Decision-making system for rice production: a case study in the Araranguá River Valley

Sistema decisório para a produção de arroz: estudo de caso no Vale do Rio Araranguá

Sistema de toma de decisiones para la producción de arroz: estudio de caso en el Valle del Río Araranguá

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Marcos Antonio Martins Giassi
Master in Energy and Sustainability
Institution: Universidade Federal de Santa Catarina
Address: Araranguá, Santa Catarina, Brasil
E-mail: marcosgiassi7@gmail.com

Analúcia Schiaffino Morales
PhD in Artificial Intelligence
Institution: Universidade Federal de Santa Catarina
Address: Araranguá, Santa Catarina, Brasil
E-mail: analucia.morales@ufsc.br

Carla de Abreu D’aquino
PhD in Oceanography
Institution: Universidade Federal de Santa Catarina
Address: Araranguá, Santa Catarina, Brasil
E-mail: carla.daquino@ufsc.br

Ricardo Alexandre Reinaldo de Moraes
Doctor in Real Time Systems
Institution: Universidade Federal de Santa Catarina
Address: Araranguá, Santa Catarina, Brasil
E-mail: ricardo.moraes@ufsc.br

ABSTRACT
This paper addresses the challenges faced by small-scale rice producers in Santa Catarina, including water consumption, salinity issues, and high production costs. To support these producers, a computer-assisted decision-making system is proposed to enhance the production process. The system utilizes a computational model and simulations based on real crop data for validation. The contributions of this study include optimizing water and
electricity usage, minimizing losses from excess irrigation and saline water collection. This is achieved through a system that forecasts future flow, determines the optimal timing and amount of irrigation, and evaluates water availability in the river to mitigate salinity risks caused by low rainfall.

**Keywords:** Rice Production, Irrigation, Neural Networks, Energy and Sustainability.

**RESUMO**
Este artigo aborda os desafios enfrentados pelos pequenos produtores de arroz de Santa Catarina, incluindo consumo de água, problemas de salinidade e altos custos de produção. Para apoiar estes produtores, propõe-se um sistema de tomada de decisões assistida por computador para melhorar o processo de produção. O sistema utiliza um modelo computacional e simulações baseadas em dados de corte real para validação. As contribuições deste estudo incluem a otimização do uso de água e eletricidade, minimizando as perdas de irrigação excessiva e coleta de água salina. Isso é obtido por meio de um sistema que prevê o fluxo futuro, determina o tempo e a quantidade ideais de irrigação e avalia a disponibilidade de água no rio para reduzir os riscos de salinidade causados pela baixa precipitação pluviométrica.

**Palavras-chave:** Produção de Arroz, Irrigação, Redes Neurais, Energia e Sustentabilidade.

**RESUMEN**
Este artículo aborda los desafíos que enfrentan los pequeños productores de arroz en Santa Catarina, incluido el consumo de agua, los problemas de salinidad y los altos costos de producción. Para apoyar a estos productores, se propone un sistema de toma de decisiones asistido por ordenador para mejorar el proceso de producción. El sistema utiliza un modelo computacional y simulaciones basadas en datos reales de cultivos para su validación. Las contribuciones de este estudio incluyen la optimización del uso de agua y electricidad, minimizando las pérdidas por exceso de riego y recolección de agua salina. Esto se logra a través de un sistema que pronostica el flujo futuro, determina el momento y la cantidad óptimos de riego y evalúa la disponibilidad de agua en el río para mitigar los riesgos de salinidad causados por las bajas lluvias.

**Palabras clave:** Producción de Arroz, Riego, Redes Neuronales, Energía y Sostenibilidad.

**1 INTRODUCTION**

In the 2018/2019 harvest, Brazil’s rice production reached 10.4 million tons, with the south region (Paraná, Santa Catarina, and Rio Grande do Sul) accounting for 8.6
million tons. The microregion of Araranguá, located in the extreme south of Santa Catarina (SC), stands out with a cultivation area of 51.53 thousand hectares and a high average yield of 7.45 tons per hectare, contributing 35% of the state's total production. Most farmers in this region use soil flooding and intermittent management for irrigation, relying on water collected from the rivers using pumps. The water consumption in rice crops in Brazil typically ranges from 6,000 m³ to 12,000 m³ per hectare, varying based on soil characteristics and crop requirements (EPAGRI/CEPA, 2019).

In addition to requiring a large volume of water, rice crops also demand water of good quality. In the Araranguá valley region, the water used for irrigation is adversely affected by the influx of saline water from the sea into the coastal springs (D’Aquino; Filho; Schettini, 2010). This salinity issue impacts approximately 5,000 to 6,000 hectares (ha) of cultivated land, which is tended to by 300 local farmers. The excessive consumption of water can lead to reduced water availability in the rivers of the production areas. Furthermore, it is crucial to consider the high electrical power consumption associated with irrigation practices, with irrigation systems being the main electricity consumers in the rice farming industry of the region.

Despite recent advancements in the agroindustry, the management of irrigation systems in the extreme south of SC region still relies heavily on manual methods with limited use of technology. This work aims to introduce an automated system for managing irrigation and water usage in rice crop cultivation using control techniques and Artificial Intelligence (AI). By utilizing these technologies, this study demonstrates the suitability of automated control techniques for monitoring and assessing water usage in irrigated rice crops. It also highlights how AI resources can aid in monitoring water availability, promoting sustainable production and improving irrigation methods in the region.

The development of a novel irrigation system tailored for the region is intricately linked to responsible water management from the local rivers and the mitigation of production expenses. The objective behind this model is to cultivate consciousness and advocate for sustainable agricultural practices within the region, thereby catalyzing enhancements within the sector in alignment with United Nations Sustainable Development Goal (SDG) number 2 (Food and Agriculture Organization of the United
Nations, 2015) (Food and Agriculture Organization of the United Nations, 2015). Furthermore, SDG 6 highlights the imperative of reducing water consumption while maintaining or even enhancing food production efficiency. This entails optimizing water resource utilization and striving towards a decrease in agricultural water withdrawal, which currently stands at approximately 70% (Food and Agriculture Organization of the United Nations, 2015, 2020) (Food and Agriculture Organization of the United Nations, 2015, 2020). Lastly, SDG 12 aims to catalyze a comprehensive overhaul of the food production system, prioritizing sustainable practices to mitigate environmental repercussions such as water wastage, greenhouse gas emissions, and ecosystem degradation (Food and Agriculture Organization of the United Nations, 2015).

The subsequent section of this paper is structured as follows: Section 2 presents the main works found in the literature on the proposed subject. Section 3 outlines the methodology employed in this study. Section 4 presents the key findings and corresponding discussions. The paper concludes with final remarks and a list of references.

2 BIBLIOGRAPHIC REVIEW

From a review of the scientific literature across prominent databases such as IEEE Xplore, ScienceDirect, and Periódicos CAPES, primary research papers focusing on optimizing water utilization through innovative irrigation techniques, leveraging IoT advancements in irrigation management, and accurate river flow forecasting were selected. We stress the importance of this theoretical investigation in developing the proposed model from the following works.

Pfitscher et al. (2012) introduced a comprehensive approach for automated rice crop irrigation employing water layer sensors, a remote monitoring system equipped with wireless communication. Remarkably, their findings revealed substantial water conservation benefits, with water savings reaching an impressive 85%. Additionally, the method of maintaining soil saturation at a 10 mm water layer yielded an 81% reduction in energy consumption compared to the conventional irrigation technique prevalent in the
region, which relies on maintaining a 100 mm water layer without sensor-based optimization. Uberti et al. (2017) outlined a methodology for evaluating the energy efficiency of irrigation systems. The authors conducted a comprehensive survey encompassing various factors including soil composition, climatic conditions, irrigation practices, and equipment utilized in irrigation systems. Their analysis revealed energy inefficiencies of up to 40% during certain periods throughout the seasons. Furthermore, they compared the efficiency of existing crop irrigation methods with the potential benefits of transitioning to a highly efficient system, maintaining a 10 mm water layer, building upon the research conducted by Pfitscher et al. (2012). The concept of employing the alternating wetting and drying technique is explored in-depth in the study conducted by Carrijo, Lundy, and Linquist (2017). This method involves maintaining flooding during flowering periods and utilizing low water layers during other stages, followed by a designated drying period. The authors documented notable water savings of up to 25% through this approach. Similarly, Jiang et al. (2019) investigated the same method and reported an average reduction in methane emissions by 53%, underscoring the efficacy of water-efficient practices.

In the realm of the Internet of Things (IoT), Bamurigire et al. (2020) conducted a study centered on tackling water management challenges in the efficient irrigation of rice crops, particularly employing flooding techniques in Rwanda, Africa. Their innovative low-cost system presents automated irrigation control, capable of adapting to seasonal and daily irrigation needs provided that sensors and communication systems are operating effectively. Furthermore, Liu et al. (2021) proposed the development of an intelligent field cultivation server based on water-saving irrigation techniques suitable for Taiwan. This system evaluates various parameters including soil temperature and humidity, air temperature and humidity, illuminance, and water level to optimize irrigation practices.

In the domain of AI focusing on flow prediction utilizing Long Short-Term Memory (LSTM) neural networks, Hunt et al. (2022) introduced a study aimed at evaluating the effectiveness of the network in forecasting flow across ten river gauge stations spanning diverse climatic regions. Their model was trained using data encompassing average meteorological and hydrological variables alongside historical
flow observations. During operational deployment, the study elaborates on the model's efficacy in predicting flow up to ten days in advance. Addressing the prediction of river water levels in regions influenced by tides, Ho et al. (2022) aimed to enhance sluice operation management, thereby mitigating the risk of tidal impact on irrigation water. LSTM was employed to forecast water levels for the subsequent six to 48 hours, leveraging historical data with intervals of five to eight hours. Reiterating the LSTM's effectiveness in future flow prediction, Silva et al. (2021) proposed a solution for predicting flow up to five days in advance based on preceding flow data, further underscoring the network's predictive capabilities in this domain.

During the course of our research in the scientific literature, we observed a notable gap in studies proposing technologies tailored to farmers in the Araranguá valley region, specifically focusing on river water collection, intermittent irrigation methods, and water salinity considerations.

This work stands out from existing literature by addressing crucial aspects pertaining to the irrigation management of rice crops and the utilization of river water in the study area, coupled with the implementation of control techniques and artificial intelligence modeling. Additionally, we emphasize the creation of a simulation incorporating real data from rice crops in the Araranguá valley, further distinguishing our study from previous efforts.

3 METHODOLOGY

A computational environment, utilizing an algorithm with control resources and AI techniques, is proposed based on farmers’ irrigation management expertise. Figure 1 provides an overview of the methodology.

In this study, input data including crop data (C.D.), irrigation management data (I.M.D), meteorological data (M.D.), river data (R.D.), and irrigation system data (I.S.D.) are utilized. Mathematical methods are employed to estimate crop irrigation needs, aiming for a reduced irrigation water layer compared to current practices in the Araranguá River basin region.
The assessment of river flow, representing water availability, utilizes AI resources for predicting future flow. Simultaneously, predictions are generated for the next irrigation day. Estimates for water and total energy consumption throughout the season are calculated and stored in a database. The decision to irrigate is influenced by the risk associated with the river flow. Farmers have the flexibility to cross-reference weather and tide predictions and make their own decisions regarding the activation of the irrigation system. The system functions as a recommendation tool, with the ultimate decision-making authority lying with the farmers.

Figure 1. Proposed methodology for irrigation management

Source: Authors

3.1 INPUT VARIABLES

Considering the important aspects of irrigation management in rice cultivation, our aim was to replicate the conditions experienced by farmers in the region. We determined the key variables for water replenishment in rice cultivation and flow prediction based on previous studies (Uberti et al., 2017). Figure 2 illustrates the input variables classified in our proposed methodology for irrigation management. The crop data, obtained directly from farmers, are essential for calculating the water consumption required to flood the cultivated area, as well as the irrigation system data.
3.2 IRRIGATION MANAGEMENT AND DATA PROCESSING

In the considered region, irrigation management is currently performed manually, leading to a lack of control and wastage of water resources. The region receives an average annual precipitation of 1,670 mm, with the majority during the rice crop sowing period. The irrigation method used is intermittent, with water layers often exceeding recommended levels. To improve water efficiency, a maximum irrigation water layer of 80 mm is suggested, considering the potential for rainwater storage and water scarcity. When the water layer exceeds 150 mm, it is drained, and replenishment occurs when it reaches the proposed minimum layer limit of 50 mm or 40 mm, depending on the stage. Land unevenness poses challenges for managing lower water layers, necessitating terrain leveling by farmers (Climatempo, 2022; STONE, 2005).

Meteorological data for this methodology was obtained from the INMET website, specifically from the automatic data station (INMET-ARARANGUA (A867)) located near the study area (-28.93, -49.50) (INMET, 2022). River data was obtained through the HidroWeb Portal, which integrates the National System of Water Resource Information (Snirh) (Ana, 2018). The fluviometric and pluviometric station used in the study has coordinates -28.958 and -49.603. Flow and precipitation data from this station were recorded from 1946 to 2011, comprising a total of 47,000 data points.

Regarding flow estimation data, around 47,000 data points on flow and precipitation were processed to eliminate noise and address missing data. The data were normalized using the MinMaxScaler function from the Python sklearn package, scaling them to the range of zero to one.
3.3 IRRIGATION REQUIREMENT MODELING

To determine the reference evapotranspiration (ETo), data on temperature, air humidity, wind speed, and solar radiation were used, following the Penman-Monteith FAO method recommended in (Allen et al., 1998).

Crop evapotranspiration is calculated by multiplying the ETo value with a crop coefficient \((kc)\), which varies depending on the crop, location, and management practices. In this study, \(kc\) values ranging from 1.00 to 1.85 were employed, as reported in (Rosso; Back, 2010), which surveyed data for a crop similar to the one studied in the region. For irrigated rice, the irrigation requirement encompasses the water needed to saturate the soil during the initial stage of the crop, accounting for lateral and vertical percolation losses and determining the water layer height. The irrigation requirement model can be found in (Brouwer; Heibloem, 1986). Based on this model, a daily water balance equation (Equation 1) was formulated to suit the characteristics of flood irrigation for pre-germinated rice. Equation 2 calculates the corrected water layer height \((AC_{cor})\). In the equations, \(AC\) represents the current water layer height (mm), \(Et\) is the crop evapotranspiration (mm), \(L\) accounts for losses from vertical and lateral percolation (mm), \(Ss\) indicates soil saturation (mm), \(P_{day}\) represents daily precipitation (mm), \(I_{day}\) represents irrigation applied on the day (mm), \(AC_{bef}\) is the water layer height from the previous day (mm), and \(D\) represents the daily water drainage of the block, accounting for any drainage or surface runoff due to excess water in the block water layer height.

\[
AC = - Et - L - Ss + P_{day} + I_{day} + AC_{bef} \quad (1)
\]

\[
AC_{cor} = AC - D \quad (2)
\]

To calculate the accumulated daily irrigation requirement, Equation 3 is used. It evaluates whether the corrected water layer height is smaller than the water layer for the day, considering the plant’s growth stage and the prediction of future flow to avoid exceeding the maximum supported limit.

\[
NI = HAC_{max} - AC_{cor} \quad (3)
\]
In this equation, \( NL \) is the accumulated irrigation need (mm), and \( HAC_{\text{max}} \) is the height of the maximum water layer (mm) determined by the irrigation management factors. Lastly, when the accumulated daily irrigation need is lower than or equal to the minimum limit layer, the system will add water to the block.

In irrigation systems like spray or drip irrigation, future irrigation scheduling is typically determined based on the irrigation frequency for each stage of the plant, as described in (Albuquerque, 2010). However, for flood irrigated rice, it varies significantly over time based on the water layer in the block, growth stages, and water removal. To estimate the future irrigation day for pre-germinated rice irrigation, an adapted water balance equation (Equation 4) was applied.

\[
AC_f = -ET_{\text{ave}} - L - Ss + P_{\text{two}} + AC_{\text{beff}}
\]  

(4)

In the equation, \( AC_f \) represents the water layer height for the future (mm), \( ET_{\text{ave}} \) is the average crop evapotranspiration over the past two weeks (mm), \( P_{\text{two}} \) is the average precipitation over the past two weeks (mm), and \( AC_{\text{beff}} \) is the updated previous water layer adjusted for the future (mm). The equation is used in a sequential loop, continuously updating the future water layer until it becomes equal to or lower than the minimum limit layer. The future irrigation day is determined when this condition is met.

3.4 FLOW ESTIMATION AND RIVER SALINITY

In this study, an LSTM network is utilized to estimate the flow of the Araranguá River. This model was implemented in Python and predicts the flow five days in advance, focusing on periods characterized by potential rainfall scarcity and low flows (Silva et al., 2021). It takes into account previous precipitation and flow data as input.

Furthermore, the study investigates the relationship between flow and river salinity, drawing insights from studies conducted by Silvestrini and D’Aquino (2020). The Araranguá River exhibits a flow range from 0.05 m³ s⁻¹ to values exceeding 1350 m³ s⁻¹, with an average long-term flow of 33.9 m³ s⁻¹. Depending on the flow rate, the
estuary either acts as an exporter or importer of suspended particulate matter (SPM), with a corresponding saline wedge extending upstream from the mouth. To enhance data interpretation for farmers, flow predictions are presented in levels rather than numerical values, providing ease in reading and facilitating decision-making.

To facilitate data interpretation for farmers, a proposal is made to present the flow information in levels rather than numerical values. This approach, depicted in Figure 3, aims to enhance readability of the predictions and enable faster decision-making processes. By representing the flow in levels, it becomes easier for farmers to grasp the information and make informed choices regarding irrigation management.

Figure 3. Proposal of flow levels and information

<table>
<thead>
<tr>
<th>Flow Levels</th>
<th>Description of the Limits</th>
<th>Flow Levels by Color</th>
<th>Description of Salinity Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very high flow</td>
<td>Lower than 73 m$^3$s$^{-1}$</td>
<td></td>
<td>Salinity risk for crops up to 8 km from the mouth</td>
</tr>
<tr>
<td>High flow</td>
<td>Higher than 33.9 m$^3$s$^{-1}$ lower than 73 m$^3$s$^{-1}$</td>
<td></td>
<td>Salinity risk for crops up to 20 km from the mouth</td>
</tr>
<tr>
<td>Maximum normal flow</td>
<td>Higher than 22.5 m$^3$s$^{-1}$ lower than 33.9 m$^3$s$^{-1}$</td>
<td></td>
<td>Salinity risk for crops up to 20 km from the mouth</td>
</tr>
<tr>
<td>Average normal flow</td>
<td>Higher than 12 m$^3$s$^{-1}$ lower than 22.5 m$^3$s$^{-1}$</td>
<td></td>
<td>Salinity risk for crops up to 45 km from the mouth</td>
</tr>
<tr>
<td>Low normal flow</td>
<td>Higher than 5.09 m$^3$s$^{-1}$ lower than 12 m$^3$s$^{-1}$</td>
<td></td>
<td>Salinity risk for crops up to 45 km from the mouth</td>
</tr>
<tr>
<td>Critical low flow</td>
<td>Higher than 0 m$^3$s$^{-1}$ lower than 5.09 m$^3$s$^{-1}$</td>
<td></td>
<td>Salinity risk for crops up to 45 km from the mouth</td>
</tr>
</tbody>
</table>

Source: Authors

3.5 SIMULATION

The selected crops in this study are situated in partially flat floodplain soils, which may exhibit some variation in terrain between blocks. Considering the location's characteristics, a vertical percolation rate of 5 mm per day, along with lateral flow, was adopted. Table 1 provides an overview of the key crop data collected for this study. While the crops share similar characteristics, the irrigation duration will vary depending on the area, impacting water and energy consumption. The significance of these factors will depend on the specific timing and day of irrigation.

The proposed methodology was implemented in a Python environment, simulating four scenarios for each crop over two seasons: 2009/2010 and 2010/2011. Considering the variation in the start of the season from September to late November, the
Simulations were conducted as follows: for the first season (2009/2010), the first scenario began on September 1, 2009, and the second on October 1, 2009. For the second season (2010/2011), the third scenario commenced on September 1, 2010, and the fourth on October 1, 2010.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Area (ha)</th>
<th>Pump flow (m³.h⁻¹)</th>
<th>Energy consumption (kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CROP-01</td>
<td>10</td>
<td>280</td>
<td>11.5</td>
</tr>
<tr>
<td>CROP-02</td>
<td>9</td>
<td>280</td>
<td>11.5</td>
</tr>
</tbody>
</table>

Source: Authors

### 4 RESULTS

The study focused on the region of the Araranguá river valley, comparing the water consumption under the current irrigation management practices of farmers with the simulated irrigation management using the proposed control method. Additionally, the response of the river flow estimate was analyzed.

#### 4.1 PRESENTATION OF THE RESULTS OF THE CONTROL SYSTEM

Table II provides an overall summary of the water and energy savings achieved across the four simulated scenarios. It is important to note that the crops cultivated in the region have a long cycle, taking approximately 150 days from sowing to harvest. The irrigation cycle for the blocks consists of around 20 days for preparing the flooded soil, followed by 130 to 140 days of irrigation with the established crop. According to the simulations, the total water consumption for the crops, including rainwater, exceeds 18,000 m³ per hectare in the region due to the extended irrigation period.
Table 2. Summary of the main simulation results

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Total pumpet water without control (m³)</th>
<th>Total pumpet water with control (m³)</th>
<th>Total pumpet water savings (m³)</th>
<th>Electrical power savings with control (KWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CROP-01</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1st</td>
<td>141,32</td>
<td>130,71</td>
<td>10,61</td>
<td>435,80</td>
</tr>
<tr>
<td>2nd</td>
<td>150,80</td>
<td>142,02</td>
<td>8,78</td>
<td>360,60</td>
</tr>
<tr>
<td>3rd</td>
<td>152,28</td>
<td>138,66</td>
<td>13,62</td>
<td>559,39</td>
</tr>
<tr>
<td>4th</td>
<td>153,30</td>
<td>132,25</td>
<td>21,05</td>
<td>864,55</td>
</tr>
<tr>
<td>CROP-02</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1st</td>
<td>122,94</td>
<td>117,70</td>
<td>5,30</td>
<td>217,72</td>
</tr>
<tr>
<td>2nd</td>
<td>138,64</td>
<td>127,82</td>
<td>10,82</td>
<td>444,30</td>
</tr>
<tr>
<td>3rd</td>
<td>137,05</td>
<td>124,79</td>
<td>12,26</td>
<td>503,45</td>
</tr>
<tr>
<td>4th</td>
<td>137,13</td>
<td>119,02</td>
<td>18,11</td>
<td>743,72</td>
</tr>
</tbody>
</table>

Source: Authors

Significant water consumption reduction was achieved through irrigation control, optimizing rainfall usage, minimizing waste, and reducing water layer height. Pump activation management and precise water level control were key factors in the observed savings. Table II shows varied non-linear savings in pumped water and energy across scenarios, primarily influenced by precipitation. Greater savings were observed during seasons with lower rainfall. Implementing the system in the field may yield even higher savings by reducing soil water load and considering weather forecasts to avoid excessive irrigation during heavy rainfall periods.

4.2 PRESENTATION OF THE RESULTS OF THE CONTROL SYSTEM

This assessment focuses on the 3rd scenario of CROP-01, considering flow levels indicated by color in Figure 3. The control system prevents irrigation on days with a risk of salinity in the region. Simulations were conducted, resulting in the chart presented in Figure 4, which highlights specific periods of salinity issues.

In Figure 4, two periods are identified where the controlled system indicates a critical low flow risk without significant rainfall predicted in the following five days. This
information assists farmers in decision-making, such as whether to increase the water layer height. Following the controlled irrigation, there is a three-day period in which the flow poses a salinity risk. The system restricts irrigation on this day and reschedules it for November 7 and 8 after a forecasted rainfall event that increases the river flow. However, starting from November 9, another alert is triggered for critical flow risk, and it becomes the farmer's discretion to activate irrigation to prevent saline water issues. Activation is recommended on November 11.

Figure 4. Comparison of the controlled and uncontrolled irrigation system - 3rd scenario CROP-01 - with a risky irrigation period

Uncontrolled irrigation practices (orange line in Fig. 4) supply excessive water compared to the controlled system, risking saline water issues on days like November 5, 13, and 14.

The highlights of this work include modeling with control techniques and AI, developing a methodology using actual data to enhance crop management for farmers. The study is relevant due to the irrigation management challenges and salinity issues faced by farmers in the Araranguá valley. The collection of high-quality data was a significant challenge.

The employed methodology resulted in up to 13.7% pumped water savings without altering the irrigation method, mitigating risks associated with saline water collection. In contrast to the saturated method proposed in previous works (Pfitscher et al., 2012; Uberti et al., 2017) for irrigated rice crops in the Araranguá region, which faces
challenges due to soil unevenness and dependence on river water flow, this study incorporates flow estimation to assess water availability and customizes irrigation modeling for the region. Additionally, the proposed system has the potential to integrate sensors in the future for real-time data collection and automated pump activation using IoT resources.

5 CONCLUSION

The implementation of the proposed computational method contributes to improving irrigation management and promoting sustainable production through the efficient use of river water. It serves as a decision support tool for farmers, helping them identify the optimal timing for activating the pump system and scheduling future events. The integration of control techniques and AI resources proves effective in monitoring and assessing water use and availability in rice farming.

This study aimed to foster sustainable agriculture and encourage the use of water-efficient practices to achieve equal or greater food production. By addressing issues related to saline water and excessive water in the blocks, the approach reduces productivity losses and decreases electricity consumption, thereby reducing production costs for farmers.

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