A Fuzzy Decision Support System to Optimize Irrigation Practices in Trentino Region

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***Abstract*—This paper presents the development and evaluation of a Fuzzy Decision Support System for irrigation management to promote sustainable water use in precision agriculture. A Mamdani-type fuzzy logic model was designed to optimize irrigation scheduling for vineyards in the Val d'Adige region of Trentino, Italy. The system integrates expert knowledge with real-time data from tensiometers and weather stations to generate adaptive, site-specific recommendations. Bayesian optimization was used to fine-tune the membership functions of fuzzy variables, enhancing system performance. Field evaluations conducted in 2023 across multiple sectors assessed total water use, average soil moisture, and days exceeding critical moisture thresholds. Results show that the system reduced total water consumption by over 52% compared to traditional methods while maintaining soil moisture within optimal levels. These findings underscore the potential of combining fuzzy logic and IoT-based sensing to support scalable, adaptive irrigation strategies across various crops and regions.**

***Index Terms*—Fuzzy Logic, Irrigation Management, Precision Agriculture, Recommendation System, Soil Moisture Monitoring.**

I. Introduction

The increasing demand for sustainable agriculture underscores the urgent need for innovative precision farming methods that optimize resources, enhance productivity, and manage soil moisture effectively. Modern agriculture faces challenges such as climate change, water scarcity, and the need to feed a growing population with minimal environmental impact. Efficient water management, especially through advanced irrigation strategies, is crucial to addressing these challenges.

In areas characterized by seasonal drought or unpredictable precipitation, such as Trentino vineyards in Northern Italy — the focus of this study — precision irrigation is the key to balancing water conservation with high-value crop needs. Grapevines, particularly, are highly sensitive to soil moisture levels and require an optimal water balance to maintain yield and quality. Therefore, using advanced tools capable of adapting irrigation to dynamic environmental and crop-specific conditions is important.

Recent Internet of Things (IoT) advances have revolutionized agricultural monitoring, enabling high-resolution, real-time data collection through devices like tensiometers and weather stations [1]. These support informed irrigation decisions by replacing traditional heuristics with data-driven insights. However, converting raw sensor data into actionable plans is challenging due to environmental variability and system complexity.

Traditional irrigation scheduling methods, often based on fixed thresholds or heuristic rules, frequently fail to capture the mutual interactions of all factors involved, resulting in inefficient water use and suboptimal outcomes for crop health and yield. This limitation has sparked a growing interest in advanced computational solutions [2].

One such approach employs Mamdani Fuzzy-based Decision Support Systems (hereafter referred to as Fuzzy DSS), which are particularly suitable for agricultural applications as they emulate human reasoning and handle the vagueness and imprecision inherent in agro-ecosystems [3]. These systems process input data through linguistic variables (*e.g.*, *"temperature IS low"*) and logical rules (*e.g.*, *"IF antecedent THEN consequent"*) to enable flexible and interpretable decision-making (*e.g.*, *"IF temperature is low THEN heating is high"*). They are especially effective at integrating expert knowledge into intuitive rule sets, producing practical and comprehensible outputs. This adaptability makes them ideal for applications like irrigation management, where uncertain factors (*e.g.*, fluctuating weather, variable crop demands, soil heterogeneity) must be simultaneously accounted for.

This study focuses on designing, developing, and validating a Fuzzy DSS tailored for vineyard irrigation within an agricultural consortium located in the Roverè della Luna municipality (hereafter RdL), Val d'Adige region of Trentino, Italy. The provided system integrates historical and real-time data from tensiometer networks and weather patterns to generate effective irrigation recommendations, refined by expert knowledge to meet the area's specific needs. The proposed approach provides a practical tool for agronomists and irrigation managers to implement sustainable irrigation solutions. Furthermore, this work contributes to the broader field of smart agriculture by showcasing the potential of integrating fuzzy logic with modern IoT infrastructure.

The paper is structured as follows: Sec. II reviews related works, while Sec. III describes the technological framework and the rationale behind the system. Next, Sec. IV describes the system details for the specific case study, including variables, rule design, and optimization strategies. Finally, Sec. V presents the system assessment and an analysis of the main results, followed by insights and future directions in Sec. VI.

II. Related Works

Fuzzy logic has emerged as a robust methodology for handling uncertainty and imprecision in irrigation systems.

Several studies have demonstrated its utility in improving water efficiency, enabling intelligent and autonomous control. For example, the authors of [4] proposed a water-saving irrigation system based on fuzzy logic, which shows a significant improvement in water utilization efficiency. Similarly, the authors in [5] designed a fuzzy system for automatic agricultural irrigation, integrating real-time data to achieve autonomous control. More recently, in [6], the computational efficiency of fuzzy logic controllers in agriculture has been highlighted, addressing the limits of traditional methods.

The integration of fuzzy logic with IoT technologies has advanced smart irrigation. In [3], IoT-enabled fuzzy systems were implemented to enable real-time adaptation to dynamic field conditions. Zoning-based approaches, such as that described in [7], introduced fuzzy control for water and energy savings, offering targeted irrigation in distinct field areas.

In parallel, traditional DSSs have been augmented by fuzzy logic to provide actionable insights. The authors of [8] developed a DSS for agricultural irrigation management, focusing on user-friendly interfaces and data visualization. Meanwhile, in [9], the authors explored the application of machine learning techniques within DSS, demonstrating enhanced predictive accuracy and system robustness. Along the same line, [10] presented a comprehensive survey on smart irrigation DSS, emphasizing the integration of machine learning and fuzzy inference for automated decisions. This combination has proven to be effective in managing complex irrigation scenarios with varying soil, weather, and crop conditions.

III. Use Case Description and Technology

Irrigation decision-making in RdL involves multiple stakeholders, including agronomists, vineyard managers, and technical staff, who collaborate to design irrigation schedules based on various factors. The area of RdL is divided into water sectors, each with distinct requirements influenced by geography, soil composition, and plant type. The number of rows per sector is variable, reflecting the heterogeneity of the terrain. This segmentation also allows custom irrigation strategies for each sector. In this consortium, irrigation planning typically involves determining the number of cycles per sector, the duration of each cycle, and the specific water volume to be delivered. These schedules are designed in advance to meet the water needs of the vineyards while minimizing resource waste. Flexibility in irrigation plans allows for real-time adjustments or interruptions of cycles when field data reveal unexpected soil moisture patterns. In such cases, sprinkler systems can be remotely controlled to stop or modify irrigation immediately.

To support this process, RdL employs a network of IoT sensor deployment consisting of 16 geo-referenced tensiometers strategically placed within the vineyards to accurately monitor soil moisture. Installed in pairs at depths of 30 and 60 centimeters, each pair corresponds to a specific row, chosen as representative of a water sector. The depths are chosen to capture the moisture dynamics within the root zones critical to grapevine growth. Sensors record soil moisture levels in millibars (mbars) at 15-minute intervals, generating four readings per hour per sensor. This high temporal resolution provides detailed insights on daily soil moisture fluctuations.

Sensor data is transmitted to a cloud-based IoT platform, where it undergoes pre-processing to ensure consistency and reliability. Temporal alignment synchronizes readings across sensors, missing data points are linearly interpolated, and anomalies, such as outliers from sensor malfunctions or environmental interference, are corrected using domain-specific heuristics. The processed data is then stored in a PostgreSQL database. Each pair of tensiometers is associated with a sprinkler system assigned to irrigate the corresponding water sector, directly connecting sensor data to irrigation control.

Additionally, historical weather data from nearby meteorological stations is integrated into the system. This provides context for understanding long-term climate trends and their impact on vineyard water needs. A web-based weather forecasting service delivers localized meteorological predictions via APIs. By integrating real-time and forecasted data, this technological stack enables precise and adaptive irrigation strategies that align with resource efficiency and sustainability goals in the target area.

IV. Design and Optimization of the Fuzzy DSS

The proposed Fuzzy DSS is designed to improve water management for specific agricultural consortia equipped with sensor and actuation capabilities, as described in Sec. III. More specifically, the primary goal is to provide daily irrigation recommendations, focusing on the duration of each watering turn, to minimize water consumption while maintaining soil moisture within optimal levels. The following subsections elaborate on its design and optimization.

A. Fuzzy DSS Design

The system is based on four input variables:

- *Last Avg Tensiometer*: previous day's average tensiometer reading (expressed in millibars), which reflects the most recent soil moisture levels:

$$\overline{T}_d = \frac{\sum_{t=1}^{N_d} T_{d,t}}{N_d}$$

  where $T_{d,t}$ is the tensiometer reading on day d at moment t, and N_d is the total number of readings during the day.
- *Predicted Avg Tensiometer*: predicted tensiometer reading for the day of interest (expressed in millibars), calculated through a machine learning model trained on historical data from multiple tensiometers:

$$\hat{T}_{d+1} = f(F_1, F_2, ..., F_J)$$

  where f is the machine learning model and F_j is the j-th factor influencing the prediction. The prediction relies on careful selection and engineering of features that effectively capture the soil moisture dynamics. Although choosing a model is crucial to ensure prediction accuracy, it is also important to consider the computational cost, scalability, and the ability to generalize across varying environmental conditions. However, without loss of generality, the deep learning model presented in [1], specifically an LSTM (Long Short-Term Memory), will be adopted in this study, as it has been shown to excel in capturing complex, non-linear dependencies in soil moisture prediction tasks.

- *Predicted Rain Amount*: predicted cumulated rain amount over the next three days (expressed in millimeters):

$$\hat{R}_{d,3}^{tot} = \sum_{i=1}^{3} R_{d+n}$$

where R_{d+n} is the predicted rain amount for day $d+n$.

- *Predicted Max Temperature*: maximum predicted temperature over the next three days (expressed in Celsius):

$$\hat{T}_{d,3}^{\max} = \max\{T_{\max,d+1}, T_{\max,d+2}, T_{\max,d+3}\}$$

where $T_{\max,d+n}$ is the predicted maximum temperature for day $d+n$.

Afterward, a fuzzification process is applied to all variables, as illustrated in Fig. 1. Specifically, each input variable is described using three linguistic terms (*Low*, *Medium*, and *High*), which qualitatively represent its possible states. The terms *Low* and *High* are modeled with trapezoidal membership functions, whereas the term *Medium* uses a triangular one.

The output variable, *Decision*, is instead defined by four linguistic terms (*Not Recommended*, *Half Turn*, *Single Turn*, and *Double Turn*), which specify the recommended duration of the irrigation turn relative to the standard duration. Similarly to the input variables, the output linguistic terms at the extremes are represented with trapezoidal membership functions, while the intermediate terms use triangular membership functions.

The DSS's fuzzy rule base was developed through a collaborative effort involving engineers, agronomists, water managers, and other key stakeholders. The outcome of this process is a set of 21 fuzzy rules that consider a wide range of scenarios, as shown in Table I. These rules incorporate critical variables, capturing specific combinations of antecedent conditions and aligning them with the most suitable consequent actions. Although the variables define a complete input space of $3^4 = 81$ possible combinations, the rules were designed to compactly cover this space by generalizing the inputs that do not influence the output. In cases where multiple rules are equally activated, the system applies standard fuzzy inference mechanisms based on a weighted average of consequents.

The DSS employs a min-max inference method, where the minimum operator evaluates rule activation and the maximum operator aggregates the outputs of all active rules. A control surface analysis was also performed to examine the relationship between the output and tensiometer inputs, with other variables kept constant. This helped to visually validate trends against expert expectations and identify potential inconsistencies or overlapping rule effects. While this validation was conducted thoroughly, the corresponding results and plots were omitted for the sake of space.

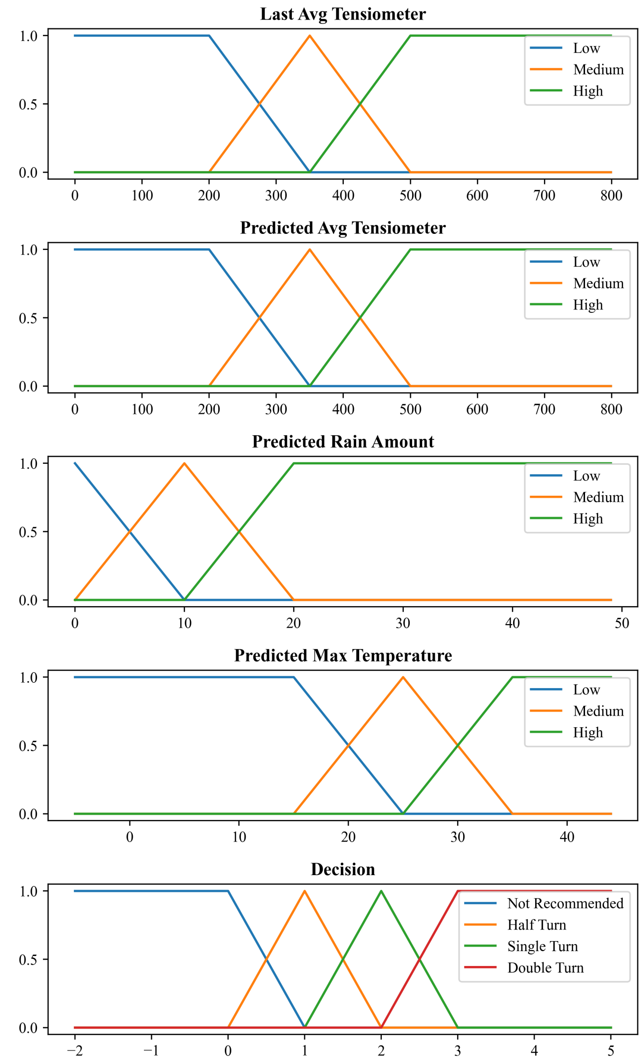

Fig. 1. Fuzzy linguistic variables of the Fuzzy DSS (the first four represent inputs, while the last represents the output).

TABLE I
FUZZY RULE BASE

Rule	Antecedent				Consequent
	Last Tens	Pred Tens	Pred Rain	Pred Temp	
1	High	High	Low	-	Double Turn
2	High	High	Medium	-	Single Turn
3	High	High	High	-	Not Recommended
4	High	Medium	Low	Low	Not Recommended
5	High	Medium	Low	Medium	Not Recommended
6	High	Medium	Low	High	Single Turn
7	High	Medium	Medium	Low	Not Recommended
8	High	Medium	Medium	Medium	Not Recommended
9	High	Medium	Medium	High	Half Turn
10	High	Medium	High	-	Not Recommended
11	High	Low	-	-	Not Recommended
12	Medium	High	Low	-	Single Turn
13	Medium	High	Medium	Low	Half Turn
14	Medium	High	Medium	Medium	Single Turn
15	Medium	High	Medium	High	Single Turn
16	Medium	High	High	-	Not Recommended
17	Medium	Medium	-	-	Not Recommended
18	Medium	Low	-	-	Not Recommended
19	Low	High	-	-	Double Turn
20	Low	Medium	-	-	Not Recommended
21	Low	Low	-	-	Not Recommended

After defuzzification using the centroid method, the goal is to provide a recommendation that is as easily interpretable as possible. To this end, the defuzzified output was converted back to the fuzzy term with the highest membership degree. This step ensures that the final output remains intuitive and straightforward, allowing the recommendations to be translated into practical actions without ambiguity.

B. Fuzzy DSS Optimization

A structured online questionnaire was distributed to the consortium experts to validate the Fuzzy DSS. This included targeted questions on sensor types used, decision-making processes employed, and general domain knowledge. Experts were also asked to provide irrigation recommendations based on scenarios presented to them through sensor data and weather forecasts. The suggestions were then used to calibrate the DSS through Bayesian optimization, which refines the parameters of the membership functions. The algorithm employs a probabilistic model to guide the search for optimal parameters by minimizing an error function $E(\mathbf{p})$, defined as:

$$E(\mathbf{p}) = \frac{1}{N} \sum_{i=1}^{N} \left(y_i(\mathbf{p}) - \hat{y}_i \right)^2 , \qquad (1)$$

where $y_i(\mathbf{p})$ is the current output of the DSS for the i-th input, $\hat{y}_i$ is the corresponding expert's recommendation, and N is the number of data points used for evaluation.

The dependency of (1) on $\mathbf{p}$, which represents the parameter space, is noteworthy. This vector encodes the breakpoints of the membership functions for each linguistic term: triangular functions use three parameters (left base, peak, right base), and trapezoidal ones use four (left base, left shoulder, right shoulder, right base). Thus, $\mathbf{p} = [p_1, p_2, \ldots, p_M]$, where each p_j lies within a bounded interval $[p_j^{\min}, p_j^{\max}]$, based on the physical or observed domain of the corresponding variable.

The optimization was limited to discrete integer values within these bounds to maintain tractability and avoid overfitting. The algorithm searches for the optimal set $\mathbf{p}^*$ that minimizes the error function and represents the ideal configuration. In other words, the system better aligns with empirical data and expert insights. The results are specific to the structure and variables of the proposed DSS and cannot be generalized to other fuzzy systems.

V. Analysis and Results

For the scope of this study, a portion of the data available in the IoT platform described in Sec. III was used. More in detail, the time-frame from May 1, 2023, to August 31, 2023, was selected as it aligns with the critical irrigation phase of the growing season when soil moisture management directly influences vine health, yield, and grape quality. Soil moisture readings during this period range from approximately 15 to 650 mbar, a broad range reflecting varying field conditions. This range is particularly relevant as typical irrigation thresholds for grapevines fall between 200 mbar (the lower wet limit) and 400 mbar (the upper dry limit), providing a basis for evaluating irrigation effectiveness [1]. Lastly, meteorological data were managed using the OpenMeteo API.

The implementation was carried out on a local machine using Python version 3.11. Scikit-Fuzzy was used for the fuzzy logic modeling block, while Scikit-Optimize was adopted for the optimization algorithm.

To evaluate the system's performance, the actual irrigation decisions made by experts were compared with those generated by the DSS under an iteratively applied configuration of 1-day recommendation. At each iteration, the DSS was applied to provide updated irrigation suggestions, and the corresponding tensiometer was subsequently updated. The comparison is made for five sectors, representative of the field, by analyzing the tensiometers and sprinklers involved. Predictive models were developed to simulate tensiometer behavior and were individually trained using their own historical data. In contrast, the DSS uses data from all tensiometers on the farm to generate an adaptable suggestion and a fair comparative value. Key metrics included the total volume of water use, the average tensiometer value, and the number of days during which soil moisture exceeded the critical dry threshold.

It is important to note that the DSS provides a generic numerical output designed to be adaptable to various setups, ensuring scalability across different configurations of consortia. Specifically, for RDL, the output directly relates to the number of irrigation cycles and the total water volume applied by all sprinklers in a sector. For example, an output value of 2 corresponds to a standard cycle, representing the application of 650 liters of water for each sector row. Therefore, the output was discretized as needed to provide a more realistic and practical operational context. In general, the total water volume applied by all sprinklers in a sector, V_t, can be calculated as:

$$V_t = \sum_{i=1}^{N} (T_i \cdot D_i \cdot Q_i), \qquad (2)$$

where N is the total number of sprinklers in the sector, T_i is the number of irrigation cycles for the i-th sprinkler in the sector, D_i is the duration of each irrigation cycle for the i-th sprinkler, and Q_i is the water flow for the i-th sprinkler.

Bayesian optimization significantly improved the performance of the irrigation system, reducing the mean squared error (MSE) from 0.71 to 0.39 after 100 iterations, a 45% decrease. This demonstrates the optimization's effectiveness in calibrating the system, leading to more accurate irrigation recommendations against the validation dataset. Near-optimal performance was reached within just 25 iterations, highlighting the algorithm's capacity to quickly identify effective configurations while minimizing computational cost. Moreover, Table II details the adjustments to the fuzzy variables, showing them before and after optimization. Although the specific peak values were adjusted, it is important to note that the universes of discourse for all variables remained unchanged, maintaining the same domain for each fuzzy variable.

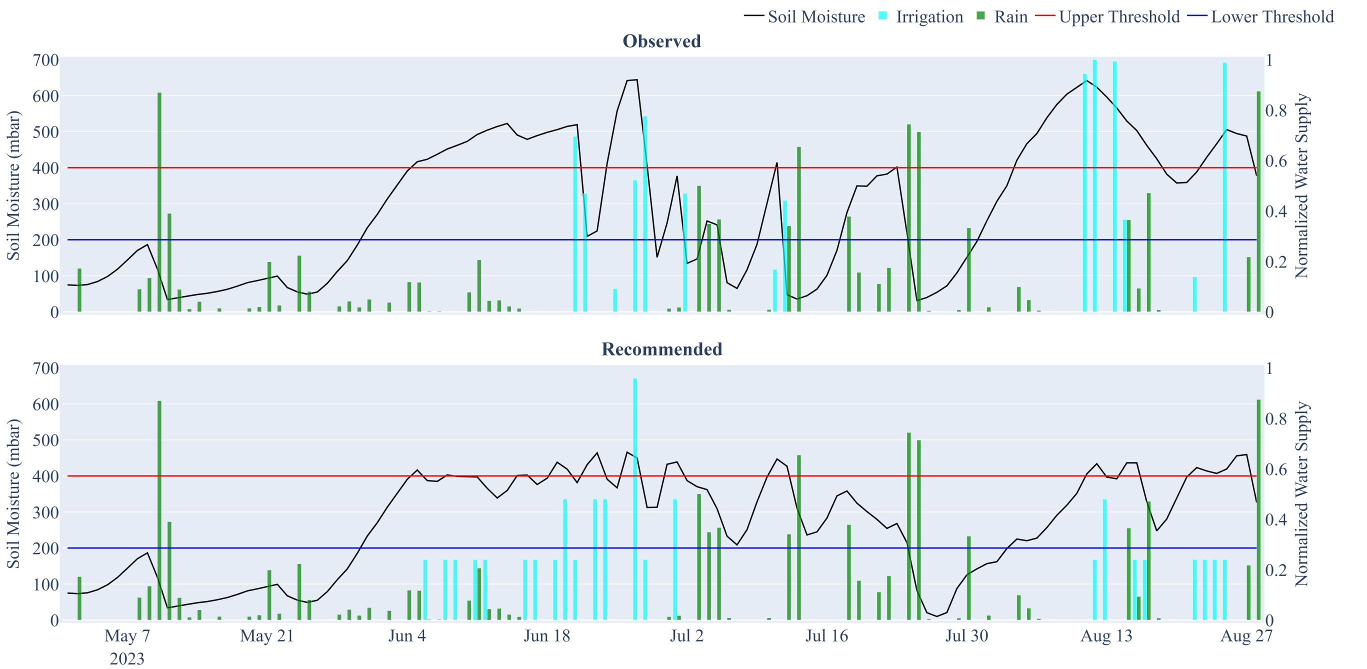

Fig. 2. Comparison of actual and DSS-simulated irrigation schedules for a specific water sector in RDL during 2023. The upper graph shows the real tensiometer readings and irrigation events, while the lower graph displays the simulated trend based on DSS recommendations.

An example of the final results for a specific sector is presented visually in Fig. 2. The upper graph displays the actual trend of the reference tensiometer at a depth of 30 cm, along with the corresponding real irrigation events. The lower graph shows the simulated trend of the same tensiometer using the irrigation inputs provided by the recommendation system. Both graphs include the actual precipitation recorded for that geographical area. Irrigation and precipitation are normalized on the same scale. In the actual scenario, irrigation starts relatively late, around June 20, and is managed on a case-by-case basis to bring the tensiometer values from above the upper limit to below the lower limit. These irrigation events tend to be more concentrated than the recommendations provided by the DSS. The water recommended by the DSS appears to be more evenly distributed over time. However, the total water volume applied over the entire period is similar between the two approaches. The actual irrigation events frequently occur on the same days as rainfall, suggesting that the traditional approach does not systematically consider precipitation when scheduling irrigation. This overlap may lead to unnecessary water applications and reduced irrigation efficiency. The tensiometer trend under the DSS recommendations appears more consistent, with soil moisture frequently staying within the defined thresholds. Despite these differences, the average tensiometer values remain comparable between methods.

Table III summarizes the results corresponding to the individual rows within each sector. To obtain the total water volume applied to the entire sector, this value has to be multiplied by the number of rows of the sector. However, this is not the focus of the present study. The results have revealed a clear distinction between actual irrigation practices, the standard DSS recommendations, and the optimized DSS (DSS_{opt}). Overall, the application of the DSS methods demonstrates a significant reduction in water use while maintaining soil moisture levels within desirable thresholds.

TABLE II
FUZZY VARIABLES BEFORE AND AFTER OPTIMIZATION

Fuzzy Variable	Membership Function Peaks	
	Before	After
Last Avg Tensiometer	{200, 350, 500}	{136, 300, 545}
Predicted Avg Tensiometer	{200, 350, 500}	{0, 300, 711}
Predicted Rain Amount	{0, 10, 20}	{3, 15, 40}
Predicted Max Temperature	{15, 25, 35}	{18, 20, 50}

The total water volume applied in the real scenario (52’501 liters) was significantly higher than the amounts recommended by both the DSS (27’950 liters) and the DSS_{opt} (25’025 liters) strategies. This trend highlights the efficiency of the DSS approaches in saving water resources without compromising the primary objective of maintaining soil moisture within target ranges. The reduction in water usage was particularly pronounced in sectors with high initial irrigation demand.

Beyond water savings, the DSS strategies also reduced the number of critical days. This suggests that both methods effectively minimized instances where soil moisture fell outside the acceptable range. This improvement is crucial to reducing crop stress and promoting healthier growth patterns.

Despite these substantial differences in water usage and critical days, the average tensiometer values remained comparable between the actual and DSS scenarios. This similarity

TABLE III
COMPARISON OF IRRIGATION SECTOR PERFORMANCES FOR RDL.

Sector	**Water Volume per Row (L)**			**Critical Days**			**Avg Tensiometer (mBars)**		
	Real	**DSS**	**DSS$_{opt}$**	**Real**	**DSS**	**DSS$_{opt}$**	**Real**	**DSS**	**DSS$_{opt}$**
1	1'828	325	325	3	1	1	110	196	196
2	4'479	4'550	1'300	9	5	3	174	184	184
3	11'486	5'200	5'200	29	10	9	245	254	253
4	10'931	10'075	9'750	44	24	33	291	266	270
5	23'757	7'800	8'450	29	20	15	239	272	269
Total	52'501	27'950	25'025	114	60	61	1'059	1'172	1'172

indicates that DSS methods achieve efficient water distribution without sacrificing the overall effectiveness of irrigation in maintaining soil moisture. Furthermore, the optimized DSS strategy consistently brought the tensiometer values closer to the recommended thresholds, suggesting a more precise alignment with agronomic targets.

VI. CONCLUSIONS

The described results reveal significant potential for optimizing irrigation practices and reducing water usage across various consortia. The DSS achieved an average reduction in water volume of approximately 47% for a sector in RDL, with the optimized variant DSS$_{opt}$ achieving an even greater reduction of 52%. These percentages reflect the system's ability to manage water resources more efficiently than traditional methods, ensuring soil moisture levels remain within desirable thresholds while minimizing irrigation inputs. In addition to water savings, both DSS methods successfully reduced the number of critical days, highlighting the system's capacity to maintain consistent soil moisture conditions, which is essential for crop health.

While these results are promising, some limitations and areas for future improvement need to be addressed. First, simulating DSS using larger temporal windows could provide a broader perspective on long-term irrigation needs. However, it is important to note that incorporating machine learning models for the tensiometer data could significantly impact the results. Larger time-frames may introduce variability that could reduce the accuracy of the DSS evaluation. Future work should also assess the system using additional key performance indicators, such as irrigation timing precision (*e.g.*, avoiding overlap with rainfall), proxies for crop yield, and energy consumption.

Another potential area for expansion is the applicability of the DSS to other agricultural consortia or setups. Testing the system across different environmental conditions and crop types would provide valuable insights into its adaptability. This would help determine whether the DSS can be generalized to various contexts or if adjustments are needed to tailor it to specific needs. In addition, expanding the collection of expert feedback is crucial for enhancing the system's architecture. The DSS can be further refined to address practical challenges and incorporate local knowledge by gathering more input from agronomists and other stakeholders. Moreover, integrating a feedback platform directly into the system would facilitate real-time corrections and continuous improvement, creating a dynamic and evolving tool for irrigation management.

Finally, evaluating potential cost savings or return on investment, along with exploring alternative optimization algorithms and plant-specific variables (*e.g.*, crop type and stress levels), could further enhance the impact of the DSS.

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