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Statistical characterization of a capacitive soil moisture probe, integrated into the water balance system in agriculture in a semi-arid region

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Juvenaldo Florentino Canja[1*]; Benito Moreira de Azevedo[1]; George André Pereira Thé[2]; Michela Mulas[2]; Diogo Sales Frazão[1]; Luís Gonzaga Medeiros de Figueredo Júnior[3]

[1]Departamento de Engenharia Agrícola. Universidade Federal do Ceará (UFC), Campus do Pici, s/n, CEP: 60455-970, Fortaleza, CE, Brazil. E-mail: benitoazevedo@hotmail.com, dsfrazao3@gmail.com
[2]Departamento de Engenharia de Teleinformática. Universidade Federal do Ceará (UFC), Campus do Pici, s/n, CEP: 60455-970, Fortaleza, CE, Brazil. E-mail: george.the@ufc.br, michela.mulas@ufc.br
[3]Centro de Ciências Agrárias. Universidade Estadual do Piauí (UESPI), Rua João Cabral, n° 2231, CEP: 64002-150, Teresina, PI, Brazil. E-mail: luisjr@cca.uespi.br
[*]Corresponding author. E-mail: batchijuve@gmail.com

ABSTRACT

Soil water balance serves as a key indicator of moisture variability across the soil profile. Traditional instrumentation can significantly benefit from advancements in soil moisture monitoring technologies. The sensors can be integrated into precision irrigation systems. This study aimed to assess the water balance in a drainage lysimeter, integrated with a low-cost soil moisture monitoring system using the HD38 sensor. Soil moisture was tracked over a 50 cm depth using four capacitive probes. Environmental variables, including temperature and relative humidity, were monitored using a low-cost DHT11 thermo-hygrometer. Statistical analyses highlighted the dynamics of the water balance and sensor at various depths, with a particular focus on the sensor installed near the soil surface.

Keywords: Arduino, irrigation, Pearson correlation, probe, soil moisture.

Caracterização estatística de uma sonda de umidade do solo capacitiva, integrada ao sistema de balanço hídrico na agricultura em região semiárida

RESUMO

O balanço hídrico do solo serve como um indicador-chave da variabilidade da umidade no perfil do solo. A instrumentação tradicional pode se beneficiar significativamente dos avanços nas tecnologias de monitoramento da umidade do solo. Os sensores podem ser integrados em sistemas de irrigação de precisão. O estudo teve como objetivo avaliar o balanço hídrico em um lisímetro de drenagem, integrado a um sistema de monitoramento de umidade do solo de baixo custo usando o sensor HD38. A umidade do solo foi monitorada em uma profundidade de 50 cm usando quatro sondas capacitivas. Variáveis ambientais, incluindo temperatura e umidade relativa, foram monitoradas usando um termo-higrômetro DHT11 de baixo custo. As análises estatísticas destacaram a dinâmica do balanço hídrico e do sensor em níveis de profundidades,

com foco particular no sensor instalado próximo à superfície do solo.

Palavras-chave: Arduino, correlação de Pearson, irrigação, sonda, umidade do solo.

1. INTRODUCTION

One of the challenges facing global agriculture is the accelerated process of climate change, which has resulted in water imbalances, both quantitatively and qualitatively, that have become the main obstacles to food production, ensuring food sovereignty and sustainability (Cerdà and Doerr, 2007; Jiménez *et al.*, 2024; González-Sosa *et al.*, 2024). In arid and semi-arid regions, climate adversity is more significant, with irregular rainfall and, especially at certain times of the year, higher evapotranspiration than rainfall. In the semi-arid context of the Brazilian Northeast, where much of the water in reservoirs and wells contains dissolved salts (Holanda *et al.*, 2016), irrigation has been a great ally for farmers.

From an agronomic aspect, soil is a highly complex system, responsible for several processes, including water retention, which is directly linked to its texture. The variability in soil texture implies the distribution and retention of water along the profile. This factor directly influences the supply of water to plant roots, highlighting the need to maintain the physical quality of the soil (Moreira *et al.*, 2016; Hara *et al.*, 2018). Sustainable soil management practices that preserve its structure and physical quality deserve constant attention to guarantee its capacity to store water and promote gas exchange. Integrating soil water flow quantification and monitoring systems can improve irrigation efficiency and management (Canet-Martí *et al.*, 2023).

There are several methods used to enhance water management in agriculture, with a focus on soil water balance. In this context, the drainage lysimeter, a multi-format device widely used in scientific research, is used to study the interactions between water, soil, plants and atmosphere (Wilczek *et al.*, 2023; Tison *et al.*, 2016).

This approach is essentially based on the climate variable (rainfall) or water application assisted by human action (irrigation). Both processes are classified as water input into the system, and the outputs are runoff or drainage and the water content evapo transpired in the soil (Wilczek *et al.*, 2023; Tison *et al.*, 2016). The estimation of crop evapotranspiration using a drainage lysimeter depends on factors such as soil type, crop planted, and the installation area (Gashaw *et al.*, 2018; Sun *et al.*, 2018; Guadagnin *et al.*, 2018), and the installation area (Geroy *et al.*, 2011); in addition, it is quite laborious and difficult to maintain. Nevertheless, the drainage lysimeter represents a good alternative for soil water balance.

In the current scenario of availability of technological resources for the agricultural environment, water and soil management can benefit from the adoption of smart devices and a wide range of instruments (Cepuder and Nolz, 2007; Gałęzewski *et al.*, 2021). An example is the use of soil moisture sensors, low-cost electronic devices designed to measure the volumetric water content in the soil. These measurements can be obtained through the calibration curve or by direct correlation from its reading range. They consist of probes or electrodes that, inserted into the soil and assisted by low-cost microcontrollers (Loureiro *et al.*, 2023; Keerthana *et al.*, 2015), serve to monitor the soil water status in real time.

The popularization of low-cost sensors for soil moisture monitoring, coupled with embedded systems, like Arduino ESP32, has gained prominence in the agricultural sector, especially in conditions where water efficiency is essential for achieving sustainability. Studies indicate successes in several regions, using this monitoring technology integrated with the principles of precision irrigation (PI), which is a component of precision agriculture (PA), and the internet of things, IoT (Pereira *et al.*, 2019; Morchid *et al.*, 2024; Sneineh *et al.*, 2023; Swetha *et al.*, 2017; Anandkumar *et al.*, 2018; Ghosh *et al.*, 2016). These works demonstrate significant advancements in agricultural activities involving irrigation; however, they do not account for other variables that need to be measured to ensure greater reliability, which can be achieved by installing probes along the soil profile (Wilczek *et al.*, 2023).

Silva *et al.* (2016), highlight the variability in irrigation efficiency when sensors are installed in different positions. The authors state that knowledge of the variability in water extraction can improve the reliability of the soil water balance; therefore, it is extremely valuable to define the depth at which the sensors should be placed.

By nature, soils have distinct properties, and the interaction of these properties can affect the volumetric water content, which, in turn, can lead to inconsistencies in the readings of sensors, especially capacitive sensors, which perform measurements based on dielectric processes. These factors can be affected by other elements, such as soil texture, electrical conductivity and temperature, especially when the sensors are installed in the surface layers of the soil (Ma *et al.*, 2020; Gałęzewski *et al.*, 2021).

Although calibration using a small amount of soil sample under controlled conditions is the most common approach when working with this type of instrumentation, it is essential to conduct field monitoring. This monitoring should account for the influence of key environmental factors, especially when making decisions about activating the irrigation system with the assistance of smart devices. Zhang *et al.* (2018) state that, at depths between 4 and 20 cm, the moisture probe is affected by solar radiation, which induces high temperatures in the soil. Wilczek *et al.* (2023) support these findings, noting greater inconsistencies in readings, particularly in the 5 cm soil layer during the daytime. Their study examined the variation in moisture along a 34 cm profile. Other studies also describe similar occurrences, highlighting the influence of temperature on dielectric permittivity (Wilczek *et al.*, 2023; Skierucha, 2009; Or and Wraith, 1999). From the perspective of irrigation management, understanding the behavior of these factors in sensor use, especially in the context of the semi-arid region, requires a timely investigation. This investigation should consider the type of soil, its variability, and the installation depths, to achieve clear and unequivocal interpretations of the measured data. From this perspective, and with the aim of efficient water-resource management through the integration of meters and estimators, the development of an intelligent moisture monitoring system, capable of sensing environmental variables and supporting decision-making through a computer system, emerges as a viable and sustainable alternative response to climate change (Zhang *et al.*, 2023; Stocker *et al.*, 2014). In this context, it is crucial to conduct a timely experimental characterization of the devices used. Research indicates that low-cost soil moisture sensors, such as the HD38 model, require careful evaluation as their popularity increases.

In this scenario, our research has two main objectives: i) to assess the water balance by integrating the moisture variability monitoring system with a low-cost sensor in clayey loam, installed at different depths in a drainage lysimeter; ii) to analyze the behavior of the moisture sensors both with and without living cover through a homemade low-cost acquisition system. This analysis is supported by a study of significance and statistical correlation among the variables in the investigated irrigation scenario, with the aim of guiding future implementation in the field.

2. MATERIAL AND METHODS

The experiment was conducted from October to December 2023 (spring and early summer in the southern hemisphere) in the experimental area of the Agrometeorological Station, PICI Campus, Federal University of Ceará (Fortaleza, Brazil). The experimental area has geographic coordinates 3°44'S, 38°34' W, with an altitude of 19.5 m above mean sea level. According to the Brazilian Classification Legend, the soil of the experimental area is classified as “Red Yellow Argisol”, with a clayey loam texture. The experiment aimed to evaluate the sensitivity of the probe when installed at different soil depths. For this purpose, soil was collected at a depth ranging from 0 to 30 cm in the experimental area, then sifted through a 2 mm mesh and dried in an agricultural greenhouse. The drainage lysimeter was constructed from a round polyethylene water tank with a capacity of 250 L, measuring 0.5 meters in height and 0.95 meters in width, and with an area of 0.71 m^2. To facilitate drainage, a 30 mm diameter hole was made in the lower part, installing a PVC pipe of the same diameter to collect the percolate water. A valve was added to control the flow of drainage water.

Bricks and wooden pallets, stacked to a height of 0.20 m were used to support the equipment. A trench was dug in the ground at a depth of 0.25 m to accommodate the collector, which was a five-liter bottle. From there, the box was filled, placing gravel in the first layer of 0.10 m at the bottom and a “bidim” blanket on top, aiming to prevent the soil from descending into the drainage system. Four sensors were installed at depths of p1 = 0.0; p2 = 12.5; p3 = 25.5; p4 = 37.5 cm (Figure 1). After the construction and installation of the lysimeter in the experimental area, the verification and measurement phase began. Initially, the lysimeter area was irrigated until drainage was observed, ensuring that all the air in the soil pores was removed and the soil was saturated, followed by the installation of the probes (sensors).

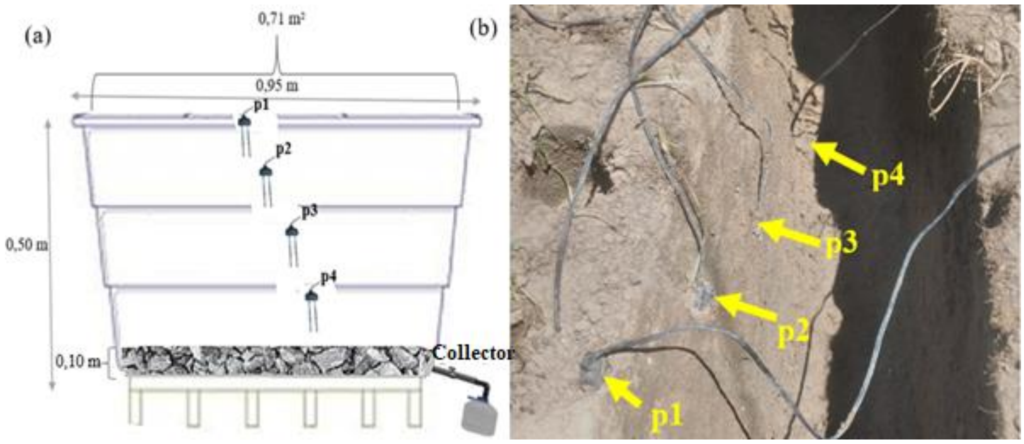

Figure 1. Sensor installation diagram (a) and field visualization (b).

The capacitive probes used in the test are HD38 models, which are corrosion-resistant and feature a comparator circuit with a 10-bit analog-to-digital converter established in MHz (Seethalakshmi *et al.*, 2021), reading range, 0 to 1023. Values close to zero (0) indicate moist soil conditions, while values close to 1023 indicate dry soil. These ranges are converted based on the operator's expectations and the programming that is desired to meet the specific crop requirements. The HD38 capacitive sensor is classified as an indirect method (Abdulraheem *et al.*, 2024; Szerement *et al.*, 2020; Majcher *et al.*, 2021).

The data acquisition system consisted of an Arduino® UNO microcontroller and a program developed to take sensor readings over time and store them with a time tag. Two meteorological variables, temperature and relative humidity, were monitored by installing a low-cost hygrothermal sensor, model DHT11.

Water was applied to the soil daily, the soil had an average electrical conductivity (EC) of 0.9 dS m^{-1}, using a conductivity meter for this measurement every 10 days. Water replenishment in the lysimeter system was done daily to ensure drainage. The replenishment water was calculated based on the volume (L) and height converted to mm day^{-1} considering the lysimeter area (0.71 m^2), between 8:00 and 9:00 a.m., over a period of 50 consecutive days with bare soil. After this stage, coriander (*Coriandrum sativum* L.) was sown under the area of the lysimeter, with a quantity of 100 grams of seed. From the date of sowing to harvest, 40 days were counted, resulting in a total of 90 days of soil water balance monitoring, including water inputs and outputs in the system. One rainfall event was recorded during this period, and was counted as water input into the system, along with irrigation, while the drained and evaporated volumes were counted as outputs. To measure the water balance (WB) at the site, the simplified soil water balance equation proposed by Reichardt (1987) was used, presented in Equation 1.

$$WB = (AW + P) - (DW - EW) \quad (1)$$

Where, WB is the water balance (mm); AW is the applied water (mm), P is the precipitation (mm), DW is the drained water in the collector (mm) and EW is the evaporated water from the soil, obtained by the difference between the inputs and the amount drained during the period. The data on water inputs and outputs in the lysimeter were analyzed in terms of daily and monthly averages, aiming to identify and compare them regarding variations in inputs and outputs, along with the values read by the probe during the tests. A correlation was made between the climate variables and the probe response at the depths evaluated, as well as soil sampling to estimate the gravimetric moisture content at the installation depths. The relationship between the water balance components and the monitored environmental variables, temperature and relative humidity, was also analyzed, considering that the intensity of such factors directly influences the processes of water loss to the atmosphere (evapotranspiration). The DHT11 sensor was installed at a height of 2 m, near the lysimeter, and the data are presented in Figure 2.

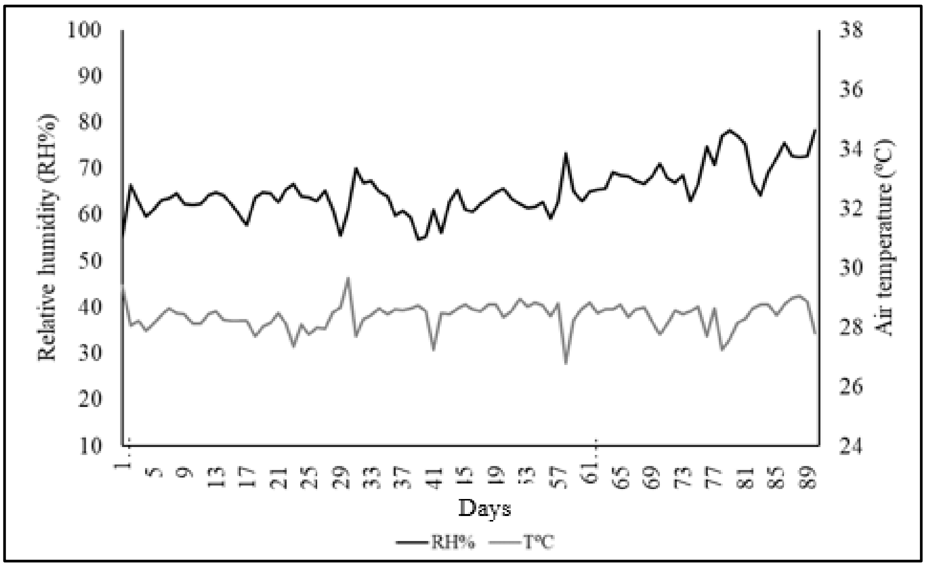

Figure 2. Monitoring of meteorological variables throughout the experiment.

At the end of the water balance estimation stage, the water inflows were stopped, and soil samples were collected. The data readings from the probe at different depths were converted to percentage values, using the map() function in the Arduino Integrated Development Environment (IDE).

The undisturbed samples were collected using an Uhland model TU manual auger with a stainless steel volumetric featuring cutting edges. They were hermetically sealed and taken to the laboratory for initial mass estimation using a precision scale with three decimal places. Subsequently, the samples were dried in an oven until they reached a constant mass. The gravimetric soil moisture (GSM%) was obtained using Equation 2, according to Embrapa (1997).

$$GSM(\%) = \frac{(WSM - DSM)}{DSM} x100 \quad (2)$$

Where, GSM is the gravimetric soil moisture (%); WSM is the wet soil mass (g), and DSM is the dry soil mass (g). In total, eight soil samples were collected at each depth, amounting to 34 samples, which were used for moisture analysis.

From the perspective of data analysis, a set of statistical tools was selected. For inference between variables, a Pearson product-moment correlation analysis, or simply Pearson's coefficient, *r* (Equation 3), was used. This analysis assumes Gaussian distribution of two or more samples and linear behavior of the relationship between variables (Zou *et al.*, 2003; Norman *et al.*, 2014).

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2} * \sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (3)$$

Where $x_1, x_2, ..., x_n$ and $y_1, y_2, ..., y_n$ are the measured values of both variables. In addition Equation 4:

$$\bar{x} = \frac{1}{n} * \sum_{i=1}^{n} x_i \text{ e } \bar{y} = \frac{1}{n} * \sum_{i=1}^{n} y_i \quad (4)$$

Represent the arithmetic means of both variables. For correlation analysis, performed in R (R Core Team, 2016), the data were normalized. The Pearson correlation was used to determine the strength and direction of the linear relationship between variables, allowing us to infer whether there are redundant variables and, therefore, capable of being removed in later stages of data processing. The normalized data were then subjected to analysis of variance (ANOVA). ANOVA was used to compare the means of the variables under study, indicating whether there are significant differences. The comparison of means was performed using the Tukey test, with the ASSISTAT program (Silva and Azevedo, 2016). The Tukey test aims to identify which readings differ from each other after the ANOVA, controlling the Type I error rate, based on the minimum significant difference (MSD). A list of acronyms was created to facilitate understanding of the terms used in the article.

3. RESULTS AND DISCUSSION

Table 1 provides a comprehensive summary of the water balance components observed during the study; it includes the applied water, drained water and evaporated water, in mm day^{-1}, along with the analog readings from the sensors at the different depths and the accumulated values of WB (water balance). Elements related to surface runoff and changes in storage were excluded from the analysis, because the irrigation was managed to prevent water overflow. The analysis of water balance data and analog readings revealed distinct daily patterns, likely influenced by weather conditions and variations in soil cover. Before the establishment of living soil cover, the daily readings showed an increasing trend across all components. However, after sowing on November 18, 2023, as highlighted in Table 1, a new dynamic emerged, with values beginning to stabilize particularly for the sensor installed near the surface (p1). On the other hand, the accumulated totals provide insights into the distribution of water throughout the test. The accumulated totals show an increase in AW from 221.7 to 253.6 mm in December. Concurrently, DW decreased from 45.4 to 31.1, while the EW rose from 176.3 to 222.5 mm in December. Overall, there was a general trend of increase in AW and EW, alongside a decrease in DW. The data presented in Table 1 illustrate the dynamics of the processes observed throughout the test period, both in terms of water balance and sensor readings. These measurements can be used to extract information related to the management of hydrological processes in the soil, particularly for estimating soil moisture content. In the present study, the recorded readings served as a reference for characterizing the sensor, response to moisture detection, at depths, providing a basis for sensor placement in future tests.

Table 1. Average water balance values in drainage lysimeter and probe values, in clayey loam soil and moisture probe.

	October							November							December						
Days	AW	DW	EW	p1	p2	p3	p4	AW	DW	EW	p1	p2	p3	p4	AW	DW	EW	p1	p2	p3	p4
	mm			%				mm			%				mm			%			
1	7.0	2.0	5	70	52	53	63	7.3	1.0	6.3	70	66	65	71	8.9	1.0	7.9	68	70	69	70
2	7.0	2.0	5	68	61	65	70	7.6	1.3	6.3	63	65	66	62	9.2	1.1	8.1	70	67	73	72
3	7.0	1.8	5.2	69	64	55	73	7.9	1.8	6.1	61	61	63	65	8.7	1.3	7.4	59	58	59	61
4	7.9	1.8	6.1	50	65	46	63	8.5	1.7	6.8	63	66	64	70	8.7	1.4	7.3	64	69	72	70
5	7.0	1.4	5.6	72	88	57	57	7.0	1.8	5.2	61	64	73	71	7.7	1.3	6.4	66	56	62	63
6	7.9	1.8	6.1	68	77	69	81	7.0	1.5	5.5	61	73	62	64	9.7	1.2	8.5	70	72	69	70
7	7.0	2.0	5	55	82	90	80	7.3	1.3	6.0	64	71	70	77	9.2	1.1	8.1	66	72	70	73
8	7.0	1.3	5.7	73	64	76	76	7.5	1.6	5.9	59	65	71	71	9.2	1.2	8.0	63	66	65	60
9	7.0	1.3	5.7	71	79	66	78	7.6	1.5	6.1	63	71	67	75	9.2	1.3	7.9	64	62	67	65
10	7.0	0.9	6.1	67	66	78	81	7.0	1.3	5.7	64	74	75	71	7.9	1.1	6.8	68	70	68	67
11	7.0	0.8	6.2	69	79	77	85	7.2	1.3	5.9	69	71	67	75	8.0	1.0	7.0	69	69	71	72
12	7.0	0.9	6.1	54	56	63	64	7.0	1.3	5.7	62	70	65	70	9.2	1.2	8.0	70	73	62	74
13	7.6	1.3	6.3	54	64	57	57	7.3	1.4	5.9	70	60	72	71	8.6	1.2	8.0	65	59	52	66
14	8.3	1.5	6.8	45	56	59	64	7.5	1.3	6.2	59	64	64	66	9.6	1.3	8.3	62	62	65	70
15	7.0	1.5	5.5	45	64	69	75	8.6	1.7	6.9	62	58	61	75	9.2	1.4	7.8	66	65	61	62
16	7.5	1.7	5.8	59	56	87	70	7.3	1.1	6.2	70	71	69	68	8.2	1.0	7.7	66	62	64	64
17	7.0	1.3	5.7	63	76	85	76	7.2	1.6	5.6	68	72	71	74	7.3	0.9	6.4	61	63	63	67

Continue...

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18	7.0	1.3	5.7	60	57	58	64	7.0 *	1.9	5.1	70	71	72	70	7.9	1.1	6.8	59	61	64	68
19	7.0	1.6	5.4	65	58	72	71	7.0	1.6	5.4	66	69	68	73	8.2	1.0	7.2	59	61	61	62
20	7.0	1.5	5.5	60	60	63	73	7.9	1.2	6.7	68	62	73	73	7.9	1.1	6.8	56	67	66	67
21	7.0	1.0	6	60	60	68	67	6.9	1.6	5.3	68	71	70	75	8.7	1.0	7.7	58	68	74	73
22	7.0	1.2	5.8	59	67	71	75	7.0	2.1	4.9	62	60	67	65	8.7	1.0	7.7	69	73	72	72
23	7.3	1.2	6.1	64	58	77	73	7.0	1.3	5.7	66	68	65	70	9.2	1.1	8.1	58	59	68	68
24	7.0	1.6	5.4	59	70	68	68	7.0	1.9	5.1	65	71	72	72	9.2	1.0	8.2	69	68	75	73
25	7.0	1.6	5.4	65	66	60	63	7.0	1.4	5.6	62	75	73	72	9.2	1.0	8.2	62	61	70	68
26	7.2	1.7	5.5	59	60	64	65	8.7	1.9	6.8	70	69	70	71	9.0	0.9	8.1	62	62	62	64
27	7.0	1.6	5.4	66	69	68	74	8.5	1.5	7.0	68	67	69	71	9.2	0.7	9.0	67	66	68	69
28	7.0	1.5	5.5	62	68	60	71	8.3	1.8	6.5	70	74	72	71	8.6	0.6	8.0	58	64	60	66
29	7.0	1.4	5.6	67	55	69	71	7.2	1.9	5.3	54	68	66	72	7.7	0.6	7.1	52	65	67	67
30	7.0	1.5	5.5	57	61	56	71	8.4	2.0	6.4	68	70	69	70							
31	7.0	1.4	5.6	67	61	69	65														
Average																					
	7.2	1.5	5.7	62	65	67	70	7.5	1.5	5.9	65	68	68	71	8.7	1.1	7.6	64	65	66	68
Accumulated values																					
	221.7	45.4	176.3					224.7	46.6	178.1					253.6	31.1	222.5				

(*) Date of sowing coriander in drainage lysimeter.

Data reported in Table 1 show that the total accumulated applied water (AW) at the end of the test was 700 mm, of which 123.1 mm was drained and 576.9 mm was used for evapotranspiration, representing 82.4% of the return in relation to the total water depth used. To understand the relationship between water dynamics during the test, a statistical analysis was performed comparing the WB, considering daily measurements. As presented in Table 2, the F test indicated statistical significance for the effects of the months on AW, DW and EW with $p < 0.01$ (**). This significance reveals the importance of meteorological factors and soil cover as key elements in the water balance and evapotranspiration processes, where the seasonality of climatic conditions is pronounced, such as in the semi-arid region of the Northeast, Brazil.

Table 2. Summary of the analysis of variance for the daily mean of AW, DW and EW over the months of study, under drainage lysimeter in clayey loam soil and moisture probe.

SV	DF	AW	DW	EW
Months	2	19.55 **	1.67 **	32.42 **
Residual	84	0.27	0.09	0.28
Total	86			
CV (%)		6,67	22.63	8.35

SV – source of variation; DFGL – degrees of freedom; CV – coefficient of variation; ** – significant a 0.01 according to Tukey's test.

Figure 3 (a, b, c) shows the breakdown of the average values of the BH constituents. The average AW was 7.2; 7.5 and 8.7 (mm day^{-1}), respectively, in October, November and December, corresponding to a 20.83% increase in the period. On the other hand, the EW was 1.5 (October), 1.6 (November) and 1.1 (December), mm day^{-1}, a decrease of -26.66% in relation to the largest drained depth in the period.

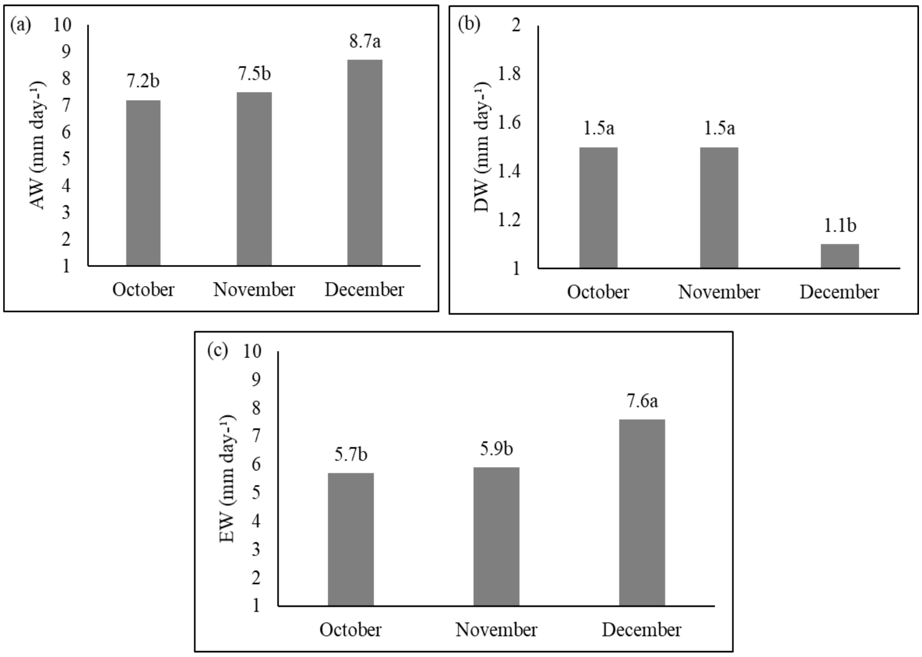

Figure 3. Daily average of applied water (a), drained water (b) and evaporated water (c), under a drainage lysimeter in clayey loam soil and capacitive probe.

The difference between inputs (AW) and outputs (DW) resulted in the daily balance (EW), which corresponds to the water content used in the various processes, including the thermal regulation of soil constituents and evapotranspiration.

From October to December, there was a 33.33% increase in evapotranspiration, which was more pronounced when the live crop was present in the soil, as previously mentioned. The study region is known for its higher evapotranspiration rate during this time of year (second half), due to the high daily radiation balance, elevated temperatures, low humidity, increased wind speeds and prolonged drought periods, which create conditions favorable for atmospheric demand (Holanda *et al.*, 2016). Furthermore, in crop environments, mulching and irrigation can reduce the impact of temperature on the soil and promote an increased water potential by modifying the thermal amplitude (Carneiro, 2014). This leads to longer water retention time in the soil solution and, consequently, greater availability to plants. It is important to note that water retention in the soil is not uniform and can vary with the soil type, as previously mentioned. Estimation of moisture can be achieved through the application of the extraction method. Table 3 presents the summary of the analysis of variance for gravimetric moisture at different depths. The collected samples did not show significant differences in the means within the collected profiles (repetitions); however, significant effects were observed between the depths, as evidenced by the Tukey test ($p < 0.01$).

Table 3. Summary of analysis of variance for gravimetric moisture variable (GH%) under drainage lysimeter in clayey loam soil and capacitive probe.

SV	DF	MS
		GH
Replications	7	11334.703 ns
Depth	3	12711.6974 **
Residual	21	11.700
Total	31	-
CV (%)		6.,67

SV – source of variation; DF – degree of freedom; MS - mean square; CV – coefficient of variation; ns – not significant; ** – significant at 0.01 by Tukey's test.

Based on the sample averages, the initial soil layer exhibited low water content when compared to other levels (Table 4). This phenomenon may be attributed to external factors, since, in the absence of cover, uncovered soils tend to rapidly lose moisture from the surface layers (Singh *et al.*, 2023). Conversely, as the soil depth increases, moisture content correspondingly increases. In the surface layer, corresponding to probe p1 (0.0 cm), the moisture content was lower at 12.26%. Studies on soil moisture have reported similar behaviors, indicating that surface layers typically have lower moisture content as they represent the transition zone to the atmosphere (Singh *et al.*, 2023). At the deepest depth, p4 (37.5 cm), the soil had a moisture content of 16.45%. This represents a 24.86% difference compared to the surface layer. From the second depth (p2) onwards, despite variations in the average values, the statistical test did not reveal significant differences. Thus, there was a relatively uniform trend in water distribution starting from this depth.

Table 4. Average values of wet and dry (WSM and DSM), respectively, and GSM (%) and respective average deviation (mean d.) under drainage lysimeter in clayey loam soil and capacitive probe.

Depth	Wet mass	Dry mass	GSM	Mean deviation
(cm)	(g^{-1})		(%)	(DSM)
p1	162.74	144.96	12.26 b	13.9
p2	200.10	174.94	14.38 a	4.4
p3	185.33	161.95	14.43 a	5.3
p4	193.74	166.36	16.45 a	6.9
-	-	-	57.5	-

Means followed by the same letter in the column are not different, based on Tukey's test at 5% of probability.

It was observed, through regression analysis, that with soil depth, there was greater retention of water content, and the best fit was the increasing linear model, with coefficients of determination of 0.91 (Figure 4). Clayey loam soils are characterized by having good water distribution along the profile (Zhang *et al.*, 2023), however there may be small variations as observed in the present case study. The soil sample identified that, at depth p1, after drying, it contained 12.26% of its structure filled with moisture, 14.38 (p2), 14.43 (p3) and 16.45 (p4), with a sum of 57.5%, this indicates an excellent capacity of the soil to retain water after each irrigation event.

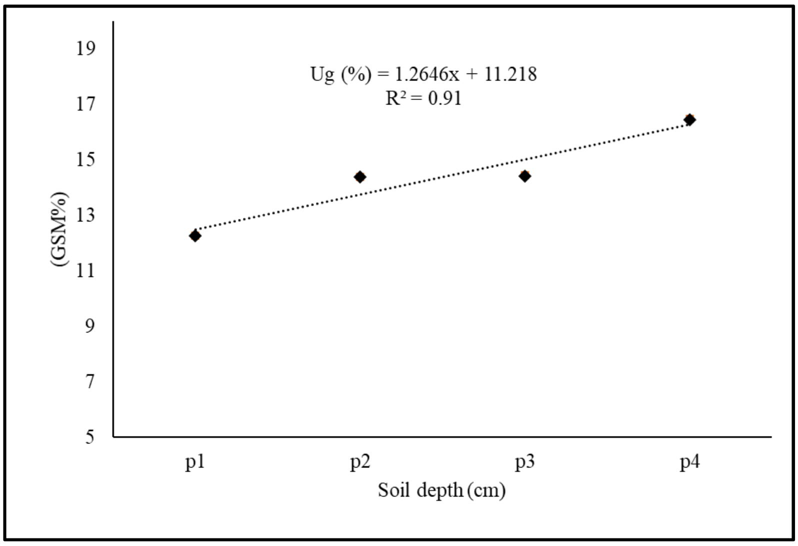

Figure 4. Variation of gravimetric soil moisture (GSM%) under drainage lysimeter in clayey loam soil and capacitive probe.

Based on this information on soil moisture at different depths, the analysis of variance (Table 5) shows that, as this depth varied, the probes were able to detect this variability, suggesting that it is a good alternative for monitoring soil moisture.

Seeking to gain insights into the behavior of the probes as a function of depth, Figure 5 illustrates the daily fluctuations in sensor readings throughout the test. The bars represent estimated evapotranspiration (EW in mm day^{-1}). Lines p1 to p4 represent, respectively, the installation depths of the humidity sensors. The sensor located in the surface layer (p1) exhibits greater variation compared to the other sensors. Behavior of this nature may be linked to the rapid drying of the soil in the first layers, caused by the interference of environmental factors, such as solar radiation, temperature, relative humidity and wind speed (Singh *et al.*, 2023; Zhang *et al.*, 2018; Ma *et al.*, 2020).

Table 5. Summary of the analysis of variance for the daily average of the sensor depths throughout the test, under drainage lysimeter in clayey loam soil and capacitive probe.

SV	DF	Sensor
Days	89	1436.9 ns
Depths	3	179782.8 **
Residual	267	1183.7
Total	359	
CV (%)		22.08

SV – source of variation; DF – degree of freedom; CV – coefficient of variation; ns – not significant; ** – significant at 0.01 by Tukey's test.

The strategy to improve these fluctuations could include the use of soil cover (Zhang *et al.*, 2023). In the present study, after sowing coriander (11/18/2023), p1 decreased its fluctuation, maintaining readings close to the other probes until the end of the experiment. It is worth mentioning that low readings indicate an increase in humidity and, consequently, an increase in the electrical conductivity of the solution (Schimanski *et al.*, 2015). In contrast when humidity decreases due to evapotranspiration or deep percolation, the dielectric effect of the sensor increases, leading to higher soil resistance. This effect is more pronounced at the surface layer.

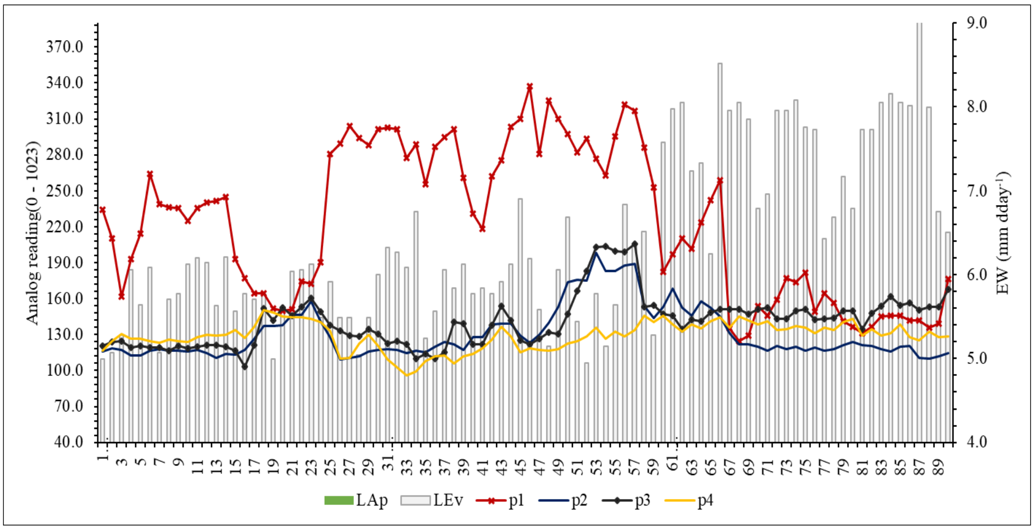

Figure 5. Moisture variation under drainage lysimeter in clayey loam soil and capacitive probe.

It is important to note that, after the start of the coriander crop was established, a reduction in the fluctuation of sensor readings was observed. This suggests that the crop cover mitigates high variability in soil thermal conditions, facilitating the redistribution of water along the soil profile (Zhang *et al.*, 2023), by promoting a more extensive root system. Sousa *et al.* (2016), using grass as soil cover, found a 99.4% reduction in soil loss and 71.9% in runoff compared to soil without cover. In the present study, what was observed was a reduction in the drained layer, combined with the increasing applied and evapotranspiration layer. This reduction in drainage, particularly during the last month of the tests, coincided with significant coriander growth, which creates a protective layer against rapid evaporation, improves root distribution, and promotes water vapor to the atmosphere mainly through transpiration. Table 6 shows the significance of the differences in readings due to depth. It can be seen that the probe (sensor) installed at p1 presented a higher value, indicating a lower moisture content in the layer when compared to the other probes. On the other hand, from p2 onwards, despite the different values recorded, they do not differ statistically, which may reflect the inherent characteristics of the soil studied.

Table 6. Average values of depths under drainage lysimeter in clayey loam soil and capacitive probe.

Depths	Analogic readings (0 – 1023)
p1	63 b
p2	66 a
p3	67 a
p4	70 a

Means followed by the same letter in the column are not different, based on Tukey's test at 5% of probability.

Despite the observed fluctuations, the probe presented a regular reading pattern, except for the probe installed at p1, which, as previously highlighted, meteorological elements may be causing these disturbances (Zhang *et al.*, 2018). The linear model (Figure 6) had the best fit to explain the behavior of the probes. Throughout the study, the probe installed at the initial depth was the one that presented the highest values, indicating less water content, as well as greater subjection to external factors (Zhang *et al.*, 2018; Ma *et al.*, 2020).

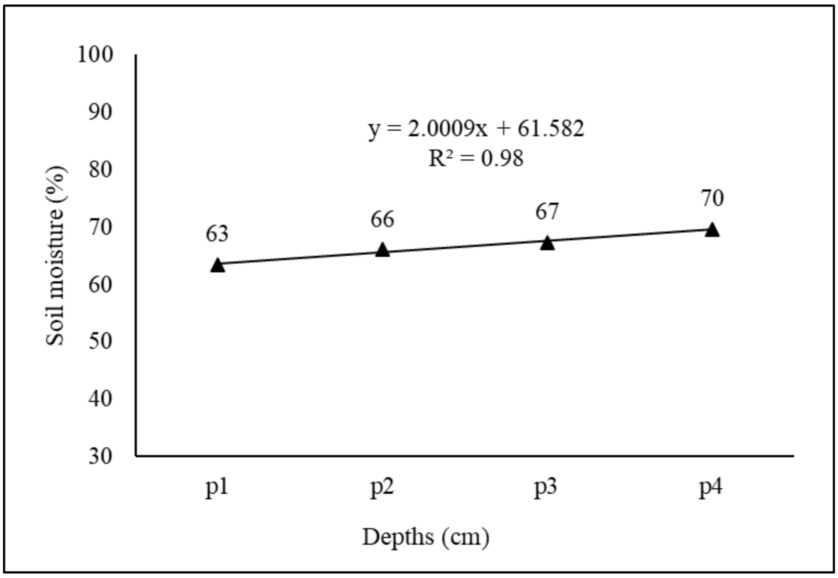

Figure 6. Average values of depths under drainage lysimeter in clayey loam soil and capacitive probe.

Moura and Querino (2010) state that soil temperature variation is the result of heat flow, being a crucial component in the energy balance from the surface, which in turn acts in the heat transfer process (Carneiro, 2014; Carvalho *et al.*, 2011) and, as a consequence, leads to oscillations in signal emission (Zhang *et al.*, 2018).

To understand the behavior of the elements that constitute the variables under study, the Pearson correlation test was employed to demonstrate the linearity of the observed data. A correlation matrix network (Figure 7) was plotted, with lines indicating the trends within the system. The green lines indicate positive correlation, while red lines indicate negative correlations. The intensities of these lines, fading towards gray, suggest a null correlation. From the network, it is possible to elucidate probable inferences between the variables. For instance, considering p1 (initial depth = 0 cm), there is a strong negative correlation with RH (relative air humidity), EW and p4 (final depth = 37.5 cm). These occurrences could be attributed to the influence of external factors, as mentioned in the introduction to this article.

RH negatively influenced DW, with this effect becoming more pronounced after the emergence of coriander. Conversely, EW showed a positive correlation with both RH and AW, indicating a positive dependency, meaning that as one variable increases, the other follows suit. This correlation reflects the meteorological behavior of the study region, where, during the second half of the year, there is a greater atmospheric demand, with potential evapotranspiration surpassing rainfall recharge. With the manual application of water, it is evident that AW increased throughout the test.

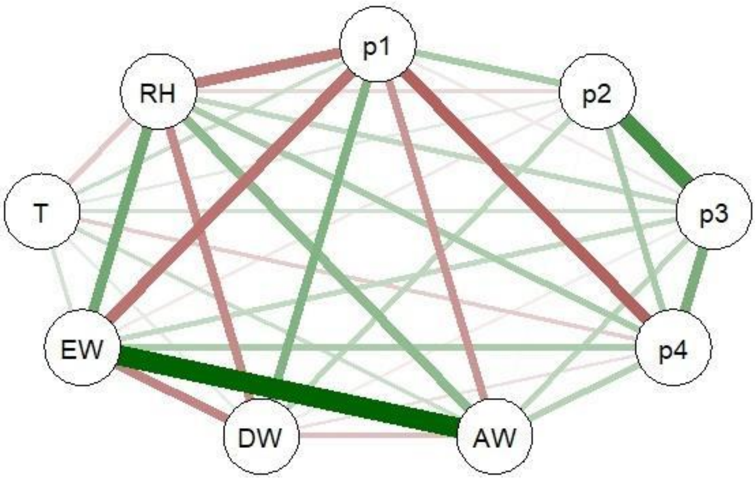

Figure 7. Pearson correlation between depths (p1 to p4), blades (AW, DW and EW), temperature and relative humidity, (n= 90). *: significant ($p<0.05$). Green – high positive correlation, light green – low positive correlation, red – high negative correlation, light red – low negative correlation.

Another way to interpret this network is through a numerical interval. Moore (2007) states that "Correlation measures the direction and degree of the linear relationship between two quantitative variables" (Moore, 2007). Cohen (1988) states that values between 0.10 and 0.29 can be considered small; scores between 0.30 and 0.49 can be considered medium; and values between 0.50 and 1 can be interpreted as large. Dancey and Reidy (2005) point to a slightly different classification: r = 0.10 to 0.30 (weak); r = 0.40 to 0.6 (moderate); r = 0.70 to 1 (strong). Using the criteria of the last author, Figure 8 presents, through graphical illustration, the correlation between the variables: the pairs (p1 vs p4, r = 0.57; p3 vs p4, r = 0.48; DW vs p1, r = 0.45; EW vs p1, r = 0.51; EW vs DW, r = 0.45; RH vs p1, r = 0.48; RH vs AW, r = 0.4; RH vs DW, r = 0.45; RH vs EW = 0.51) fall within the moderate level of correlation, both negative and positive. The pairs p2 vs p3, r = 0.67 and AW vs EW, r = 0.92, presented a strong correlation, while the remaining correlations were classified as weak.

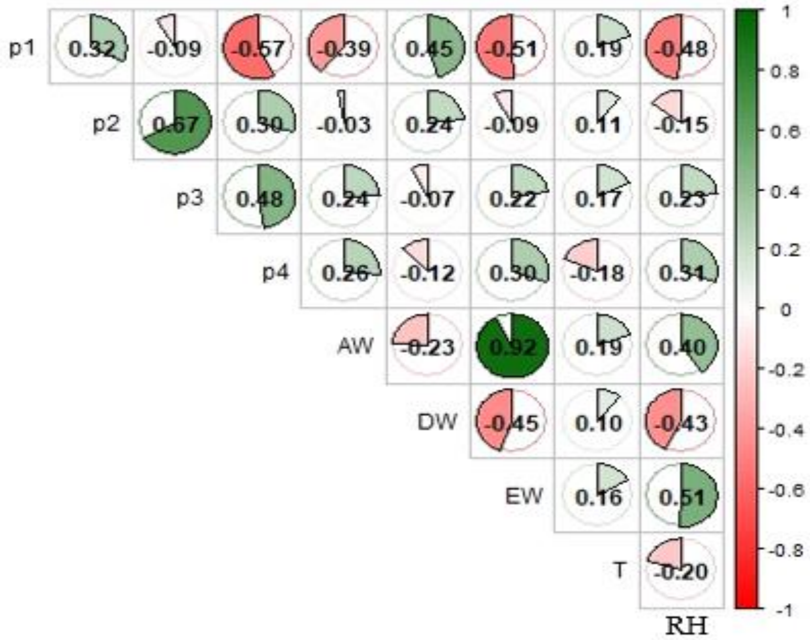

Figure 8. Pearson correlation between depths (p1 to p4), blades (AW, DW and EW), temperature and relative humidity, (n= 90). *: significant (p<0.05).

The correlation between soil depths, applied, drained and evaporated water depths, temperature and relative humidity offer valuable insights into the water and climate dynamics in the study. The analysis of Table 5 and the corresponding figures highlights how environmental variables influence water content and evapotranspiration under the conditions studied. AW and EW present a very strong correlation (r = 0.92), demonstrating that the increase in water application is directly related to the increase in evapotranspiration, likely due to the heightened atmospheric demand.

Additionally, the moderate correlation between the depth p1 and variables, such as DW (r = 0.45) and EW (r = 0.51), suggests that surface soil moisture is strongly influenced by drainage and evapotranspiration. The surface layer (p1) exhibited greater oscillation compared to the deeper layers, reflecting its higher exposure to environmental factors and agricultural practices, such as soil cover, which can mitigate these fluctuations (Zhang *et al.*, 2018; Ma *et al.*, 2020). The analysis of variance in Table 3 also reveals that there is a significant difference in water content across depths, with deeper layers (p2 to p4) maintaining higher moisture levels than the surface layer. This pattern aligns with the soil's water retention capacity, as evidenced by the coefficient of determination (R^2 = 0.91) of the increasing linear model.

A key feature of Pearson's r coefficient is that the square of its value estimates the percentage of variability in one variable that can be explained by the variability in the other (Miot, 2018). For example, in the AW vs EW correlation, (r = 0.92), this indicates that approximately 84.64% of the variability of one variable can be explained by changes in the other variable. The Pearson correlation between the variables suggests that agricultural practices, such as soil cover and irrigation, can significantly influence the water balance, which in turn affects soil moisture and thermal amplitude. Specifically, the introduction of living cover from December onwards reduced moisture in the surface layer, resulting in more stable readings throughout the remainder of the experiment.

4. CONCLUSIONS

The study and statistical analysis demonstrate the dynamics of the water balance and the dynamics of moisture in the studied soil. In water terms, an increase in applied water (AW) and evaporation (EW) was observed, while drained water (DW) showed a gradual decrease, especially in the presence of vise cover on the soil. Deeper soil layers retained more moisture, with a strong linear correlation between AW and EW (r = 0.92). The presence of soil cover minimized surface moisture fluctuations. Agronomically, the results found highlight the potential to improve irrigation efficiency and water conservation in regions with greater water restrictions. Capacitive probes have proven effective in tracking humidity variations. The study supports sustainable agricultural practices by optimizing water use and soil management, which can benefit both farmers and environmental policies aimed at sustainable water management. In environmental terms, the study can provide a vision focused on conservationist practices.

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