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Perceived Hydraulic Flow Behavior and the Use of Artificial Neural Networks in Sprinkler Irrigation Systems in the District of Pucará, 2024

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Abstract **Objective:** This study aimed to determine the relationship between the perceived hydraulic behavior of flows and the reported use of artificial neural networks (ANNs) in sprinkler irrigation systems in the Pucará District (Pucapuquio annex), during 2024. **Method:** A quantitative approach was employed, using correlational research with a non-experimental, cross-sectional design. The study variables were (1) perceived hydraulic flow behavior and (2) the use of artificial neural networks, both categorical in nature. The population consisted of 42 owners of sprinkler irrigation systems, and the sample included 37 systems selected through non-probabilistic sampling. Data were collected using a Likert-type questionnaire with an ordinal scale. Two instruments were applied: one with 16 items to measure hydraulic flow behavior and another with 16 items to assess the use of artificial neural networks. Both instruments were validated by expert judgment and demonstrated acceptable reliability according to Cronbach's alpha coefficient. **Results:** The general hypothesis yielded a Spearman's correlation coefficient of 0.932 with a significance level of 0.000, indicating a direct and highly significant relationship between the two variables. Additionally, 39.36% of participants reported that hydraulic behavior was positively associated with the use of artificial neural networks. **Conclusions:** There is a significant relationship between perceptions of hydraulic flow behavior and the use of artificial neural networks in sprinkler irrigation systems. The findings suggest that the greater use of ANNs is associated with a perceived increase in hydraulic efficiency in these systems, although a causal relationship cannot be established.

Keywords Hydraulic Behavior of Flows, Artificial Neural Networks, Sprinkler Irrigation Systems

1. Introduction

The hydraulic behavior of sprinkler irrigation systems is a key factor in achieving efficient water use in agriculture, especially in regions where water availability is limited [1], [2]. Population growth and economic development have intensified competition for freshwater, driving up its cost. In irrigated agriculture, it is therefore essential to adopt technological innovations that enhance productivity and profitability [3], [4]. Globally, agriculture accounts for approximately 70% of total freshwater consumption [4], underscoring the urgency of implementing strategies to improve water-use efficiency.

The efficiency of sprinkler irrigation systems depends on multiple factors such as pressure, flow rate, and uniformity in water distribution [5], [6]. Poor control of these parameters can result in water waste, reduced productivity, and decreased sustainability. In this context, artificial neural networks (ANNs) have emerged as powerful tools for addressing prediction and optimization problems in irrigation management. Their ability to learn from large volumes of historical and real-time data allows for the modeling of nonlinear relationships among variables such as pressure, flow rate, soil moisture, and weather conditions [7]. ANNs can be applied to support decision-making processes aimed at improving irrigation uniformity, reducing water and energy use, and increasing the overall sustainability of agricultural systems [8].

The integration of ANNs with sensor networks and remote monitoring systems provides real-time data that can be used to determine appropriate irrigation scheduling and water distribution. Recent studies have reported that ANN-assisted systems can enhance irrigation efficiency and optimize resource use [9]. The development of digital technologies has therefore opened new possibilities for modeling and predicting hydraulic phenomena in irrigation systems [10], [11]. However, despite their potential, the application of ANNs in agriculture remains limited due to technological, economic, and social barriers that hinder large-scale adoption, particularly in developing regions.

Previous studies have highlighted the usefulness of ANNs in improving irrigation system performance. Boundi et al. [12] analyzed irrigation under Mediterranean conditions and demonstrated that wind speed and pressure significantly affect efficiency, emphasizing the need to adjust operational parameters to local environments. Similarly, Álvarez [13] evaluated the hydraulic design of sprinkler irrigation systems in Cusco and noted that emerging technologies can enhance flow performance and water use. Jiménez López [14] developed an intelligent irrigation management system that reduced water consumption by 20–30% and increased water distribution efficiency by 25%, showcasing the contribution of artificial intelligence to irrigation optimization. Likewise, Vázquez Rueda et al. [15] designed an automated irrigation system for basil cultivation that combined sensors with ANN modeling to predict the optimal amount of water required, achieving high precision with minimal error. These studies confirm that artificial intelligence–based tools can play a key role in improving irrigation performance and water-use efficiency.

In Latin America—and particularly in Peru—water resource management faces serious challenges aggravated by climate variability and change [16]. In the Pucará District, located in the Junín region, medium-scale agriculture is one of the main economic activities [17]. However, local sprinkler irrigation systems experience issues such as flow variability, pressure fluctuations, and uneven water distribution. These limitations, combined with scarce technical training among farmers and the absence of reliable hydraulic models, reduce irrigation efficiency and affect agricultural productivity. Ascencios [18] emphasized that water and energy efficiency in pressurized irrigation systems largely depend on proper control of these parameters and the use of precise hydraulic modeling.

In this context, the application of ANNs may provide an innovative and practical solution to enhance water-use efficiency and irrigation management in Pucará. This research explores the perceived relationship between the hydraulic behavior of flows and the reported use of artificial neural networks in sprinkler irrigation systems. The study aims to contribute to the limited local scientific literature on this topic and to serve as a reference for future agricultural modernization initiatives. In practical terms, the findings may benefit both farmers and public institutions by providing information to support improved decision-making in irrigation management.

Accordingly, the general objective of this research is to determine the relationship between the perceived hydraulic flow behavior and the use of artificial neural networks (ANNs) in sprinkler irrigation systems in the Pucará District (Pucapuquio annex) during 2024. The study also seeks to demonstrate how ANN-based approaches can inform water management strategies and serve as a reference model for regions with similar conditions. The specific objectives are as follows:

- To determine the correlation between perceived hydraulic parameters and the use of artificial neural networks (ANNs) in sprinkler irrigation systems in the Pucará District, 2024.
- To determine the relationship between perceived irrigation uniformity and the use of artificial neural networks (ANNs) in sprinkler irrigation systems in the Pucará District, 2024.
- To determine the association between the perceived reduction of hydraulic losses and the use of artificial neural networks (ANNs) in sprinkler irrigation systems in the Pucará District, 2024.

Based on these objectives, the general hypothesis of this study proposes that there is a statistically significant correlation between the perceived hydraulic behavior of flows and the use of ANNs in sprinkler irrigation systems in the Pucará District, 2024. This general hypothesis is divided into three specific hypotheses that link the dimensions of the first variable—hydraulic parameters, irrigation uniformity, and reduction of hydraulic losses—with the second variable, use of ANNs.

2. Methodology

This study employed a quantitative, correlational research approach following Valderrama [19], with the objective of analyzing the relationship between perceived hydraulic flow behavior and the reported use of artificial neural networks (ANNs) in sprinkler irrigation systems in the Pucará District. According to Hernández et al. [20], this type of design enables the measurement of the strength and direction of associations between variables without manipulating them experimentally.

A non-experimental, cross-sectional design was adopted, collecting data during a single period in 2024 to capture a specific snapshot of the relationship between the study variables [21]. For operationalization, each variable was divided into three dimensions represented by specific indicators, which served as the foundation for developing the data collection instruments. The operationalization of each variable is presented in Tables 1 and 2.

Table 1. Operationalization of Variable 1. Perceived Hydraulic Flow Behavior

Dimensions	Indicators	Items
Hydraulic Parameters	Operating pressure	1,2
	Emission flow rate	3,4
	Flow velocity	5,6
Irrigation Uniformity	Uniformity coefficient	7,8
	Distribution coefficient	9,10
Reduction of Hydraulic Losses	Friction losses	11,12
	Losses in fittings	13,14
	Hydraulic efficiency	15,16

Table 2. Operationalization of Variable 2: Artificial Neural Networks (ANNs)

Dimensions	Indicators	Items
Parameter Optimization	Pressure adjustment	1,2
	Flow rate adjustment	3,4
	Optimal flow velocity	5,6
Predictive Capability	Supervised training	7,8
	Errors and adjustments	9,10
Loss Simulation	Accuracy in simulating friction losses	11,12
	Simulation of pressure losses	13,14
	Model efficiency	15,16

The study population consisted of 42 sprinkler irrigation systems in the Pucará District, Pucapuquio annex, as recorded by the Pucapuquio Local Irrigation Users Board (2024). These systems vary in their technical and hydraulic characteristics. The sample was selected through non-probabilistic convenience sampling, according to the researchers' criteria and the specific requirements of the study [22]. A total of 37 representative irrigation systems were included.

Data were collected through structured questionnaires, developed following the guidelines of Hernández et al. [20]. Two instruments were used, each containing 16 closed-ended items with responses measured on a five-point Likert scale (ranging from "strongly disagree" to "strongly agree"). The instruments were validated through two complementary procedures. First, Cronbach's Alpha coefficient was applied, yielding high reliability for each instrument corresponding to the study variables. Second, expert judgment validation was conducted with three specialists: one in research methodology, one in statistics, and one in civil engineering. These experts assessed the relevance, pertinence, and clarity of each indicator in relation to the questionnaire items, concluding that all questions were sufficient to adequately measure the variables and their respective dimensions.

To ensure that participants fully understood the content of the questionnaire—particularly the technical aspects related to hydraulic parameters and artificial neural networks (ANNs)—a short training session was conducted prior to data collection. During this session, the researchers explained key concepts in accessible terms, including flow rate, pressure, irrigation uniformity, and the basic functioning of ANN-based systems. Practical examples from local irrigation practices were used to illustrate how these technologies might be perceived or applied in their agricultural context. This orientation ensured that respondents could provide informed and meaningful answers based on their own experience managing sprinkler irrigation systems.

Statistical analysis was carried out using SPSS version 27.0. Descriptive analyses were performed through frequency tables and bar charts. For inferential analysis, the Shapiro–Wilk normality test confirmed that the data did not follow a normal distribution; therefore, Spearman's Rho correlation coefficient was applied to test the study hypotheses. Statistical significance was set at $p < 0.05$. When the calculated p-value was below this threshold, the null hypothesis was rejected, confirming the existence of a statistically significant relationship between the variables [18], [23].

3. Results

Hypothesis Testing:

The results support the general hypothesis, with a p-value of 0.000 (< 0.05), indicating a statistically significant relationship between the perceived hydraulic flow behavior and the use of ANNs in sprinkler irrigation systems. Furthermore, a strong positive correlation was observed (Spearman's Rho = 0.932), as shown in Table 3.

Table 3. Spearman's Correlation Coefficient between Variable 1 (Perceived Hydraulic Flow Behavior) and Variable 2 (Artificial Neural Networks - ANN)

Spearman's Rho		Variable 1	Variable 2
Variable 1	Correlation coefficient	1,000	,932**
	Sig. (2-tailed)	.	,000
	N	37	37
Variable 2	Correlation coefficient	,932**	1,000
	Sig. (2-tailed)	,000	.
	N	37	37

**. The correlation is significant at the 0.01 level (2-tailed).

In addition, Specific Hypothesis 1 was confirmed with a p-value of 0.000 (< 0.05), indicating a statistically significant relationship between the perceived hydraulic parameters (such as pressure, flow rate, and distribution uniformity) and the use of artificial neural networks. Furthermore, a substantial positive correlation was identified (Spearman's Rho = 0.794), as shown in Table 4.

Table 4. Correlation coefficient between the dimension "Perceived Hydraulic Parameters" and Variable 2 (Artificial Neural Networks – ANN)

Spearman's Rho		Hydraulic Parameters	Variable 2
Hydraulic Parameters	Correlation coefficient	1,000	,794**
	Sig. (2-tailed)	.	,000
	N	37	37
Variable 2	Correlation coefficient	,794**	1,000
	Sig. (2-tailed)	,000	.
	N	37	37

**. The correlation is significant at the 0.01 level (2-tailed).

Specific Hypothesis 2 was also confirmed with a p-value of 0.000 (< 0.05), demonstrating a statistically significant association between perceived irrigation uniformity and the use of artificial neural networks. In addition, a high positive correlation was identified (Spearman's Rho = 0.851), as presented in Table 5.

Table 5. Correlation coefficient between the dimension "perceived Irrigation Uniformity" and Variable 2 (Artificial Neural Networks – ANN)

Spearman's Rho		Irrigation Uniformity	Variable 2
Irrigation Uniformity	Correlation coefficient	1,000	,851**
	Sig. (2-tailed)	.	,000
	N	37	37
Variable 2	Correlation coefficient	,851**	1,000
	Sig. (2-tailed)	,000	.
	N	37	37

**. The correlation is significant at the 0.01 level (2-tailed).

Likewise, Specific Hypothesis 3 was confirmed with a p-value of 0.000 (< 0.05), indicating a statistically significant relationship between the perceived reduction of hydraulic losses and the use of artificial neural networks. In addition, the correlation coefficient (Spearman's Rho = 0.789) revealed a substantial positive relationship, as shown in Table 6.

Descriptive analysis and interpretation of variable 1 and its dimensions.

The descriptive analysis reveals that 65.88% of respondents (39.36% "agree" and 26.52% "strongly agree") consider that the use of artificial neural networks (ANNs) is associated with an improvement in the hydraulic behavior of their sprinkler irrigation systems.

Regarding the specific dimensions, most farmers in Pucará expressed positive perceptions:

- 66.22% believe that ANNs help optimize hydraulic parameters.
- 75.68% perceive a favorable influence on irrigation uniformity.
- 60.01% indicate that ANNs contribute to reducing hydraulic losses.

These results reflect a generalized positive perception of the use of intelligent technologies in irrigation management; however, they are based exclusively on subjective assessments rather than on instrumental measurements (see Table 7 and Figure 1).

Descriptive analysis and interpretation of variable 2 and its dimensions.

For Variable 2 (use of artificial neural networks), 70.27% of respondents (42.06% "agree" and 28.21% "strongly agree") believe that ANNs are positively related to the hydraulic flow behavior in irrigation systems.

According to the analyzed dimensions:

- 70.27% perceive that ANNs allow for the optimization of hydraulic parameters.
- 81.08% associate their use with greater predictive capacity of the system.
- 63.06% consider that ANN-based simulations help reduce hydraulic losses.

These findings reinforce the favorable perception of the potential of ANNs in agricultural irrigation, though they should be interpreted as indicators of opinion and awareness rather than empirical evidence of hydraulic performance. These results are summarized in Table 8 and Figure 2.

Table 6. Correlation coefficient between the dimension "Perceived Reduction of Hydraulic Losses" and Variable 2 (Artificial Neural Networks – ANN)

Spearman's Rho		Perceived Reduction of Hydraulic Losses	Variable 2
Reduction of Hydraulic Losses	Correlation coefficient	1,000	,767**
	Sig. (2-tailed)	.	,000
	N	37	37
Variable 2	Correlation coefficient	,767**	1,000
	Sig. (2-tailed)	,000	.
	N	37	37

**. The correlation is significant at the 0.01 level (2-tailed).

Table 7. Frequency distribution of Variable 1 (Hydraulic Flow Behavior) and its Dimensions

LIKERT SCALE	V1	%	V1D1	%	V1D2	%	V1D3	%
Strongly Agree	157	26,52%	61	27,48%	51	34,46%	45	20,27%
Agree	233	39,36%	86	38,74%	61	41,22%	86	38,74%
Neutral	173	29,22%	69	31,08%	32	21,62%	72	32,43%
Disagree	26	4,39%	3	1,35%	4	2,70%	19	8,56%
Strongly disagree	3	0,51%	3	1,35%	0	0,00%	0	0,00%
Total	**592**	**100,00%**	**222**	**100,00%**	**148**	**100,00%**	**222**	**100,00%**

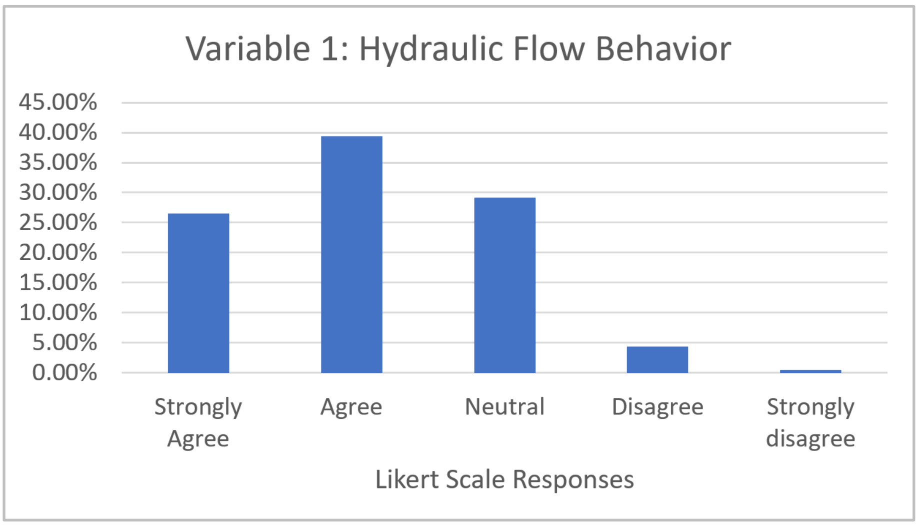

Figure 1. Frequency distribution of Variable 1 (Hydraulic Flow Behavior)

Table 8. Frequency distribution of Variable 2 (Artificial Neural Networks) and its Dimensions

LIKERT SCALE	V2		V2D1		V2D2		V2D3	
Strongly agree	167	28,21%	67	30,18%	53	35,81%	47	21,17%
Agree	249	42,06%	89	40,09%	67	45,27%	93	41,89%
Neutral	148	25,00%	55	24,77%	22	14,86%	71	31,98%
Disagree	24	4,05%	7	3,15%	6	4,05%	11	4,95%
Strongly disagree	4	0,68%	4	1,80%	0	0,00%	0	0,00%
Total	**592**	**100,00%**	**222**	**100,00%**	**148**	**100,00%**	**222**	**100,00%**

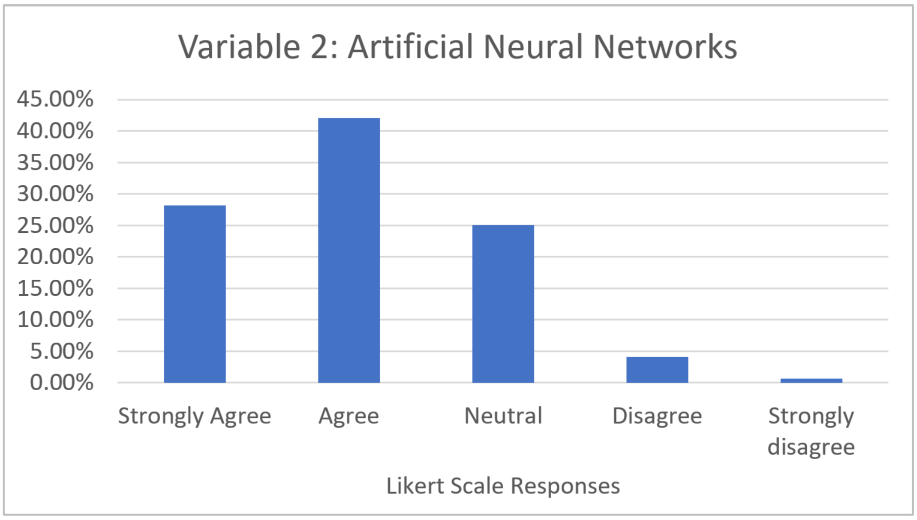

Figure 2. Frequency distribution of Variable 2 (Artificial Neural Networks)

4. Discussion of Results

The first discussion concerns the general hypothesis, which proposed that there is a significant relationship between the perceived hydraulic flow behavior and the use of artificial neural networks (ANNs) in sprinkler irrigation systems in the district of Pucará, 2024. The statistical results (Spearman's Rho = 0.932, $p < 0.05$) confirmed a strong and positive correlation between two variables. This finding suggests that, from the farmers' perspective, the use of ANNs is associated with improved hydraulic performance and more efficient water distribution. However, this perception is not based on direct technical measurements but rather on self-reported experience. Therefore, the interpretation should be understood as a perceived association rather than a proven causal effect. Similar outcomes were reported by Vázquez Rueda et al. [15], who demonstrated that ANN-assisted irrigation management could enhance operational control and crop performance. In line with these studies, the present findings indicate that intelligent technologies are perceived as valuable tools for improving the sustainability and management of irrigation systems under local conditions.

The second discussion corresponds to the first specific hypothesis, which stated that there is a significant relationship between hydraulic parameters and the use of ANNs in sprinkler irrigation systems in Pucará. The results (Spearman's Rho = 0.794, $p < 0.05$) revealed a moderate-to-strong positive relationship, indicating that participants perceive ANN-based systems as helpful in regulating pressure, flow rate, and coverage uniformity. This perception aligns with the results of Ding and Du [24], who found that deep learning models improved irrigation efficiency by optimizing the interaction between water consumption and crop yield. Although the present study relied on farmers' evaluations rather than sensor data, the consistency between perceived and reported benefits in the literature strengthens the credibility of these findings within the context of perception-based analysis.

The third discussion addresses the second specific hypothesis, which proposed that there is a significant relationship between irrigation uniformity and the use of ANNs. The results (Spearman's Rho = 0.851, $p < 0.05$) confirmed a high positive correlation, suggesting that respondents perceive ANN-assisted systems as contributing to more uniform irrigation patterns. These perceptions are consistent with Bonilla Fonte [8], who demonstrated that integrating neural networks with sensor technologies increased water distribution uniformity and reduced consumption in pasture irrigation systems. In the context of Pucará, these results indicate that ANNs are viewed as promising tools for achieving uniform irrigation despite the topographical and climatic variability that affects local water distribution.

Finally, the fourth discussion corresponds to the third specific hypothesis, which examined the relationship between the reduction of hydraulic losses and the use of ANNs. The statistical results (Spearman's Rho = 0.767, $p < 0.05$) revealed a substantial positive relationship, suggesting that participants perceive ANN-assisted management as contributing to the minimization of hydraulic losses. This perception is coherent with Martí Pérez [7], who found that neural networks could predict hydraulic variables such as pressure losses in emitters with considerable accuracy, thereby improving irrigation efficiency. Within this perception-based framework, it can be inferred that farmers recognize ANN systems as potentially useful for reducing inefficiencies, optimizing water use, and improving overall system sustainability.

In summary, the discussion of results supports the conclusion that, although the present study is based on subjective perceptions rather than empirical measurements, farmers in Pucará associate the use of artificial neural networks (ANNs) with improvements in hydraulic behavior, irrigation uniformity, and loss reduction. These perceptions highlight the importance of promoting training and gradual technological adoption, which may serve as a foundation for future empirical studies integrating ANN applications with direct field data and sensor-based monitoring. Furthermore, it is suggested that future research replicate this study across different agricultural cycles and climatic periods to assess temporal consistency and enhance the accuracy of ANN-based modeling.

4.1. Limitations of the Study

Although the findings provide valuable insights into farmers' perceptions of artificial neural networks in sprinkler irrigation systems, several limitations must be acknowledged. First, the study relies exclusively on self-reported perceptions obtained through Likert-scale questionnaires, without direct field measurements or sensor-based validation of hydraulic variables. This limits empirical robustness and prevents causal inference. Second, the use of a non-probabilistic convenience sample of 37 irrigation systems restricts the generalizability of the results to the broader agricultural population of Pucará or other regions. Therefore, future research should expand to additional areas of the Junín region to enhance the generalizability and regional applicability of the findings. Third, participants' varying levels of technical understanding of artificial neural networks may have influenced their responses, despite the brief orientation sessions provided before data collection. Future research should adopt mixed methods—combining perception surveys with real-time hydraulic data—to enhance the validity and applicability of the findings.

5. Conclusions

In relation to the general objective, the study confirmed a strong and statistically significant positive relationship between the perceived hydraulic flow behavior and the use of artificial neural networks (ANNs) in sprinkler irrigation systems in the district of Pucará (Spearman's Rho = 0.932, p = 0.000). These findings suggest that, according to the farmers' perceptions, the implementation of ANN-based technological tools contributes to optimizing hydraulic performance by improving water distribution efficiency and minimizing losses. Although the results are based on perceptual evaluations rather than direct technical measurements, they provide valuable insights into how local users recognize the potential of artificial intelligence for irrigation management. Therefore, it is recommended to strengthen training programs for farmers and local technicians to enhance their understanding and correct application of ANN systems, ensuring greater irrigation efficiency and long-term water sustainability in the region.

Regarding the first specific objective, the results indicate a considerable positive relationship between perceived hydraulic parameters and the use of artificial neural networks (Rho = 0.794, p = 0.000). This relationship suggests that farmers associate ANN use with better regulation of pressure, flow rate, and distribution coverage in sprinkler irrigation systems. Consequently, training programs and demonstration projects should be developed to help local operators adjust these hydraulic parameters accurately, allowing for better integration between technical management and ANN-assisted decision-making.

As for the second specific objective, the study found a high positive relationship between irrigation uniformity and the use of artificial neural networks (Rho = 0.851, p = 0.000), indicating that farmers perceive these technologies as essential tools for achieving more uniform and efficient water distribution. This perception highlights the need for applied field validations to corroborate these results with empirical data on uniformity coefficients. Furthermore, practical workshops and pilot projects should be promoted to demonstrate the benefits of ANN use in achieving greater irrigation uniformity and sustainable water use.

Concerning the third specific objective, the findings revealed a positive association between the reduction of hydraulic losses and the use of artificial neural networks (Rho = 0.767, p = 0.000). This suggests that farmers perceive ANN implementation as a way to minimize inefficiencies and prevent water losses in irrigation systems. Based on these insights, preventive maintenance programs supported by ANN-based monitoring could help detect anomalies and optimize irrigation operations. Future research should complement these perceptual results with physical measurements of flow and pressure losses to strengthen the scientific basis of the findings and guide the scalable application of ANN technologies in similar agricultural contexts.

Appendices

Appendix 1

Survey instrument

The questionnaire aims to collect information related to the Hydraulic Flow Behavior and the use of Artificial Neural Networks (ANNs) in sprinkler irrigation systems used in your crops. We kindly ask you to mark an "X" in the box that corresponds to your opinion. This survey is **ANONYMOUS**, and its processing will be kept **confidential**, so we ask for your **HONESTY** in your answers.

Instructions:

According to the response scale detailed below, please mark with an "X" in only one box for the alternative you consider most appropriate.

Coding				
1	2	3	4	5
Strongly agree	Agree	Neutral	Disagree	Strongly disagree

Questionnaire for Variable 1

	Variable 1 – HYDRAULIC FLOW BEHAVIOR	1	2	3	4	5
	Dimension 1: Hydraulic Parameters					
01	Is the operating pressure at the sprinkler system nozzles consistent during operation?					
02	Does the system maintain adequate operating pressure for efficient irrigation across all covered areas?					
03	Is the flow rate emitted by the sprinklers in the irrigation system constant during operation?					
04	Does the flow rate from each sprinkler meet the technical specifications required for your crop?					
05	Is the flow velocity in the main pipes of the sprinkler irrigation system stable during operation?					
06	Do you believe that variations in flow velocity affect the pressure and performance of the irrigation system?					
	Dimension 2: Irrigation Uniformity					
07	Do you believe that the sprinkler irrigation system distributes water evenly across all crop areas?					
08	Have you noticed significant differences in the amount of water applied in different areas due to uneven irrigation distribution?					
09	Do you think the sprinkler irrigation system achieves a homogeneous water distribution throughout the irrigated area?					
10	Have you identified recurring patterns of overwatering or under-watering in some areas that indicate distribution issues?					
	Dimension 3: Reduction of Hydraulic Losses					
11	Do you believe that friction losses in the pipes significantly affect the performance of the sprinkler irrigation system?					
12	Does the material of the pipes and fittings in the system minimize friction losses during operation?					
13	Do you consider that the fittings (valves, elbows, joints) of the sprinkler irrigation system generate significant pressure losses?					
14	Does the system design minimize pressure losses associated with installed fittings?					
15	Do you believe the sprinkler irrigation system uses available water efficiently to maximize irrigation?					
16	Do you think the system achieves adequate hydraulic efficiency in relation to your crop's demands?					

Coding				
1	2	3	4	5
Strongly agree	Agree	Neutral	Disagree	Strongly disagree

Questionnaire for Variable 2

	Variable 2 – ARTIFICIAL NEURAL NETWORKS (ANN)	1	2	3	4	5
	Dimension 1: Optimization of Parameters					
01	Does the neural network correctly adjust the nozzle pressure to ensure uniform irrigation?					
02	Do the pressure adjustments made by the ANN adequately respond to variable system conditions?					
03	Does the neural network correctly adjust the flow rate emitted by the sprinklers according to crop needs?					
04	Do the flow adjustments made by the ANN efficiently respond to variations in the field's water demand?					
05	Does the neural network maintain flow velocity within optimal ranges for efficient irrigation?					
06	Do you consider that the ANN's recommendations for adjusting flow velocity help prevent pressure and energy losses?					
	Dimension 2: Predictive Capability					
07	Are the data used to train the neural network representative of the real conditions of your sprinkler irrigation system?					
08	Do you consider that the supervised training of the neural network enables accurate prediction of irrigation needs?					
09	Does the error level in irrigation decisions generated by the ANN significantly affect system performance?					
10	Have the adjustments made to the ANN model improved the accuracy and efficiency of irrigation in your system?					
	Dimension 3: Loss Simulation					
11	Does the neural network accurately simulate friction losses in the pipes of the irrigation system?					
12	Do you consider that the accuracy in friction loss simulation helps optimize the hydraulic efficiency of the system?					
13	Do you consider that the pressure loss simulations performed by the artificial neural network (ANN) accurately reflect the real conditions of your sprinkler irrigation system?					
14	Does the ANN model correctly identify the critical points where the greatest pressure losses occur in the system?					
15	Do you consider the ANN model efficient in integrating multiple variables (moisture, pressure, flow) to improve system performance?					
16	Has the ANN model significantly contributed to reducing costs and maximizing the resources of the sprinkler irrigation system?					

Appendix 2

Instrument Reliability

Instrument Reliability – Cronbach's Alpha: Variable 1 – Hydraulic Flow Behavior.

Reliability Statistics	
Cronbach's Alpha	Number of Items
,819	16

Note: In the test performed using the SPSS software (version 27), a value of 0.819 (very close to 1) was obtained, which indicates a high reliability of the instrument for Variable 1.

Instrument Reliability – Cronbach's Alpha: Variable 2 – Artificial Neural Networks (ANN)

Reliability Statistics	
Cronbach's Alpha	Number of Items
,813	16

Note: In the test performed using the SPSS software (version 27), a value of 0.813 (very close to 1) was obtained, which indicates a high reliability of the instrument for Variable 2.

Appendix 3

Data obtained from the surveys

Data from the instrument for Variable 1

Nº	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
1	2	2	3	1	3	2	1	3	2	3	3	1	2	3	3	1
2	3	2	3	2	3	2	1	2	2	3	3	3	3	3	3	3
3	2	1	1	2	3	2	1	1	2	1	1	1	1	1	1	1
4	4	3	1	1	1	2	2	1	4	1	2	2	2	2	2	2
5	3	2	1	1	2	2	1	2	2	2	2	2	2	2	2	2
6	2	1	3	1	2	1	1	2	2	4	3	4	2	2	4	4
7	2	2	3	3	3	3	2	3	3	3	2	2	1	4	3	4
8	1	1	3	1	3	1	1	1	1	2	1	2	3	1	1	3
9	2	2	2	2	2	2	2	2	2	3	2	2	2	2	2	2
10	3	2	3	1	3	2	1	3	2	3	3	3	3	3	3	3
11	3	2	3	3	3	2	1	2	2	3	3	3	3	3	1	3
12	2	1	1	2	1	2	1	1	2	1	1	1	1	1	1	1
13	1	3	1	1	4	2	2	1	1	1	2	2	2	2	2	2
14	3	2	1	1	1	2	1	2	2	2	2	2	2	2	2	2
15	2	1	3	1	2	1	1	2	2	2	1	1	2	3	3	2
16	1	2	2	3	3	3	2	3	3	3	4	2	4	1	4	1
17	3	1	2	1	5	1	1	1	3	2	2	3	1	3	2	3
18	2	2	1	2	2	1	2	2	2	3	2	2	2	2	2	2
19	3	2	3	3	3	2	1	3	2	3	3	3	3	3	3	3
20	3	2	3	3	3	2	1	2	2	3	3	3	3	3	3	3
21	2	1	1	2	3	2	1	1	2	1	1	1	1	1	1	1
22	3	3	1	1	2	1	2	1	4	1	2	2	2	2	2	2
23	3	2	1	1	2	2	1	2	2	2	2	2	2	2	2	2

24	2	1	3	1	2	2	1	2	2	1	2	4	1	3	1	2
25	2	2	3	3	3	3	2	3	3	3	1	1	4	1	2	4
26	3	1	3	1	5	1	1	1	2	1	2	3	4	2	2	1
27	2	2	2	2	2	2	2	2	2	3	2	2	2	2	2	2
28	1	2	3	3	3	2	1	3	2	3	3	3	2	3	3	2
29	3	2	3	3	3	2	1	2	2	3	3	3	3	3	3	3
30	2	1	1	2	3	2	1	1	2	1	1	1	1	1	1	1
31	1	2	3	3	3	3	2	3	3	3	4	1	4	4	3	4
32	2	1	3	1	3	1	1	1	1	2	2	2	3	3	1	2
33	2	2	2	2	2	2	2	2	2	3	2	2	2	2	2	2
34	4	2	2	1	3	1	1	1	2	3	3	3	3	3	3	3
35	3	2	3	3	3	2	1	2	2	3	3	3	3	3	3	3
36	3	1	2	1	5	1	1	1	3	2	2	3	1	3	2	3
37	2	1	3	1	2	1	1	2	2	4	3	4	2	2	4	4

Data from the instrument for Variable 2

Nº	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**P11**	**P12**	**P13**	**P14**	**P15**	**P16**
1	1	3	2	2	1	2	3	2	3	1	3	2	3	3	3	1
2	2	3	2	2	2	2	2	2	2	1	2	2	3	3	3	3
3	2	3	2	1	1	1	1	2	1	1	1	2	1	1	1	1
4	1	1	2	2	1	2	1	4	2	2	1	4	1	2	2	2
5	1	2	2	1	2	3	2	2	1	1	2	2	2	2	2	2
6	1	2	1	2	1	4	2	2	1	1	2	2	4	2	3	4
7	3	3	3	3	3	3	3	3	2	2	3	3	3	4	2	2
8	1	3	1	3	1	2	1	1	1	1	1	1	2	1	1	2
9	2	2	2	2	2	2	2	2	2	2	2	2	3	2	2	2
10	1	3	2	2	1	2	3	2	3	1	3	2	3	3	3	3
11	3	3	2	2	2	2	2	2	2	1	2	2	3	3	3	3
12	2	1	2	1	1	1	1	2	1	1	1	2	1	1	1	1
13	1	4	2	2	1	4	1	1	4	2	1	1	1	2	2	2
14	1	1	2	1	1	3	2	2	1	1	2	2	2	2	2	2
15	1	2	1	2	1	4	2	2	2	1	2	2	2	3	1	1
16	3	3	3	3	3	3	3	3	4	2	3	3	3	1	4	2
17	1	5	1	3	1	3	1	3	3	1	1	3	2	3	2	3
18	2	2	1	2	2	2	2	2	2	2	2	2	3	2	2	2
19	3	3	2	2	1	2	3	2	3	1	3	2	3	3	3	3
20	3	3	2	2	2	2	2	2	2	1	2	2	3	3	3	3
21	2	3	2	1	1	1	1	2	1	1	1	2	1	1	1	1
22	1	2	1	2	1	4	1	4	1	2	1	4	1	2	2	2
23	1	2	2	1	1	3	2	2	1	1	2	2	2	2	2	2
24	1	2	2	2	2	4	2	2	2	1	2	2	1	3	2	4
25	3	3	3	3	3	3	3	3	4	2	3	3	3	1	1	1

26	1	5	1	3	1	1	1	2	3	1	1	2	1	2	2	3
27	2	2	2	2	2	2	2	2	2	2	2	2	3	2	2	2
28	3	3	2	2	1	2	3	2	3	1	3	2	3	3	3	3
29	3	3	2	2	2	2	2	2	2	1	2	2	3	3	3	3
30	2	3	2	1	1	1	1	2	1	1	1	2	1	1	1	1
31	3	3	3	3	2	3	3	3	4	2	3	3	3	4	4	1
32	1	3	1	3	1	5	1	1	2	1	1	1	2	3	2	2
33	2	2	2	2	1	2	2	2	2	2	2	2	3	2	2	2
34	1	3	1	2	1	2	1	2	3	1	1	2	3	3	3	3
35	3	3	2	2	3	2	2	2	2	1	2	2	3	3	3	3
36	1	5	1	3	1	3	1	3	3	1	1	3	2	3	2	3
37	1	2	1	2	1	4	2	2	1	1	2	2	4	2	3	4

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