monitoring interface in this study, that is, between the limits defined for field capacity and wilting point.

Similar behavior was reported by Abdelmoneim et al. (2025) [16], who observed high variability in the response of capacitive sensors under saturated conditions. In their study with 12 SKU: SEN0193 sensors in clay soil, the coefficient of variation reached 10 % to 16 % for volumetric moisture above 30 %, indicating reduced sensor sensitivity at higher moisture levels.". According to the authors, this behavior is because water has a much higher dielectric constant compared to air and dry soil. However, at higher moisture levels, the dielectric constant changes less significantly with variations in soil water content, making it more difficult for the sensor to detect small moisture changes. This results in lower sensitivity, greater reading variability, and increased errors in estimating actual moisture.

In addition to the limitations observed under high soil moisture conditions, low-cost capacitive sensors also present significant constraints when the soil is dry or tending to dry out. Since moisture measurement by the sensor depends on variations in the dielectric constant of the medium, the predominant presence of air (under minimum moisture or dry soil conditions) hinders the detection of small moisture changes and consequently reduces the sensor's sensitivity. Pahuja (2022) observed that the accuracy of soil moisture estimation using a capacitive sensor (SoilWatch 10) decreased at the lower end of the volumetric moisture range, particularly below 10 %. The limitation of capacitive sensors in estimating moisture under saturated, dry, or low-moisture soil conditions observed in this study aligns with what is commonly reported in literature. These limitations highlight the need for rigorous calibration.

The R^2 values recorded in this study (Table 5) fall within the range ($0.88 < R^2 < 0.98$) observed by Vandôme et al. (2023) [17] when calibrating capacitive sensors in different soil types, who classified the models as having a satisfactory fit. Aringo et al. (2022) [40], in their evaluation of the SKU: CE09640 sensor, reported R^2 values of 0.96, 0.92, and 0.92 during calibration, validation, and comparison with the MP306 moisture sensor. Datta et al. (2018) [21], assessing the performance of various soil moisture sensors (TDR315, CS655, GS1, SM100, and CropX) under field conditions, recorded lower R^2 values ($0.20 < R^2 < 0.85$) compared to those found in the present study. Additionally, these researchers concluded that the TDR315, CS655, and GS1 sensors showed satisfactory accuracy based on RMSE values of 0.028, 0.019, and 0.048, respectively, which are slightly higher than the RMSE values recorded in this study.

The results of the performance of the SKU: CE09640 sensors in estimating volumetric moisture, as tested in this study, confirm that these sensors can be a low-cost alternative for soil moisture monitoring in irrigated cropping areas, as also reported in several other studies [28, 40]. For this reason, they were adopted for the monitoring interface (MI) in the irrigated kale cultivation carried out in this research, the results of which are presented below.

3.2. Irrigation management

The cultivation of kale was carried out in two cycles: the first from May 30 to June 28, and the second from July 17 to September 19, 2024. The climatic conditions during this period (Fig. 12) were reasonably favorable for kale cultivation, with an average temperature of approximately 23.03 °C (±1.94) in cycle 1 and 22.23 °C (±4.70) in cycle 2. The accumulated precipitation was 59.43 mm in cycle 1 and 42.67 mm in cycle 2, while the accumulated evapotranspiration reached 167.09 mm (±0.62) in cycle 1 and 207.44 mm (±0.89) in cycle 2.

At the end of the two cultivation cycles, a total gross irrigation depth of 241.40 mm was applied for the climate-based IM (114.08 mm in cycle 1 and 127.32 mm in cycle 2), 315.61 mm for IM using tensiometers (119.36 mm in cycle 1 and 196.24 mm in cycle 2), and 258.90 mm using low-cost capacitive sensors (90.20 mm in cycle 1 and 179.70 mm in cycle 2). For all IM techniques, the irrigation depth applied in cycle 1 (Fig. 13) was lower than in cycle 2, with differences of 13.24 mm, 76.88 mm, and 89.50 mm for climate-based IM, tensiometers, and capacitive sensors, respectively. Since the recorded precipitation was low in both cycle 1 and cycle 2, it was considered to have had no significant effect on the crop's development and productivity.

The total irrigation depth applied in the 100 % crop evapotranspiration replacement treatment in this study was not significantly different from that reported by Pitoro et al. (2021) [54] in a study conducted in the same experimental area (140.48 mm in cycle 1 and 114.37 mm in cycle 2), during the period from March 28 to May 26 (cycle 1), and July

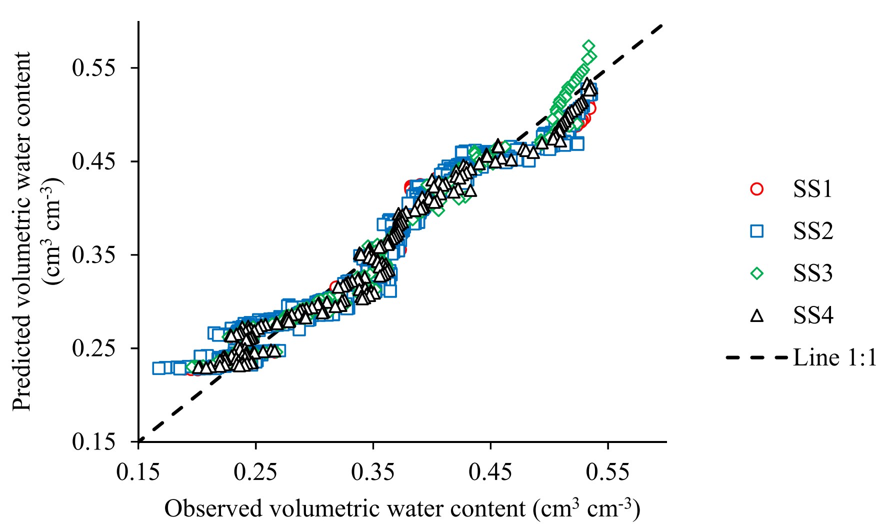

Fig. 11. Relationship between volumetric water content predicted by the calibration equation and measured (observed) using the gravimetric method.

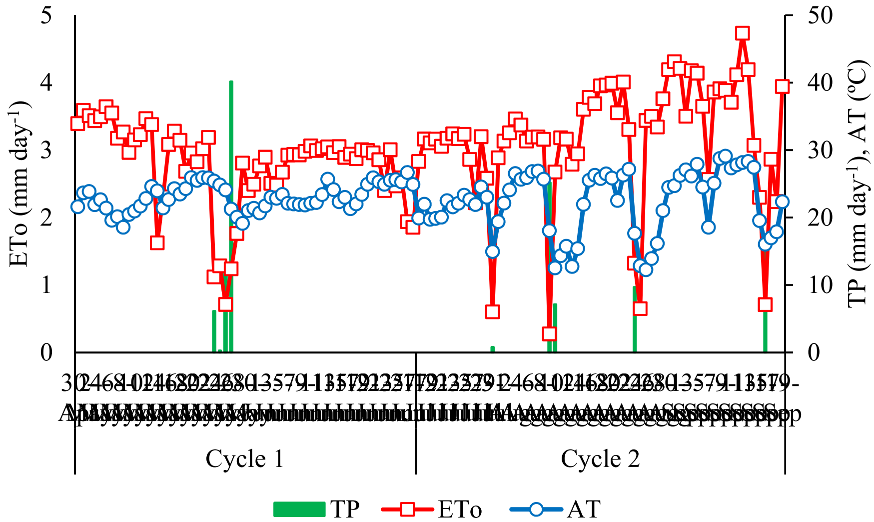

Fig. 12. Average temperature (AT), total precipitation (TP), and reference evapotranspiration (ETo) data recorded during the study.

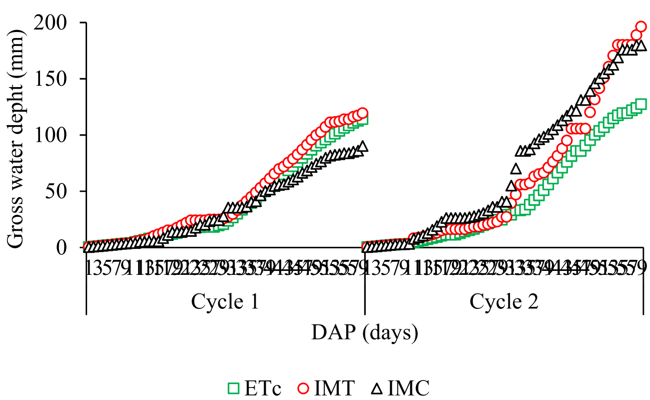

Fig. 13. Accumulated gross irrigation depth from different irrigation management techniques in the cultivation of kale (brassica oleracea var. acephala), cycle 1 and cycle 2 (ETc - climate-based irrigation management, IMT – irrigation management based on tensiometers, IMC - irrigation management based on capacitive sensors).

6 to August 4 (cycle 2) of 2018.

3.3. Growth, yield, and water use productivity

Table 6 presents the summary of the ANOVA for the variables NCL, NNCL, NML, FMML, and WUP. The results indicate that there was no interaction between the factors studied, and the irrigation management techniques only had a significant effect on WUP in cycle 2, where the climate-based MI showed higher WUP, significantly different from the WUP obtained with MI using tensiometers and capacitive sensors. On the other hand, the variation in irrigation depths had a significant impact on NCL, ML, FMML, and WUP in both cycle 1 and cycle 2.

The fact that no significant differences were observed among the IM techniques for most of the variables analyzed can be interpreted as an indication that the low-cost capacitive soil moisture sensors studied in this research can be used with reasonable reliability for IM in irrigated kale cultivation. These sensors responded adequately to changes in soil moisture throughout the crop's growth cycle, like tensiometers, which are well-tested, widely recommended, and long-used devices for soil-based IM, as well as climate-based IM.

In the case of WUP in cycle 2, where the IM techniques showed significant effects, it was observed that the average values for IM using tensiometers (10.02 g L^{-1}) and low-cost capacitive sensors (9.69 g L^{-1}) were statistically similar reinforcing the idea that the capacitive sensors studied here may represent a promising low-cost solution for IM. Comparing different IM strategies in cucumber cultivation, Rahil; Qanadillo (2015) [55] observed that although the use of tensiometers led to greater water savings, it resulted in lower total yield, yield per plant, number of harvests per plant, and maximum plant height compared to climate-based IM (ETc). They attributed these results to the fact that tensiometers do not function effectively in certain soil types.

The average values of NCL, NNCL, NML, and FMML in cycle 2 were higher compared to cycle 1 across all MI techniques (Table 5). The climatic conditions, especially the mild temperatures between 15 °C and 20 °C considered favorable for kale cultivation [56] may have contributed to greater plant development, which in turn resulted in increased water demand, as reflected in the soil-based MI techniques previously mentioned.

The average NML recorded in this study (Table 7) was higher than

Table 6
Summary of analysis of variance (ANOVA) for number of commercial leaves (NCL), number of non-commercial leaves (NNCL), number of mature leaves (NML), fresh mass of mature leaves per plant (FMML), and water use productivity (WUP).

SV	df	Mean square NCL	NNCL	NML	FMML (g)	WUP (g L-1)
			Cycle 1			
IMT	2	39.89 ^{ns}	53.17 ^{ns}	39.34 ^{ns}	18,702.62 ^{ns}	22.50 ^{ns}
IL	3	226.67 **	71.70 ^{ns}	201.04 **	37,230.06 **	48.08 *
Block	3	253.96 **	49.13 ^{ns}	181.83 **	26,677.62 *	55.33 *
IMT x IL	6	32.73 ^{ns}	142.57 ^{ns}	26.99 ^{ns}	9233.16 ^{ns}	11.19 ^{ns}
Residuals	33	50.24	36.50	38.14	6359.21	13.31
Cycle 2						
IMT	2	80.08 ^{ns}	178.91 ^{ns}	17.39 ^{ns}	11,036.19 ^{ns}	44.59 *
IL	3	461.89 **	162.83 ^{ns}	447.91 **	26,901.22 *	123.47 **
Block	3	153.02 ^{ns}	107.72 ^{ns}	146.00 ^{ns}	51,662.84 **	58.32 **
IMT x IL	6	4.75 ^{ns}	96.31 ^{ns}	18.71 ^{ns}	2772.25 ^{ns}	3.45 ^{ns}
Residuals	33	87.68	153.63	73.26	8183.16	9,57

ns – non-significant effect; * – significant effect at $p < 0.05$; ** – significant effect at $p < 0.01$ according to Tukey's test; SV – source of variation; df – degrees of freedom; IMT – irrigation management techniques; IL – irrigation levels.

that reported by Pitoro et al. (2021) [54], who obtained, for example, 9.26 leaves per plant in cycle 1 and 9.32 leaves per plant in cycle 2 under conventional cultivation with potable water irrigation. The climatic conditions may have contributed significantly to the differences observed between the results of this study and those of Pitoro et al. (2021), as in the present research, cultivation took place mostly during a period of mild temperatures, which are considered favorable for kale production.

The NML results recorded in this study were even higher than those reported by Viana et al. (2021) [57], who evaluated the effect of different irrigation levels and irrigation water salinity, obtaining NML values ranging from 8 to 11 leaves per plant; and by He et al. (2023) [58], who assessed the impact of deficit irrigation and obtained an NML of approximately 10 leaves per plant.

The average results (Table 7) for NCL (8.59 in cycle 1, and 16.23 in cycle 2), NML (15.84 in cycle 1, and 25.45 in cycle 2), and FMML obtained in this study (243.15 g per plant in cycle 1 and 344.09 g per plant in cycle 2) do not differ much from the values reported by Barickman; Ku; Sams (2020) [59], who evaluated different levels of water replacement based on soil volumetric moisture and obtained an average of 359.77 g per plant. Ben Ammar et al. (2023) [60], assessing the effects of water stress, reported FMML values of 256.5 g per plant and 211 g per plant in non-stressed and deficit-irrigated plants, respectively. Viana et al. (2021) [57] obtained FMML values ranging from 97 to 206.67 g per plant when evaluating different irrigation levels and irrigation water salinity. Overall, the results obtained in this study are not significantly different from those commonly reported in literature, which may indicate that, in general, the irrigation management (IM) was properly conducted.

According to the results presented in Table 7, WUP values in Cycle 1 were 12.11 g L^{-1} for the ETc, 11.87 g L^{-1} for the IMC, and 9.94 g L^{-1} for the IMT. In Cycle 2, the WUP values were 12.73 g L^{-1} for ETc, 10.02 g L^{-1} for IMC, and 9.69 g L^{-1} for IMT. Compared to IMT, the use of IMC resulted in a relative increase in water use productivity of approximately 19.4 % in Cycle 1 and 3.4 % in Cycle 2, reinforcing its potential as a low-cost and efficient alternative for irrigation management. Although IMC values were slightly lower than those obtained with the ETc method, they still reflect a favorable balance between water savings, ease of implementation, and performance.

An increase in NCL, NML, and FMML was observed with the amount of water applied across the three IM techniques, showing a direct linear relationship in both cycle 1 and cycle 2 (Fig. 14). This behavior may have influenced WUP, as the highest WUP was recorded at the level where the least amount of water was applied. In contrast, Barickman; Ku; Sams (2020) [59] observed that the lowest WUP occurred in plants that received the smallest water volume.

The trend observed in this study between irrigation levels, FMML yield per plant, and WUP is not very different from what is commonly reported in the literature. Singh et al. (2021) [18] noted that for most of the crops analyzed, vegetable productivity increases with greater water input, while WUP decreases. In the meta-analysis by Cheng et al. (2021) [61], it was observed that yields under deficit irrigation conditions were lower compared to full irrigation, while the corresponding WUP values were significantly higher.

The results obtained in this study, which indicate higher WUP under the IMC compared to the IMT, are consistent with findings from other crops, where sensor-based scheduling has improved irrigation efficiency relative to conventional approaches. Abdelmoneim et al. (2025) [16], for instance, reported that low-cost capacitive sensors reduced water use and pumping hours by approximately 28.8 % and 16.2 %, respectively, while maintaining crop performance, when compared to a weather-based schedule. Similarly, Sui; Vories (2020) [62] observed differences in irrigation events and water savings between soil moisture sensor-based and ETc-based scheduling. In line with the findings of Aldaz-Lusarreta et al. (2023) [63], the present results also demonstrate that capacitive sensors can outperform tensiometers in operational simplicity and irrigation efficiency, although their performance remains slightly below that of optimized ETc-based methods. These outcomes highlight the potential of capacitive sensors as a viable and scalable alternative for IM, particularly in contexts where access to costly equipment and technical expertise is limited. They also contribute novel evidence to the field, given the limited availability of studies involving kale and other leafy vegetables.

While the results demonstrate the potential of low-cost capacitive sensors for IM, several practical challenges remain. Sensor durability under long-term field conditions, user training requirements, and maintenance needs may affect adoption by smallholder farmers, particularly in low- and middle-income countries [64,65]. Similar studies in Africa have reported that even affordable and technically sound smart irrigation technologies face barriers related to cost, operational complexity, and limited technical support [10,35]. These findings underscore the importance of integrating training and supporting mechanisms when scaling up low-cost sensor solutions. Furthermore, this study was conducted on a single crop and over one season with a limited sample size, which may restrict the generalization of the results. Future research should therefore assess sensor performance over multiple seasons, in different crops and soil conditions, to validate its broader applicability and to address constraints related to durability, adoption, and scalability.

4. Conclusions

The results of this study demonstrated that the SKU: CE09640 capacitive sensors were effective in monitoring soil moisture under field conditions throughout the crop cycle. After calibration, sensor readings showed a strong negative correlation with gravimetric measurements ($-0.977 < R < -0.964$), high goodness of fit ($0.95 < R^2 < 0.97$), and acceptable accuracy ($0.01 < \text{RMSE} < 0.05$). As a result, no statistically significant differences were observed among the irrigation management (IM) techniques evaluated, supporting the conclusion that the SKU: CE09640 sensors represent a viable low-cost alternative for IM in irrigated kale cultivation.

Under conditions where financial and skilled human resources are available, climate-based IM may be more appropriate, as it resulted in higher WUP, with values of 12.11 g L^{-1} in cycle 1 and 12.73 g L^{-1} in cycle 2, compared to IM using capacitive sensors (WUP between 10.02 and

Table 7
Mean values of number of commercial leaves (NCL), number of non-commercial leaves (NNCL), number of mature leaves (NML), fresh mass of mature leaves per plant (FMML), and water use productivity (WUP) under different irrigation management techniques.

IMT	NCL *Cycle 1*	NNCL	NML	FMML (g)	WUP (g L^{-1})	NCL *Cycle 2*	NNCL	NML	FMML (g)	WUP (g L^{-1})
ETc	10.08	7.14	17.22	280.36	12.11	14.94	9.82	24.77	318.86	12.73 a
IMT	8.75	7.42	16.17	235.95	9.94	14.94	9.99	24.94	371.28	9.69 b
IMC	6,94	7.20	14.14	213.13	11.87	13.81	7.83	21.65	342.12	10.02 b
Mean	8.59	7.25	15.84	243.15	11.31	16.23	9.21	25.45	344.09	10.02
p-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	*

ns, *, ** – non-significant effect, significant effect at $p < 0.05$, and significant effect at $p < 0.01$, respectively, according to the T-test; IMT – irrigation management techniques; ETc – irrigation management based on climate; IMT – irrigation management using tensiometers; IMC – irrigation management using capacitive sensors.

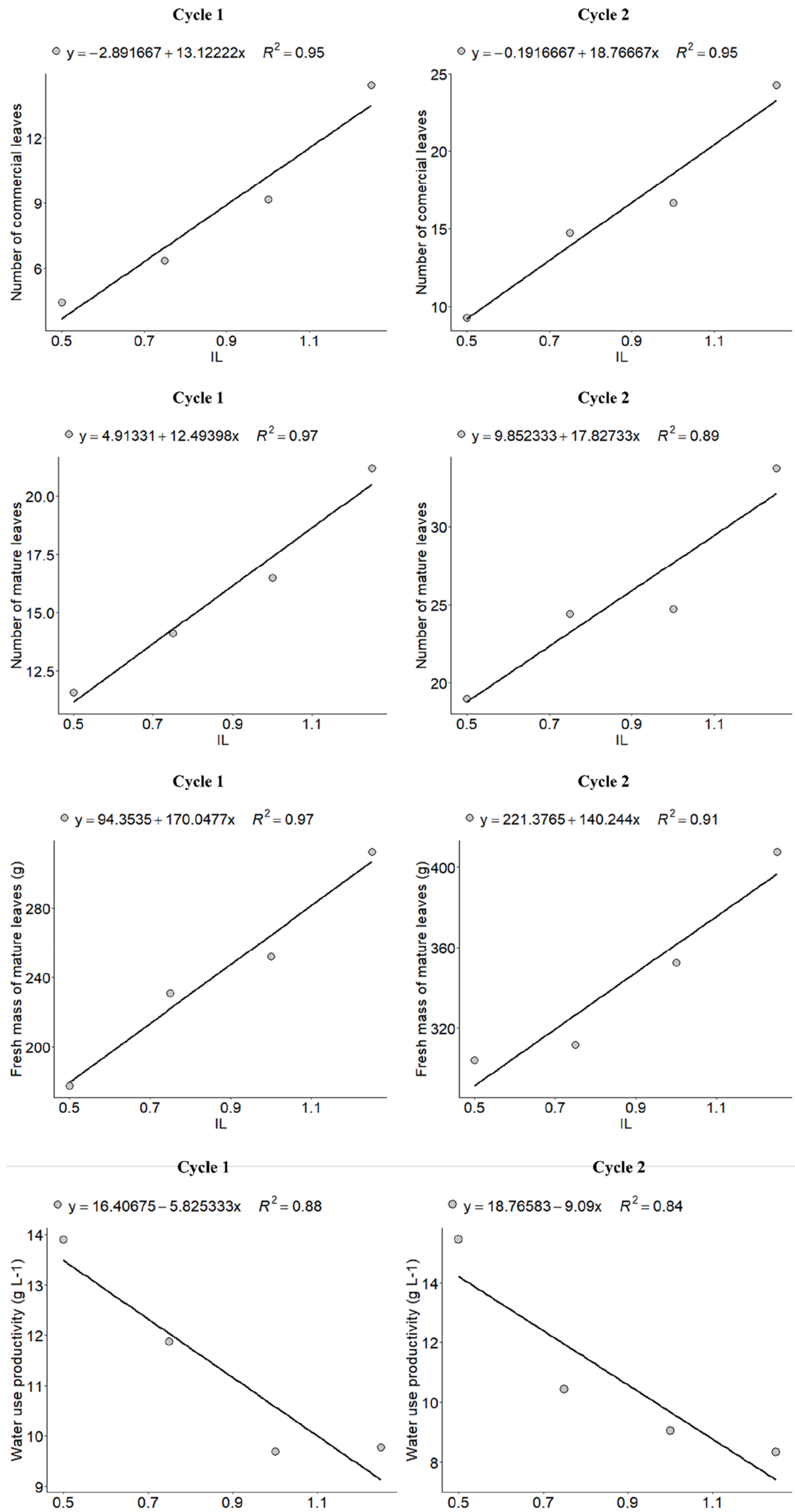

Fig. 14. Number of commercial leaves (NCL), number of mature leaves (NML), fresh mass per plant (FMML), and water use productivity (WUP) under different irrigation levels in cycle 1 and cycle 2.

11.87 g L^{-1}) or tensiometers (WUP between 9.69 and 9.94 g L^{-1}), reflecting the greater accuracy and robustness of climate-based methods, which are more established and widely validated.

However, under resource-limited conditions, both financial and human, especially in contexts involving farmers with limited technical training to interpret complex information, or those seeking simple, low-cost, and user-friendly solutions, the use of SKU: CE09640 capacitive sensors combined with the visual interpretation system for soil moisture proposed in this study may represent a suitable alternative. This is supported by the fact that the results obtained were statistically similar to those of the other two IM techniques for most of the variables analyzed.

The low-cost irrigation management solution using capacitive soil moisture sensors developed and evaluated in this study has the potential to be patented. Future research should aim to assess the applicability of this solution under real farming conditions, particularly among smallholder farmers with limited technical training. Such studies could help identify both the potential and the limitations of the proposed system in diverse socio-agricultural contexts, contributing to its refinement and broader adoption in resource-constrained environments.

Code availability (custom code)

The codes used in this research are available at: https://github.com/vpitoro/kale_irrigation_management_techniques-.git

The code used in this study and released as custom code in the link above (identified as "IMC_RGB_LEDs.txt" in repository) is registered in Brazil as a computer program with the National Institute of Industrial Property (INPI), Certificate/Process No [BR512025003717–1], filed on [12 08 2025].

Ethical statements

The authors declare that:

- The work described in this manuscript has not been published previously, except in the form of a preprint, abstract, academic thesis, published lecture, or registered report.
- The manuscript is not currently under review or being considered for publication elsewhere.
- The publication of this article has been approved by all authors and, where applicable, by the relevant institutional authorities at which the work was conducted.
- If accepted for publication, this article will not be published in the same form in any other language or format, including electronic formats, without prior written consent from the copyright holder.

CRediT authorship contribution statement

Valdemiro Simão João Pitoro: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Cleber Alexandre de Amorim:** Writing – review & editing, Writing – original draft, Validation, Supervision. **José Rafael Franco:** Writing – review & editing, Visualization, Formal analysis. **Rodrigo Máximo Sánchez-Román:** Writing – review & editing, Writing – original draft, Validation, Resources, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors would like to express our sincere gratitude to the National Council for Scientific and Technological Development (CNPq) for the scholarships that made this work possible. We also thank São Paulo State University (UNESP) for the institutional support and infrastructure provided, which were essential for the development of this research.

Data availability

Data will be made available on request.

References

[1] V. Kumar, J. Singh, Trends in hydroponics practice/technology in horticultural crops: a review, Int. J. Plant Soil Sci. 35 (2023) 57–65, https://doi.org/10.9734/ijpss/2023/v35i22759.
[2] United Nations, Department of Economic and Social Affairs, Population Division. World Population Prospects 2019 [Internet]. New York: United Nations; 2019 [cited 2025 Out 1]. Available from: https://population.un.org/wpp/.
[3] B. Jamshidi, H.K. Jolfaee, K. Mohammadpour, M. Seilsepour, H. Dehghanisanij, H. Hajnajari, H. Farazmand, A. Atri, Internet of things-based smart system for Apple orchards monitoring and management, Smart Agric. Technol. (2024) 100715, https://doi.org/10.1016/j.atech.2024.100715.
[4] Q. Li, T. Sugihara, S. Shibusawa, M. Li, A case study on water use efficiency in extreme water-saving cultivation of tomato plants, Eur. J. Hortic. Sci. 5 (2021) 556–566, https://doi.org/10.17660/eJHS.2021/86.5.11.
[5] D.D. Champaneri, K.D. Desai, V. Sharma, D.A. Madane, S.J. More, A synoptic review of deficit irrigation methods: sustainable water-saving strategies in vegetable cultivation, Water Supply 24 (2024) 3132–3147, https://doi.org/10.2166/ws.2024.195.
[6] M.Y. Kabir, S.U. Nambeesan, J. Bautista, J.C. Díaz-Pérez, Effect of irrigation level on plant growth, physiology and fruit yield and quality in bell pepper (Capsicum annuum L.), Sci. Hortic. 281 (2021) 109902, https://doi.org/10.1016/j.scienta.2021.109902.
[7] A. Fares, A.K. Alva, Evaluation of capacitance probes for optimal irrigation of citrus through soil moisture monitoring in an entisol profile, Irrig. Sci. 19 (2000) 57–64.
[8] R. Schlank, C.M. Kidman, D. Gautam, D.W. Jeffery, V. Pagay, Data-driven irrigation scheduling increases the crop water use efficiency of Cabernet Sauvignon grapevines, Irrig. Sci. 42 (2024) 29–44, https://doi.org/10.1007/s00271-023-00866-7.
[9] A.D. Chukalla, M.L. Mul, P. Karimi, Establishing the water resources implications for closing the land and water productivity gaps using remote sensing–A case study of sugarcane, Field Crops Res. 318 (2024) 109589.
[10] F. Wamala, A. Gidudu, J. Wanyama, P. Nakawuka, E. Bwambale, A.D. Chukalla, Assessment of irrigation water distribution using remotely sensed indicators: a case study of Doho Rice Irrigation Scheme, Uganda, Smart Agric. Technol. 4 (2023) 100184, https://doi.org/10.1016/j.atech.2023.100184.
[11] A. Margiwiyatno, A. Sudarmaji, S. Siswantoro, M. Masrukhi, I. Irawadi, K. Wijaya, P.H. Kuncoro, S.B. Sulistyo, F. Furqon, Use of capacitive sensors for measuring soil water content in irrigation systems: a review, in: BIO Web Conf. EDP Sci., 2025 01001, https://doi.org/10.1051/bioconf/202515801001.
[12] S. Mane, G. Singh, N.N. Das, A. Kanungo, N. Nagpal, M. Cosh, Y. Dong, Development of low-cost handheld soil moisture sensor for farmers and citizen scientists, Front. Environ. Sci. 13 (2025) 1590662, https://doi.org/10.3389/fenvs.2025.1590662.
[13] S.M.M. Meshram, S. Adla, L. Jourdin, S. Pande, Review of low-cost, off-grid, biodegradable in situ autonomous soil moisture sensing systems: is there a perfect solution? Comput. Electron. Agric. 225 (2024) 109289 https://doi.org/10.1016/j.compag.2024.109289.
[14] R. Nandi, D. Shrestha, Assessment of low-cost and higher-end soil moisture sensors across various moisture ranges and soil textures, Sensors 24 (2024) 5886, https://doi.org/10.3390/s24185886.
[15] A.Z. Bayih, J. Morales, Y. Assabie, R.A. De By, Utilization of internet of things and wireless sensor networks for sustainable smallholder agriculture, Sensors 22 (2022) 3273, https://doi.org/10.3390/s22093273.
[16] A.A. Abdelmoneim, C.M. Al Kalaany, R. Khadra, B. Derardja, G. Dragonetti, Calibration of low-cost capacitive soil moisture sensors for irrigation management applications, Sensors 25 (2025) 343.
[17] P. Vandôme, C. Leauthaud, S. Moinard, O. Sainlez, I. Mekki, A. Zairi, G. Belaud, Making technological innovations accessible to agricultural water management: design of a low-cost wireless sensor network for drip irrigation monitoring in Tunisia, Smart Agric. Technol. 4 (2023) 100227, https://doi.org/10.1016/j.atech.2023.100227.
[18] M. Singh, P. Singh, S. Singh, R.K. Saini, S.V. Angadi, A global meta-analysis of yield and water productivity responses of vegetables to deficit irrigation, Sci. Rep. 11 (2021) 22095, https://doi.org/10.1038/s41598-021-01433-w.
[19] D.K. Asmamaw, P. Janssens, M. Dessie, S. Tilahun, E. Adgo, J. Nyssen, K. Walraevens, W. Cornelis, Deficit irrigation as a sustainable option for improving water productivity in Sub-Saharan Africa: the case of Ethiopia. A critical review, Environ. Res. Commun. 3 (2021) 102001, https://doi.org/10.1088/2515-7620/ac2a74.

[20] S. Bhatti, D.M. Heeren, S.A. O'Shaughnessy, C.M. Neale, J. LaRue, S. Melvin, E. Wilkening, G. Bai, Toward automated irrigation management with integrated crop water stress index and spatial soil water balance, Precis. Agric. 24 (2023) 2223–2247, https://doi.org/10.1007/s11119-023-10038-4.
[21] S. Datta, S. Taghvaeian, T.E. Ochsner, D. Moriasi, P. Gowda, J.L. Steiner, Performance assessment of five different soil moisture sensors under irrigated field conditions in Oklahoma, Sensors 18 (2018) 3786, https://doi.org/10.3390/s18113786.
[22] M Padhiary, A Kumar, LN Sethi, Emerging technologies for smart and sustainable precision agriculture, Dis. Robot. 1 (2025) 1–28, https://doi.org/10.1007/s44430-025-00006-0.
[23] D.M. Kadyampakeni, E. Scudiero, R. Shrestha, Advances in precision irrigation management in the twenty-first century, Irrigat. Sci. 43 (2025) 989–994, https://doi.org/10.1007/s00271-025-01038-5.
[24] R. Sui, Irrigation scheduling using soil moisture sensors, J. Agric. Sci 10 (2017) 1–10, https://doi.org/10.5539/jas.v10n1p1.
[25] S. Indurthi, I. Sarma, D.V. Vinod, Horticultural innovations elevating crop yields and agricultural sustainability for a flourishing future, Plant Cell Biotechnol. Mol. Biol. 25 (2024) 22–44, https://doi.org/10.56557/pcbmb/2024/v25i1-28560.
[26] A. Rai, Y. Dong, A scoping review of irrigation scheduling methods in potato (Solanum tuberosum L.) production, American J. Potato Res. 102 (2025) 348–371, https://doi.org/10.1007/s12230-025-09997-3.
[27] S. Cominelli, L.D. Rivera, W.G. Brown, T.E. Ochsner, A. Patrignani, Calibration of TEROS 10 and TEROS 12 electromagnetic soil moisture sensors, Soil Sci. Socie. America J. 88 (2024) 2104–2122, https://doi.org/10.1002/saj2.20777.
[28] S. Verma, R. Pahuja, Recalibration and performance comparison of soil moisture sensors using regression and neural network characteristic models, Mater. Today: Proc. 45 (2021) 4852–4861, https://doi.org/10.1016/j.matpr.2021.01.306.
[29] P. Dobriyal, A. Qureshi, R. Badola, S.A. Hussain, A review of the methods available for estimating soil moisture and its implications for water resource management, J. Hydrol. 458 (2012) 110–117, https://doi.org/10.1016/j.jhydrol.2012.06.021.
[30] L. Yu, W. Gao, R.R. Shamshiri, S. Tao, Y. Ren, Y. Zhang, G. Su, Review of research progress on soil moisture sensor technology, Int. J. Agri. Bio. Eng. 14 (2021) 32–42, https://doi.org/10.25165/j.ijabe.20211404.6404.
[31] E. Vories, K. Sudduth, Determining sensor-based field capacity for irrigation scheduling, Agric. Water Manag. 250 (2021) 106860, https://doi.org/10.1016/j.agwat.2021.106860.
[32] A. Alhadchiti, B. Nikolic, P. Ioakim, M.B. Powner, I.F. Triantis, Identification and analysis of key factors limiting the performance of electrical soil sensors: a review, Comput. Electron. Agric. 237 (2025) 110480, https://doi.org/10.1016/j.compag.2025.110480.
[33] A.G. El-Naggar, C.B. Hedley, D. Horne, P. Roudier, B.E. Clothier, Soil sensing technology improves application of irrigation water, Agric. Water Manag. 228 (2020) 105901, https://doi.org/10.1016/j.agwat.2019.105901.
[34] A.M. Okasha, H.G. Ibrahim, A.H. Elmetwalli, K.M. Khedher, Z.M. Yaseen, S. Elsayed, Designing low-cost capacitive-based soil moisture sensor and smart monitoring unit operated by solar cells for greenhouse irrigation management, Sensors 21 (2021) 5387, https://doi.org/10.3390/s21165387.
[35] Y.G. Mekonnen, T. Alamirew, K.B. Tadesse, A.D. Chukalla, Monitoring small-scale irrigation performance using remote sensing in the Upper Blue Nile Basin, Ethiopia, Agric. Water Manag. 300 (2024) 108928, https://doi.org/10.1016/j.agwat.2024.108928.
[36] T.J. Rossi, J.F. Escobedo, C.M. dos Santos, L.R. Rossi, M.B.P. da Silva, E. Dal Pai, Global, diffuse and direct solar radiation of the infrared spectrum in Botucatu/SP/Brazil, Renew. Sustain. Energy Rev. 82 (2018) 448–459, https://doi.org/10.1016/j.rser.2017.09.030.
[37] J.R. Franco, E.D. Pai, M.V.C. Calça, M.R. Raniero, A.D. Pai, V.C.R. Sarnighausen, R.M.S. Román, Atualização da normal climatológica e classificação climática de köppen para o município de Botucatu-sp, IRRIGA 28 (2023) 77–92, https://doi.org/10.15809/irriga.2023v28n1p77-92.
[38] H.G. dos Santos, P.K.T. Jacomine, L.H.C. dos Anjos, V.A. Oliveira, J.F. Lumbreras, M.R. Coelho, J.A. Almeida, J.C. Araújo Filho, J.B. Oliveira, T.J.F. Cunha, Sistema Brasileiro de Classificação de Solos, 5th ed. rev. and enlarged, Embrapa, Brasília (DF), 2018.
[39] S. Postolache, P. Sebastião, V. Viegas, O. Postolache, F. Cercas, IoT-based systems for soil nutrients assessment in horticulture, Sensors 23 (2023) 403, https://doi.org/10.3390/s23010403.
[40] M.Q. Aringo, C.G. Martinez, O.G. Martinez, V.B. Ella, Development of low-cost soil moisture monitoring system for efficient irrigation water management of upland crops, in: IOP Conf. Ser.: Earth Environ. Sci., 2022 012029, https://doi.org/10.1088/1755-1315/1038/1/012029.
[41] Y. Xu, M. Smirnov, M.C. Kohler, Z. Dong, R.K. Amineh, F. Li, R. Rojas-Cessa, A survey of wireless soil sensing technologies, IEEE Access 12 (2024) 12010–12038, https://doi.org/10.1109/access.2024.3352006.
[42] R. Gava, E.E. da Silva, F.H.R. Baio, Calibração de sensor eletrônico de umidade em diferentes texturas de solo, Rev. Bras. Eng. Biossistemas 10 (2016) 154–162, https://doi.org/10.18011/bioeng2016v10n2p154-162.
[43] R.G. Allen, L.S. Pereira, D. Raes, M. Smith, Crop Evapotranspiration-Guidelines for Computing Crop Water requirements. FAO Irrigation and Drainage Paper 56, 56, Food and Agriculture Organization of the United Nations, Rome, 1998, p. e156.
[44] R.D. da S. Santos, Reúso de água residuária tratada no cultivo de hortaliças, PhD thesis, Faculdade de Ciências Agronômicas – UNESP, Botucatu (SP), 2019. Available at: https://repositorio.unesp.br/handle/11449/191384.
[45] K. Seki, N. Toride, M.T. Van Genuchten, Evaluation of a general model for multimodal unsaturated soil hydraulic properties, J. Hydrol. Hydromech. 71 (2023) 22–34, https://doi.org/10.2478/johh-2022-0039.
[46] F.F. Pizarro Cabello, Riegos localizados de alta frecuencia (RLAF): goteo, microaspersión, and enl, 3rd ed., Mundi-Prensa, Madrid, 1996.
[47] J.L. Merriam, J. Keller, Farm Irrigation System Evaluation: A Guide for Management, Utah State University, Logan (UT, 1978).
[48] A.G. Asuero, A. Sayago, A.G. González, The correlation coefficient: an overview, Crit. Rev. Anal. Chem. 36 (2006) 41–59, https://doi.org/10.1080/10408340500526766.
[49] A. Fares, F. Abbas, D. Maria, A. Mair, Improved calibration functions of three capacitance probes for the measurement of soil moisture in tropical soils, Sensors 11 (2011) 4858–4874, https://doi.org/10.3390/s110504858.
[50] C.J. Willmott, On the validation of models, Phys. Geogr. 2 (1981) 184–194.
[51] E.A.A.D. Nagahage, I.S.P. Nagahage, T. Fujino, Calibration and validation of a low-cost capacitive moisture sensor to integrate the automated soil moisture monitoring system, Agriculture 9 (2019) 141, https://doi.org/10.3390/agriculture9070141.
[52] E.P. Gomes, G.Q. de Oliveira, F. Schwerz, P.A. da Silva, G.A. Biscaro, R.C. Santos, Avaliação do medidor eletrônico de umidade do solo "HIDROFARM" em Latossolo Vermelho Distroférrico, Revista Brasileira de Agri. Irrigada-Rbai 7 (2013) 85–89, https://doi.org/10.7127/rbai.v7n100003.
[53] R. Pahuja, Development of semi-automatic recalibration system and curve-fit models for smart soil moisture sensor, Measurement 203 (2022) 111907, https://doi.org/10.1016/j.measurement.2022.111907.
[54] V.S.J. Pitoro, R.M. Sánchez-Román, J.G.T. Queluz, J.J. Guimarães, T.S. Lima, Production and sanitary quality of Kale (Brassica oleracea L. var. acephala) irrigated with domestic wastewater treated in vertical anaerobic filters, Agri. Res. 11 (2022) 229–239, https://doi.org/10.1007/s40003-021-00566-8.
[55] M.H. Rahil, A. Qanadillo, Effects of different irrigation regimes on yield and water use efficiency of cucumber crop, Agric. Water Manag. 148 (2015) 10–15, https://doi.org/10.1016/j.agwat.2014.09.005.
[56] P.E. Trani, B. van Raij, H. Cantarella, G.J.B. Figueiredo (Coords.), Hortaliças: recomendações de calagem e adubação para o Estado de São Paulo, Boletim Técnico n.º 251, Centro de Comunicação Rural – CATI, Campinas (SP), 2018.
[57] J. dos S. Viana, L.F. Palaretti, V.M. De Sousa, J. de A. Barbosa, A.M.P. Bertino, R. T. De Faria, A.B. Dalri, Saline irrigation water indices affect morphophysiological characteristics of collard, Hortic. Bras. 39 (2021) 79–85, https://doi.org/10.1590/s0102-0536-20210112.
[58] J. He, C. Chang, L. Qin, C.H. Lai, Impacts of deficit irrigation on photosynthetic performance, productivity and nutritional quality of aeroponically grown tuscan kale (Brassica oleracea L.) in a tropical greenhouse, Int. J. Mol. Sci. 24 (2023) 2014, https://doi.org/10.3390/ijms24032014.
[59] T.C. Barickman, K.-M. Ku, C.E. Sams, Differing precision irrigation thresholds for kale (*Brassica oleracea* L. var. *acephala*) induces changes in physiological performance, metabolites, and yield, Environ. Exp. Bot. 180 (2020) 104253, https://doi.org/10.1016/j.envexpbot.2020.104253.
[60] H. Ben Ammar, D. Arena, S. Treccarichi, M.C. Di Bella, S. Marghali, N. Ficcadenti, R. Lo Scalzo, F. Branca, The effect of water stress on the glucosinolate content and profile: a comparative study on roots and leaves of Brassica oleracea L. crops, Agronomy 13 (2023) 579, https://doi.org/10.3390/agronomy13020579.
[61] M. Cheng, H. Wang, J. Fan, S. Zhang, Z. Liao, F. Zhang, Y. Wang, A global meta-analysis of yield and water use efficiency of crops, vegetables and fruits under full, deficit and alternate partial root-zone irrigation, Agric. Water Manag. 248 (2021) 106771, https://doi.org/10.1016/j.agwat.2021.106771.
[62] R. Sui, E.D. Vories, Comparison of sensor-based and weather-based irrigation scheduling, Appl. Eng. Agric. 36 (2020) 375–386, https://doi.org/10.13031/aea.13678.
[63] A. Aldaz-Lusarreta, M.Á. Campo-Bescós, I. Virto, R. Giménez, Toward optimal irrigation management at the plot level: evaluation of commercial water potential sensors, Sensors 23 (2023) 9255, https://doi.org/10.3390/s23229255.
[64] N. Ahmed, D. De, I. Hussain, Internet of things (IoT) for smart precision agriculture and farming in rural areas, IEEE Internet Things J. 5 (2018) 4890–4899, https://doi.org/10.1109/JIOT.2018.2879579.
[65] P. Rajak, A. Ganguly, S. Adhikary, S. Bhattacharya, Internet of Things and smart sensors in agriculture: scopes and challenges, J. Agric. Food Res. 14 (2023) 100776, https://doi.org/10.1016/j.jafr.2023.100776.