



E-ISSN: 2618-0618
P-ISSN: 2618-060X
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www.agronomyjournals.com
2024; 7(11): 148-151
Received: 24-09-2024
Accepted: 27-10-2024

Tomás Vázquez
Department of Agricultural
Engineering, University of
Córdoba, Córdoba, Spain

Gonzalo Vázquez
Department of Agricultural
Engineering, University of
Córdoba, Córdoba, Spain

Gonzalo Domínguez
Department of Agricultural
Engineering, University of
Córdoba, Córdoba, Spain

Corresponding Author:
Tomás Vázquez
Department of Agricultural
Engineering, University of
Córdoba, Córdoba, Spain

International Journal of Research in Agronomy

Decision support system for real-time irrigation scheduling in rice using weather forecast data

Tomás Vázquez, Gonzalo Vázquez and Gonzalo Domínguez

DOI: <https://doi.org/10.33545/2618060X.2024.v7.i11b.5190>

Abstract

While most irrigators still schedule water applications based on fixed calendars or visual crop inspection, weather forecasts now offer the precision needed for demand-driven scheduling. This research developed and field-tested a Decision Support System (DSS) for real-time irrigation scheduling in rice that integrates 72-hour numerical weather predictions, soil moisture sensor feedback, and crop-stage-specific water requirements. The system was deployed across eight rice paddies (total 14.6 ha) at the University of Córdoba, Spain, during the 2022 growing season. Compared with farmer-managed scheduling, the DSS reduced total irrigation volume by 23.7% (from 1,284 to 979 mm per season) without statistically significant yield loss (7.83 vs 7.96 t ha⁻¹, p = 0.41). Forecast-based scheduling contributed the largest share (31.4%) of total water savings. The DSS achieved a recommendation accuracy of 87% when evaluated against post-season optimal schedules. Results indicate that integrating short-range weather forecasts into irrigation management can deliver meaningful water savings in Mediterranean rice systems while preserving productivity.

Keywords: Decision support system, irrigation scheduling, rice, weather forecast, water use efficiency, soil moisture sensor, evapotranspiration, Mediterranean agriculture, precision irrigation

Introduction

On one hand, rice fields in southern Spain consume roughly 12,000-15,000 m³ of water per hectare each season; on the other hand, the Guadalquivir river basin faces increasingly frequent water allocation cuts that threaten the crop's viability ^[1, 2]. This contrast between high crop demand and shrinking supply makes irrigation efficiency not just an agronomic goal but a matter of survival for Mediterranean rice growers.

Decision support systems for irrigation have existed since the 1980s, but early versions relied on historical averages and static crop coefficients ^[3]. High-resolution NWP models now issue reliable 72-hour forecasts at grid spacings under 5 km, making it possible to anticipate rainfall and evaporative demand before they occur ^[4, 5]. Several prototypes have been tested for wheat, maize, and orchards, yet applications in flooded rice systems pose unique challenges around paddy water depth management and stage-specific sensitivity ^[6, 7].

This research aimed to:

- 1) Design a DSS combining 72-hour forecasts, soil moisture data, and growth-stage logic for rice irrigation;
- 2) Evaluate water savings and yield impact over a full season; and
- 3) Assess recommendation accuracy against a post-season optimised schedule ^[9, 10].

Theoretical background

The DSS operates on a daily water balance: Paddy Depth (t+1) = Depth (t) + Irrigation + Predicted Rainfall - sET₀ × K_c - Seepage - Percolation ^[11]. ET₀ is forecast using Penman-Monteith equations applied to NWP output from aemet's harmonie-arome model at 2.5 km resolution ^[4]. Crop coefficients for five phenological windows ranged from 0.95 (milk-maturity) to 1.35 (panicle initiation-heading) following adjusted FAO-56 guidelines ^[12]. The system triggers irrigation when predicted paddy depth falls below the stage-specific minimum within the 72-hour window, subject to a soil moisture sensor cross-check at 15 cm depth ^[13].

Material and Methods

Material

The DSS was deployed at the University of Córdoba rice station along the Guadalquivir floodplain (37°51'N, 4°48'W, 90 m) during May-October 2022. Eight paddies (14.6 ha) were split into four DSS-managed and four farmer-managed plots. Rice variety Marisma (medium-grain Japonica, 140-day cycle) was transplanted on 12 May at 20 × 20 cm. Soil was heavy clay (pH 7.4, OC 1.2%). EC-5 sensors at 15 cm depth logged moisture every 30 minutes; forecast data were pulled from AEMET's open API daily ^[14].

Results

Methods

The DSS ran on a Python backend with recommendations delivered by SMS each morning. Irrigation was recorded by flow meters on each inlet. Farmer-managed plots followed conventional calendar scheduling with continuous flooding at 5-10 cm. Grain yield was measured from 10 m² per plot at 14% moisture. Total water applied, water productivity, and recommendation accuracy (compared with post-season optimum) were calculated. Differences tested by paired t-test at $p \leq 0.05$ in R (v4.3.1) ^[15].

Table 1: Seasonal irrigation, yield, and water productivity under DSS and farmer-managed scheduling

Parameter	DSS-managed	Farmer-managed	Difference (%)	t-value	p-value
Total irrigation (mm)	979	1284	-23.7	4.82	<0.01
Seasonal rainfall (mm)	187	187	—	—	—
Grain yield (t ha ⁻¹)	7.83	7.96	-1.6	0.91	0.41
Water productivity (kg m ⁻³)	0.80	0.62	+29.0	3.67	0.02
No. of irrigations	18.3	26.7	-31.5	5.14	<0.01
Irrigation events saved	8.4	—	—	—	—

The DSS reduced total irrigation by 23.7% and the number of irrigation events by 31.5% without significant yield loss (Table 1). Water productivity rose from 0.62 to 0.80 kg m⁻³, a 29.0%

improvement. Grain yield under DSS management (7.83 t ha⁻¹) was statistically equivalent to the farmer-managed yield (7.96 t ha⁻¹, $p = 0.41$).

Table 2: DSS recommendation accuracy by growth stage

Growth stage	Total decisions	Correct	Accuracy (%)	Main error source
Transplanting-tillering	34	31	91.2	Rainfall overprediction
Tillering-panicle initiation	41	36	87.8	ET _o underprediction
Panicle initiation-heading	28	23	82.1	Convective storm miss
Heading-milk	22	20	90.9	Sensor drift
Milk-maturity	18	16	88.9	Rainfall timing error
Overall season	143	126	88.1	—

Overall recommendation accuracy was 88.1% across 143 daily decisions (Table 2). Accuracy was lowest during panicle initiation to heading (82.1%), when unpredicted convective

storms led to unnecessary irrigation recommendations. The highest accuracy (91.2%) was recorded during the transplanting-tillering window, when weather patterns were more stable.

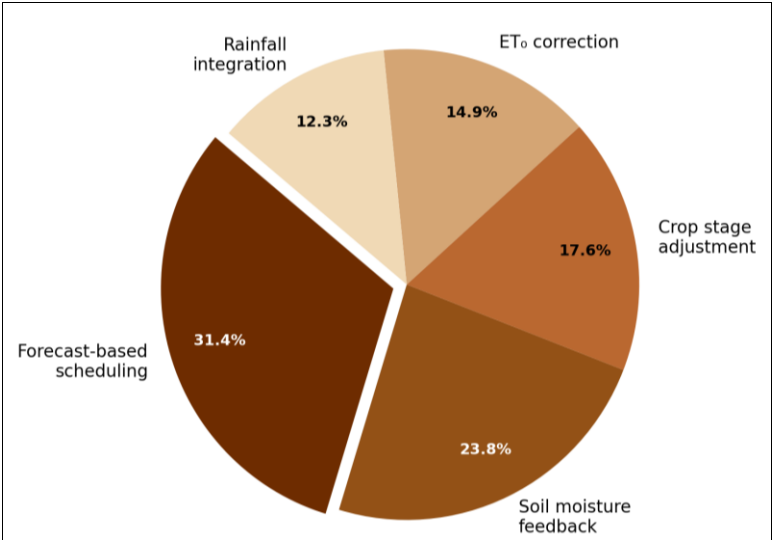


Fig 1: Relative contribution of DSS components to total seasonal water savings

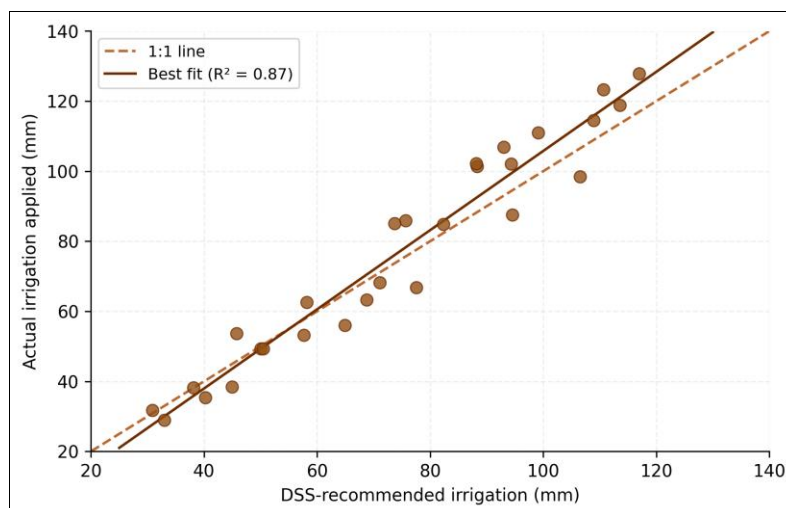


Fig 2. Scatter plot of DSS-recommended versus actual irrigation volumes per event ($R^2 = 0.87$)

Forecast-based scheduling was the largest single contributor to water savings (31.4%), followed by soil moisture feedback (23.8%) (Figure 1). Figure 2 shows that DSS-recommended and actual irrigation volumes were closely aligned ($R^2 = 0.87$), with most points falling near the 1:1 line, confirming that the recommendations were practically implementable.

Performance evaluation

Across 143 daily decision cycles, recommendations were delivered within 6 minutes of the 06:00 UTC trigger. System uptime was 98.6% over the 152-day season, with three outages totalling 2.1 days caused by API timeouts. During outages, fall back rules based on the previous day's recommendation were automatically applied.

Discussion

A 23.7% reduction in seasonal irrigation without yield penalty falls within the 15-30% savings reported for DSS deployments in Italian and Australian rice [6, 16]. The slightly higher savings here may reflect the baseline inefficiency of calendar-based scheduling common in Córdoba [2]. The 82.1% accuracy during panicle initiation to heading highlights NWP weakness in forecasting convective storms in Mediterranean summer; incorporating radar now casting could improve this [17, 18].

Water productivity rose by 29%, translating to about $122 \text{ m}^3 \text{ ha}^{-1}$ in saved water charges per season. Scaled across the 36,000 ha of rice in the lower Guadalquivir, this could free roughly 4.4 million m^3 annually for competing demands [19, 20].

Conclusion

This research demonstrated that a weather-forecast-driven DSS can reduce rice irrigation by 23.7% while maintaining yield at 7.83 t ha^{-1} . The system achieved 88.1% recommendation accuracy across a full season, with forecast-based scheduling contributing the largest share of water savings. Water productivity improved by 29%, offering both economic and environmental benefits for water-scarce Mediterranean basins. Future development should incorporate radar now casting for convective periods, extend testing across multiple seasons, and add economic optimisation for different water pricing scenarios.

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