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Season-Aware Irrigation for Lowland Rice: Aquacrop-OSPy-Guided Rules to Enhance Water Utilization and Increase Dry Yields in Malang

Johan Ericka Wahyu Prakasa*, Ajib Hanani and Shoffin Nahwa Utama
Department ofTeknik Informatika, UIN Maulana Malik Ibrahim Malang, Malang, Indonesia

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*Corresponding author:
E-mail:
johan@uin-malang.ac.id

ABSTRACT

In monsoon climates, efficient irrigation for lowland rice requires adaptive strategies that respond to rainfall and soil moisture dynamics, rather than fixed schedules. This study utilized the AquaCrop-OSPy model, an open-source Python implementation of FAO AquaCrop v7.1 parameterized for paddy rice on clay-loam soil to compare two irrigation rules in Malang, Indonesia, over a decade (2015–2024) across three key planting periods: rainy season (January), transitional season (March), and dry season (June). The first schedule was a rain-aware basin top-up rule (0/10/50 mm based on 3–7-day rainfall) versus a moisture-threshold rule that triggers 50/10/0 mm when the root-zone depletion exceeds 70%, between 70–90%, or less than 90% of RAW. In the rainy and transitional plantings, the moisture-threshold rule reduced seasonal irrigation by 26% and 15% with no loss in yield (≤0.5% difference). During the dry-season planting, it increased yield by 11.4% with a moderate water trade-off (+21%). Consequently, water-use efficiency improved when rainfall contributed to crop demand, while targeted applications stabilized dry-season yields. These results show that simple, physiologically-based thresholds based on Aquacrop-OSPy's paddy-rice parameters provide a feasible approach to year-round rice cultivation with more efficient water usage.

INTRODUCTION

Rice is a water-intensive food, so improving irrigation efficiency is a key to sustaining yields under tightening water constraints. Rice cultivation accounts for roughly one-third to two-fifths of global irrigation withdrawals, highlighting the need for enhanced on-farm scheduling (Mallareddy et al., 2023). Recent studies and meta-analyses show that water-saving schedules (e.g., non-continuous surface flooding, alternate wetting and drying) can reduce seasonal water usage while maintaining, and in some contexts improving yield and water productivity in paddy systems (Carrijo et al., 2017). Supplementary evidence from agronomic trials demonstrate that management shifts toward controlled or aerobic watering can raise water productivity, although with season-dependent yield responses (Mallareddy et al., 2023).

At the same time digital irrigation has advanced. Low-power sensing, edge/cloud connectivity and rule-based or AI controllers now allow irrigation to be triggered by soil –

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plant - atmosphere instead fixed calendars. Recent studies show that IoT-enabled smart irrigation consistently use less water while keeping crop performance high in different settings (García et al., 2020). Fuzzy logic has emerged as an effective controller for converting moisture signals into simple and reliable irrigation actions. Recent studies showing lower water waste and stable soil moisture by using fuzzy rules compared with on/off or purely time-based schedules (Neugebauer et al., 2023).

This study addresses two identified gaps. First, while IoT–fuzzy irrigation demonstrations exist, few have compared a moisture-responsive fuzzy rule against a practical rain-aware heuristic across multiple seasons representative of tropical monsoon agriculture. Second, a robust, process-based simulation framework is needed to rigorously connect irrigation decisions to crop growth and water balance under realistic, multi-year weather variability.

To this end, we employed the FAO AquaCrop-OSPy to conduct a decade-long (2015–2024), season-aware comparison in Malang, Indonesia. We evaluated two operational irrigation rules for lowland rice across three critical planting periods: the rainy season (January), transitional season (March), and dry season (June). The first rule (Basin) is a discrete, rain-aware top-up schedule (0, 10, or 50 mm) triggered by 3- and 7-day rainfall accumulations. The second rule (IoT–fuzzy) uses soil moisture status, expressed as the available soil-water fraction, to trigger the same discrete irrigation amounts via simple physiological thresholds.

Our analysis focuses on dry grain yield, total irrigation depth, and irrigation water use efficiency (IWUE). The study aims to answer a practical question for farmers and scheme managers: Can a soil moisture-responsive schedule maintain or increase annual yield while saving water when rainfall is abundant, and secure production during dry periods.

MATERIALS AND METHODS

Rice growth and water balance were simulated using the FAO AquaCrop model version 7.1 via its open-source Python port, AquaCrop-OSPy (Kelly & Foster, 2021). The simulation was configured for lowland paddy rice following the model's standard calibration for flooded conditions (Raes, 2017), using the built-in "paddy rice" crop file. The growing season length was fixed at 104 days to match local maturity in Malang. Key plant parameters include a water productivity (WP*) of 19 g m^{-2} and a reference harvest index (HI_0) ranging from 35 to 50%. Water-stress thresholds for paddy rice in the model (pexp=0.00–0.40, psto=0.50, psen=0.55, ppol ≈ 0.75) directly informed the moisture thresholds used in our fuzzy irrigation rule. Daily weather inputs (maximum/minimum temperature, precipitation, relative humidity, wind speed, and solar radiation/shortwave) were sourced from BMKG Stasiun Geofisika Malang (latitude −8.15000, longitude 112.45000, elevation 285 m). Reference evapotranspiration (ET_0) was computed using the FAO Penman–Monteith method, as recommended for standardized ET_0 estimation, and internally partitioned by Aquacrop-OSPyinto crop transpiration and soil evaporation through canopy cover.

We specified the soil as clay loam and parameterized the profile following Aquacrop-OSPy's soil module. For each horizon, Aquacrop-OSPy requires the volumetric water contents at saturation (θSAT), field capacity (θFC), and permanent wilting point (θPWP), together with saturated hydraulic conductivity (Ksat), gravel fraction (if any), and root penetrability. These inputs are then used to derive Total Available Water (TAW) for the soil water balance, Readily Evaporable Water (REW) for soil evaporation, the soil textural class for capillary rise, and hydraulic auxiliaries (capillary rise function and drainage characteristic).

For the clay loam texture, Aquacrop-OSPy's default table (twelve-class system) indicates that θSAT ≈ 50 vol%, θFC ≈ 39 vol%, θPWP ≈ 23 vol%, giving TAW ≈ 160 mm m^{-1}, with Ksat ≈ 125 mm d^{-1} and a typical bulk density of 1.32 Mg m^{-3}. These indicative values are commonly used where site measurements are unavailable and fall within the "sandy–clayey soils" hydraulic range employed by Aquacrop-OSPy.

The root-zone water balance is updated daily by tracking rainfall and irrigation inputs, surface runoff, soil evaporation (E), crop transpiration (Tr), capillary rise from a shallow water table, and deep percolation; TAW is defined between θFC and θPWP and computed using formula 1.

$$TAW = (\theta_{FC} - \theta_{PWP})\, Z \left(1 - \frac{Vol\%gravel}{100}\right) \quad (1)$$

with the depth of the considered layer (topsoil or root zone). The presence of gravel reduces TAW in proportion to its volume fraction (Raes, 2017).

Aquacrop-OSPy expresses water stress against root-zone depletion (Dr) as a fraction of TAW depleted, with process-specific thresholds and shapes of stress-response curves; this links irrigation triggers directly to the soil's extractable water in the clay-loam profile rather than to arbitrary moisture percentages. For soil evaporation, Aquacrop-OSPy uses a two-stage schemes are energy-limited Stage I that depletes REW in the thin surface layer, followed by a falling-rate Stage II governed by soil hydraulics of the upper profile. The switch occurs once REW is exhausted parameterization of Stage II considers the hydraulic properties of the texture class, with model defaults for the thickness of the top layer that supplies the surface (Z_e,top, default 0.30 m, adjustable 0.15–0.50 m). Regarding capillary rise, Aquacrop-OSPy groups textures into four hydraulic classes for deriving rise from shallow groundwater. Clay loam belongs to Class III (sandy clayey soils) with Ksat ~5–150 mm d^{-1}, for which empirical a–b parameters in the capillary-rise function are assigned as a function of Ksat. This affects upward fluxes into the root zone during dry spells and is internally determined from the specified θSAT –θFC–θPWP and Ksat.

This study evaluated two irrigation decision rules for lowland rice using a process-based crop–soil simulator (Aquacrop-OSPy; crop= paddy rice). Aquacrop-OSPy is the Food and Agriculture Organization's (FAO) crop–water productivity model that developed and maintained by FAO's Land and Water Division to simulate yield response to water and to support irrigation management analyses. It is widely adopted in research and practice in irrigation simulation research (Salman et al. 2021). Aquacrop-OSPy is an open-source python implementation of Aquacrop-OSPy to modelling crop-water productivity (Kelly & Foster, 2021).

Simulations were run for ten seasons (2015 to 2024) and three planting periods representatives of monsoon phases in Indonesia: Rainy season planting (January), transitional-season planting (March), and Dry season planting (June). The soil was set to clay loam consistent with the most common paddy rice fields soil type in Indonesia. The irrigation action set was discrete 0, 10, or 50 mm per decision step (Djaman et al., 2018). Real daily weather data was read from Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG) for Malang – East Java area (BMKG, 2025).

The Basin strategy worked as a discrete top-up regime that inspected rolling rainfall periods and the days passed since the last irrigation. If the 3-day cumulative rainfall ≥ 15 mm, irrigation was skipped. Otherwise, the 7-day cumulative rainfall was evaluated with minimum waiting times using formula 2.

$$Irr(t) = \begin{cases} 0 \ if \ R_3 \geq 15 \\ 50 \ if \ R_7 < 15 \ and \ d \geq 7 \\ 10 \ if \ R_7 < 10 \ and \ d \geq 3 \end{cases} \quad (2)$$

Where:
R_3=rainfall in last 3 days (mm)
R_7=rainfall in last 7 days (mm)
d=days since last irrigation (days)

Each planting calendar had rain periods that were attached to them so that wet and dry spells stayed the same through all the seasons.

The IoT–fuzzy strategy used the model-reported available soil–water fraction *A(t)*, which was calculated using formula 3.

$$A(t) = 1 - \frac{D(t)}{TAW}, 0 \leq A \leq 1 \quad (3)$$

where TAW and D(t) are total available water and depletion, respectively.

The IoT–fuzzy rule maps the available soil-water fraction A(t) to one of three discrete irrigation actions (0, 10, or 50 mm) using two thresholds, as defined in Equation 4:

$$Irr(t) = \begin{cases} 50 \text{ } if \text{ } A < 0.7 \text{ } (dry \text{ } condition) \\ 10 \text{ } if \text{ } 0.7 \le A \le 0.9 \text{ } (adequate \text{ } condition) \\ 0 \text{ } if \text{ } A > 0.9 \text{ } (wet \text{ } condition) \end{cases} \quad (4)$$

This rule exemplifies a simple, fuzzy-logic-based controller where soil moisture sensing directly triggers irrigation, preventing stress when the root zone is too dry and avoiding waste when it is sufficiently wet.

For each episode, the simulator returned dry grain yield (t ha^{-1}) and cumulative irrigation depth (mm). Irrigation depth was converted to volume using the standard relation that 1 mm over 1 ha equals 10,000 L and volumes were reported as litres per field according to the configured field area. The primary efficiency indicator was water-use efficiency (WUE), defined as litres of irrigation per ton of grain (L t^{-1}). The season-average soil-moisture fraction was also recorded as a descriptive state variable.

RESULTS AND DISCUSSION

To obtain seasonally robust evidence, this study simulated three planting periods namely: rainy-season planting (January), transitional-season planting (March), and dry-season planting (June) annually from 2015 to 2024 under two irrigation strategies (Basin vs IoT–fuzzy). In this study, "Basin" refers to a rain-aware, rule-based top-up schedule that uses 3 and 7 day rainfall periods and days-since-irrigation to apply 0/10/50 mm irrigation. Whereas "IoT–fuzzy" is a moisture-responsive controller that classifies the available soil-water fraction (dry < 0.70; adequate ≤ 0.90; wet > 0.90) to choose 50/10/0 mm irrigation respectively.

Across ten weather years, the January (rainy) planting showed no practical yield penalty under the moisture-threshold rule: means were 7.32±0.13 vs 7.31±0.12 t ha^{-1} (IoT vs Basin; Δ=+0.2%; $p=0.023$). Despite the very small effect size on yield, IoT had significantly less seasonal irrigation (1,270±419 vs 1,720±437 m^3 ha^{-1}; Δ=−26.2%; $p=0.014$). The resulting IWUE was higher under IoT (6.59±3.06 vs 4.50±1.15 kg m^{-3}; Δ=+46.3%), although the paired test was close ($p=0.064$). In March (transition), yields were statistically similar (7.31±0.12 vs 7.28±0.19 t ha^{-1}; Δ=+0.5%; $p=0.456$), while irrigation remained lower for IoT (2,220±718 vs 2,600±591 m^3 ha^{-1}; Δ=−14.6%; $p=0.095$). The reduction in applied water translated into a significant IWUE gain for IoT (3.65±1.27 vs 2.91±0.57 kg m^{-3}; Δ=+25.4%; $p=0.046$). In June (dry), the moisture-threshold rule increased yield relative to Basin (7.31±0.11 vs 6.56±1.00 t ha^{-1}; Δ=+11.4%; $p=0.043$) while using more irrigation (3,460±648 vs 2,860±255 m^3 ha^{-1}; Δ=+21.0%; $p=0.043$). The net effect on IWUE

Table 1. Ten-year means (±SD) and paired-test p-values for yield, seasonal irrigation, and IWUE by planting window (Malang, 2015–2024). Δ is IoT relative to Basin.

Season	Metric	Basin (mean±SD)	IoT (mean±SD)	Δ IoT vs Basin (%)	p-value
January	Yield (t ha^{-1})	7.31±0.12	7.32±0.13	+0.2	0.023
	Irrigation (m^3 ha^{-1})	1,720±437	1,270±419	−26.2	0.014
	IWUE (kg m^{-3})	4.50±1.15	6.59±3.06	+46.3	0.064
March	Yield (t ha^{-1})	7.28±0.19	7.31±0.12	+0.5	0.456
	Irrigation (m^3 ha^{-1})	2,600±591	2,220±718	−14.6	0.095
	IWUE (kg m^{-3})	2.91±0.57	3.65±1.27	+25.4	0.046
June	Yield (t ha^{-1})	6.56±1.00	7.31±0.11	+11.4	0.043
	Irrigation (m^3 ha^{-1})	2,860±255	3,460±648	+21.0	0.043
	IWUE (kg m^{-3})	2.29±0.23	2.19±0.45	−4.4	0.339

Notes: Basin represents a rain-aware, discrete top-up regime (0/10/50 mm), whereas IoT–fuzzy uses soil-moisture availability thresholds (dry=0.70; wet=0.90). IWUE is reported as kg of grain per m^3 of irrigation water (kg m^{-3}).

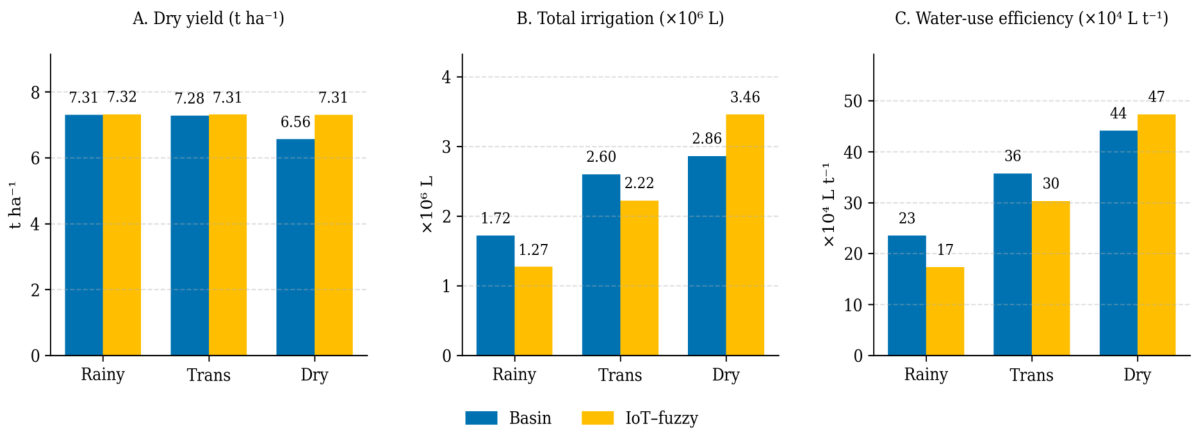

Figure 1. Average performance metrics across 2015–2024 by strategy and planting periods: “Basin” denotes a rain-aware discrete top-up regime (0/10/50 mm), whereas “IoT–fuzzy” denotes moisture-based fuzzy scheduling (dry threshold 0.70; wet threshold 0.90).

was statistically comparable between strategies (2.19±0.45 vs 2.29±0.23 kg m^{-3}; Δ=−4.4%; p=0.339). Table 1 shows a summary of these patterns for each season, and Figure 1 shows them in a picture.

The results reveal a consistent, season-dependent trade-off (Table 1). During the rainy (January) and transitional (March) seasons, the IoT–fuzzy rule significantly reduced irrigation water use by 26% and 15%, respectively, without incurring a yield penalty (yield difference ≤0.5%). This led to notable improvements in IWUE, significant in March. These water savings occur because the rule, tied directly to root-zone depletion, avoids unnecessary irrigation when rainfall already meets crop demand.

In stark contrast, during the dry season (June), the IoT–fuzzy rule increased yield by 11.4% compared to the Basin rule, albeit with a 21% increase in irrigation application. This trade-off was favorable for yield stabilization, as the IWUE did not differ significantly between the two strategies. The higher inter-annual yield variability (larger standard deviation) under the Basin rule in June (1.00 vs. 0.11 t ha^{-1} for IoT–fuzzy) underscores the vulnerability of rain-dependent schedules to dry-spell timing. The moisture-responsive rule effectively prevents mid-season water stress by ensuring timely irrigation when the soil approaches critical depletion levels.

Taken together, these results support season-specific recommendations: deploy RAW-based moisture thresholds in all seasons, expecting water savings in January–March and yield protection in June. For practice, the January–March settings can target savings (with thresholds as specified), while June can prioritize yield security, accepting a moderate, statistically supported increase in applied water. The patterns and statistics reported here derive directly from the updated Table 1 and its paired comparisons across ten years.

Overall, a clear seasonal trade-off emerges: the IoT–fuzzy rule saves water in rainy and transitional seasons, and secures higher yield (with more water) in the dry season. From a management perspective, it is preferable in the dry season for yield stabilization and in wetter seasons for water savings.

This study has limitations. The simulated 'Basin' rule represents a rain-aware top-up regime, not continuous flooding. Meteorological data, while real, may contain anomalies. Future work should include sensitivity analysis of the fuzzy thresholds (e.g., 0.70, 0.90) and field validation to strengthen the generality of these findings and guide local parameterization.

CONCLUSION

This simulation study demonstrates that for lowland rice in a monsoon climate, an adaptive irrigation schedule based on soil moisture thresholds (IoT–fuzzy) outperforms a conventional rain-aware (Basin) schedule. The key finding is a season-dependent performance: the IoT–fuzzy rule saves substantial irrigation water (15–26%) during the rainy and transitional seasons without compromising yield, while it secures a significantly higher yield (11.4%) during the dry season, albeit with a moderate increase in water use. This approach effectively decouples irrigation decisions from unreliable rainfall cues and ties them directly to plant-available water in the root zone, leading to more efficient water use and greater yield stability across variable seasons.

For practical implementation, we recommend deploying such moisture-threshold-based systems with season-specific expectations: prioritize water savings in wetter months and yield security in drier months. Translating these findings to the field requires straight-forward tuning of the moisture thresholds to local soil types and validation through on-farm trials. This pathway offers a realistic transition from simulation to practice, moving rice cultivation toward greater annual water productivity.

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