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From Water Allocation to Food Security: Irrigation System Optimization through Deterministic Dynamic Programming in the Gembolo Irrigation Area

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Abstract: Inefficient irrigation water distribution remains a critical barrier to achieving optimal crop productivity and ensuring food security in rural Indonesia. This study focuses on the Gembolo Irrigation Area, Mojokerto Regency, by applying Deterministic Dynamic Programming (DDP) to optimize water allocation under a Rice–Rice–Secondary Crop (RTTG) rotation. The comprehensive integration of hydrological, climatological, and cropping data was employed to construct a DDP model that synchronizes irrigation supply with crop water demand across nine irrigation structures (G1–G9). The optimization results reveal significant improvements: irrigated area expanded by 254 ha, cropping intensity increased from 277 to 300%, and farmers' net income rose by IDR 5.3 billion compared to the existing allocation scheme. These findings demonstrate the capacity of DDP to enhance water-use efficiency while strengthening the resilience and sustainability of rural agricultural systems. The study highlights the importance of data-driven optimization as a decision-support framework for advancing integrated irrigation management and rural development.

Keywords: Dynamic programming; Irrigation optimization; Rural development; Sustainable agriculture

Introduction

Agriculture is a vital sector in Indonesia, playing a central role in ensuring national food security and supporting rural livelihoods. A large portion of the population depends on agricultural products as their main source of food and income, making the sustainability of agricultural production essential for both economic stability and nutritional sufficiency. According to FAO (2021), cereals and other staple crops contribute more than half of the daily caloric intake of the Indonesian population. Similarly, previous studies highlight that over 90% of households rely on domestically produced staple foods for their daily consumption (Suryana, 2018). Therefore, improving agricultural productivity and efficiency, particularly through better water and land management, is crucial to guarantee long-term food availability. Karamouz & Houck (1992) discussed the optimization and simulation of multiple reservoir systems, providing analogous insights for irrigation network design.

As a strategic sector, agricultural production is strongly influenced by the availability and distribution of irrigational water. However, the efficiency of irrigation systems in many river basins across Indonesia remains relatively low. Uneven water allocation often prevents farmland from being utilized to its full potential (Ali & Talukder, 2008). This situation results in considerable water losses in irrigation channels, caused by leakage, inefficient distribution, and excessive evapotranspiration, thereby limiting the productivity of agricultural systems (Barker & Molle, 2004). Linker (2021) emphasized the need for stochastic model-based

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optimization of irrigation scheduling in the face of climatic and hydrologic uncertainties.

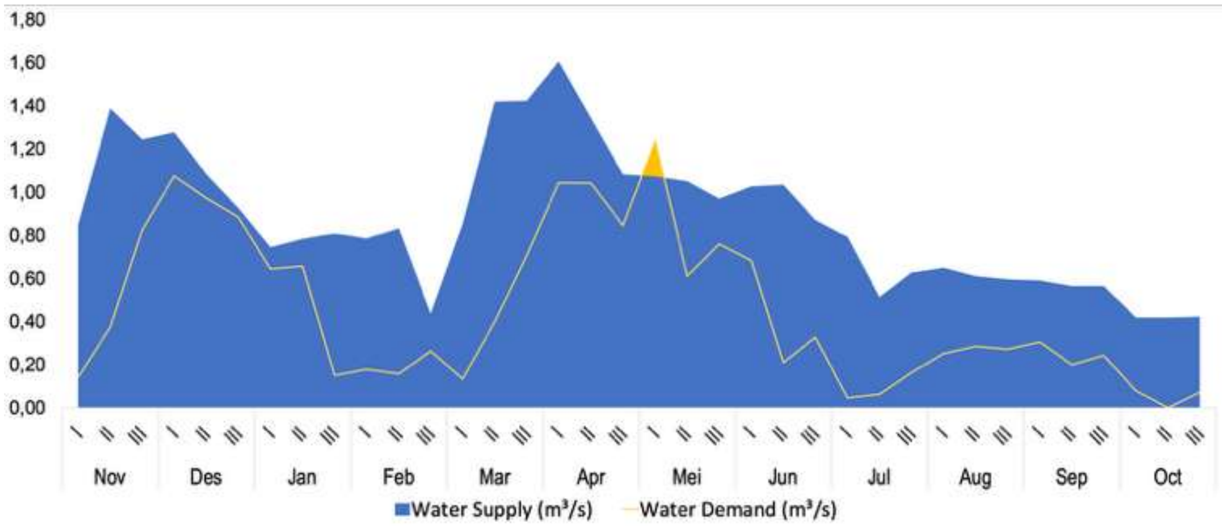

Figure 1. Water balance chart for initial planting-November I

Agricultural communities often adapt to environmental stressors through collective innovation and local knowledge. In East Java, Abdullah et al. (2023) show that participatory communication significantly empowers farmers to adapt to climate impacts, fostering resilience through shared learning and practices. These community-driven approaches underscore the need to integrate technical models like Deterministic Dynamic Programming (DDP) within participatory frameworks, ensuring that optimized irrigation management aligns with local empowerment processes. Yakowitz (1992) outlines how dynamic programming techniques are applied in water resources systems, providing a theoretical basis for sequential decision problems.

The issue of low irrigation distribution efficiency is also evident in the conditions of the Gembolo Watershed (DAS Gembolo). Figure 1 illustrates the dynamics of water supply and demand in the watershed throughout the year. It shows that water availability tends to fluctuate, with peak supply occurring in March–April, while during the dry season (July–September) river discharge significantly decreases to below 0.5 m^3/s. This condition creates an imbalance between irrigation water supply and demand, particularly in May and July–September, when crop water requirements are higher than the available supply. Jin et al. (2012) developed a hybrid Dynamic Dual Interval Programming (DDIP) model, which explicitly addresses system uncertainties in irrigation water allocation.

Table 1 presents the distribution of irrigated land across several blocks, with a total available area of 1,504 ha. However, only 1,278.35 ha are actively cultivated, while approximately 306.40 ha remain idle or unutilized. The imbalance between water availability (Figure 1) and land use patterns (Table 1) indicates that limited water supply is one of the main constraints in agricultural land utilization in the Gembolo irrigation area. This finding is consistent with previous studies, which reported that variability in water availability often leads to the inability to optimally meet rice irrigation requirements (Suryadi, 2014). Similarly, Kodoatie & Sjarief (2010) emphasized that uncertainty in water supply is a critical factor in irrigation planning and management. Therefore, adaptive water management and cropping strategies are needed to minimize the risks of drought while optimizing agricultural productivity. Archibald (2018) found that the most common methodologies in water resources research between 2010-2017 are stochastic dynamic programming and multistage stochastic programming.

The imbalance between water availability and irrigation demand demonstrates that conventional water management strategies have not been effective in addressing distribution problems. Hence, an optimization approach is required to improve the efficiency of irrigation water utilization while ensuring the sustainability of agricultural productivity. One such method is Deterministic Dynamic Programming (DDP), which provides a quantitative framework for decision-making in water allocation. Several studies have shown that optimization models based on dynamic programming can offer adaptive solutions to water availability uncertainties. For instance, Jin et al. (2012) developed a Hybrid Dynamic Dual Interval Programming (DDIP) model to allocate irrigation water more efficiently under uncertain conditions. Likewise, Laskookalayeh et al. (2022) applied an optimized water distribution model at the regional irrigation network level and found that optimized allocation strategies improved distribution efficiency while supporting more sustainable cropping patterns. Thus, DDP emerges as a crucial tool to address water scarcity challenges in the Gembolo Watershed.

Table 1. Distribution of irrigated farmland in Gembolo watershed (Bidang Sumber Daya Air, Dinas PUPR Kabupaten Mojokerto, 2025)

Irrigation Block/Unit	Available Farmland	Existing Cultivated Area	Idle Land
Sukosari	5	4.60	0.00
Mojokembang I	45	44.49	0.00
Urung-urung I	41	40.60	0.00
Urung-urung II	27	25.40	0.00
Ketidur	214	156.09	32.88
Kandangan	97	75.56	0.00
Tumpangsari	49	47.58	0.00
Jambu	40	17.42	
Jiyu	43	34.81	34.00
Jurukwangi	18	18.00	
Jabon	19	17.42	
Purworejo	79	79.00	
Dosermo	97	96.51	31.80
Bringin	42	27.49	0.00
Jeblokan	62	41.00	0.00
Sidomulyo	96	93.85	0.00
Bendungan	43	43.00	0.00
Tempuran	114	92.49	31.90
Mojojejer II	109	93.63	32.44
Dlimo	149	127.55	105.38
Ketok	78	68.64	23.00
Jabon	20	17.42	0.00
Jogodayo	17	15.80	15.00
Total	1504	1278.35	306.40

Based on the aforementioned background, this study aims to analyze the irrigation water requirements for rice cultivation in the Gembolo Watershed (DAS Gembolo) in detail. Furthermore, it develops an optimization approach for water allocation using Deterministic Dynamic Programming (DDP) to improve the efficiency of distribution and utilization of water resources. In addition, the study compares the existing conditions with the optimized results to assess the extent to which the application of DDP can enhance the productivity and effectiveness of the rice farming system within the Gembolo irrigation area.

Method

Location

This research was conducted in the Gembolo Irrigation Area (DI Gembolo), which is part of the Gembolo Watershed, Mojokerto Regency, East Java. The irrigation area covers a total rice field area of 1,504 ha and encompasses 23 irrigation zones, including Sukosari, Mojokembang, Urung-Urung, and Kandangan. Geographically, the study area is located at coordinates 111°20'13”–111°40'47” E and 7°18'35”–7°47’ S, with the main river extending approximately 31.63 km. The topography of Mojokerto varies considerably, ranging from fertile mountainous areas in the south, flat lowlands in the central region, to relatively less fertile limestone hills in the north. Elevations range from 0 to over 3,000 meters above sea level with slopes between 0° and > 22°, which in certain areas increases susceptibility to landslides. Climatically, the region falls under the tropical wet-and-dry type (Aw), with temperatures ranging from 20–34 °C in the lowlands and below 19 °C in the highlands, and is characterized by two distinct seasons, namely the rainy season and the dry season.

Hydrological and Climatological Data

The annual rainfall data from 2015 to 2024 show significant variability in total precipitation. The highest recorded rainfall occurred in 2017 with 4,175 mm, followed by 2022 with 4,030 mm, while the lowest was in 2015 with only 2,040 mm. These fluctuations indicate that rainfall distribution in the region is inconsistent, which may influence agricultural planning, water resource management, and drought mitigation strategies. Overall, the trend highlights the importance of monitoring long-term rainfall patterns to support sustainable land and water management.

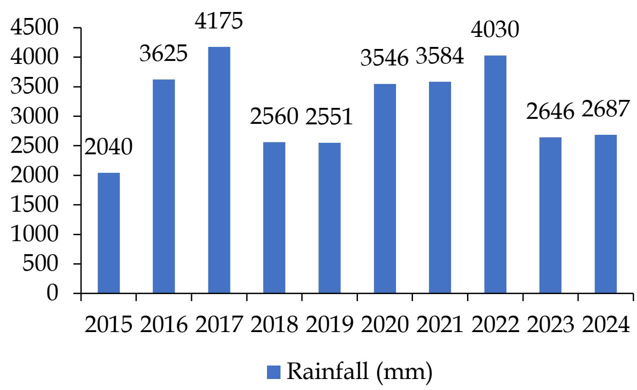

Figure 2. Total annual rainfall (Bidang Sumber Daya Air, Dinas PUPR Kabupaten Mojokerto, 2025)

The climatic conditions of Mojokerto Regency, characterized by a tropical wet–dry climate with two distinct seasons, have a direct implication on the dynamics of water availability within the study area. This is illustrated in Figure 2, which presents key meteorological parameters, including air temperature, relative humidity, wind speed, and solar radiation intensity. Seasonal variations in these parameters significantly influence the evapotranspiration process, with average temperatures ranging between 22.9–25.2 °C, relative humidity peaking during the rainy season (85–86%) and declining during the dry season (approximately 70%), while solar radiation intensity reaches its maximum in the dry period (August–September). Derived parameters such as saturated vapor pressure, solar radiation, and reference evapotranspiration (ETo) indicate that crop water demand driven by evapotranspiration peaks during the dry season (August–October), exceeding 6 mm/day, and reaches its lowest during the rainy season (April–June) at around 3.7–3.9 mm/day. These findings underscore the strong linkage between meteorological variability and irrigation water requirements throughout the year in the Gembolo Watershed. For maize under semi-arid conditions, Djaman (2018) calculated crop evapotranspiration, irrigation requirement, and water productivity, offering a benchmark for comparative results.

Table 2. Crop coefficients for paddy and palawija (FAO, 2021)

Month	Soybean	Mungbean	Groundnuts	Onion	Tobacco	Corn
0.5	0.50	0.40	0.40	0.50	0.50	0.50
1.0	0.75	0.60	0.46	0.51	0.50	0.59
1.5	1.00	0.97	0.70	0.69	0.60	0.96
2.0	1.00	1.05	0.91	0.90	0.35	1.05
2.5	0.82	0.80	0.95	0.95	0.00	1.02
3.0	0.45		0.91		0.00	0.95
Average	0.75	0.76	0.72	0.71	0.33	0.85

Table 3. Climatological data calculation for Mojokerto Regency (BMKG Juanda,2025)

Meteorological Data	Unit	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Temperature (T)	(°C)	23.82	23.61	23.78	24.06	24.16	23.47	22.91	22.86	23.9	25.08	25.19	24.06
Relative Humidity (RH)	(%)	85.65	85.88	85.44	84.83	80.77	77.79	75.57	74.07	70.02	69.95	77.21	83.59
Wind Speed (U)	(km/h; m/s)	5.63; 1.56	5.08; 1.41	4.63; 1.29	4.56; 1.27	5.04; 1.40	4.74; 1.32	5.41; 1.50	6.08; 1.69	6.16; 1.71	5.97; 1.66	6.32; 1.75	3.92; 1.09
Sunshine Duration (n/N)	(%)	38.63	39.67	42.42	55.58	66.35	65.95	68.11	76.25	75.75	69.16	50.56	36.79
Saturation Vapor Pressure (es)	mbar	29.53	29.15	29.45	29.96	30.14	28.9	27.89	27.8	29.67	31.84	32.04	29.96
Temperature and Elevation Factor (w)	-	0.73	0.73	0.73	0.74	0.74	0.73	0.72	0.72	0.73	0.75	0.75	0.74
Temperature Function (f(t))	(°C)	15.36	15.3	15.35	15.42	15.44	15.27	15.13	15.12	15.4	15.67	15.7	15.42
Actual Vapor Pressure (ea)	mbar	25.29	25.03	25.17	25.41	24.34	22.48	21.07	20.59	20.77	22.27	24.74	25.04
Vapor Pressure Function (f(ea))	mbar	0.119	0.12	0.119	0.118	0.123	0.131	0.138	0.14	0.139	0.132	0.121	012
Extraterrestrial Shortwave Radiation (Ra)	mm/day	16.06	16.09	15.51	14.44	13.14	12.45	12.75	13.74	14.91	15.79	15.97	15.96
Solar Shortwave Radiation (Rs)	mm/day	7.37	7.47	7.43	7.94	7.99	7.55	7.88	9.09	9.83	9.84	8.35	7.16
Sunshine Fraction Function (f(n/N))	mm/day	0.45	0.46	0.48	0.6	0.7	0.69	0.71	0.79	0.78	0.72	0.56	0.43
Wind Speed Function (f(U))	m/s	0.63	0.6	0.57	0.57	0.6	0.58	0.62	0.66	0.67	0.66	0.68	0.52
Net Longwave Radiation (Rn1)	mm/day	0.82	0.84	0.88	1.09	1.32	1.39	1.49	1.67	1.68	1.5	1.06	0.8
Correction Coefficient (c)	-	1.1	1.1	1.1	0.9	0.9	0.9	0.9	1	1.1	1.1	1.1	1.1
Evaporation (ETo*)	mm/day	4.17	4.14	4.09	4.26	4.35	4.12	4.37	5.05	5.76	5.99	5.15	4.05
Potential Evapotranspiration (ETo)	mm/day	4.59	4.56	4.5	3.83	3.92	3.71	3.93	5.05	6.34	6.58	5.66	4.45

According to Pereira et al. (2015a), the estimation of crop evapotranspiration with the FAO-56 methodology has significantly improved the accuracy and consistency of irrigation planning. The estimation of reference evapotranspiration (ETo) presented in the previous meteorological table serves as the basis for calculating the actual crop water requirement (ETc), which is derived by multiplying ETo by the crop coefficient (Kc).

The Kc value represents the ratio between the water demand of a specific crop and the reference evapotranspiration, varying across crop types and growth stages. The crop coefficient table indicates that maize has the highest average Kc (0.85), followed by soybean (0.75) and mung bean (0.76), while tobacco exhibits the lowest Kc (0.33). These variations highlight that crop water requirements are strongly dependent on crop physiology and growth duration. Valiantzas (2013) proposed simplified forms of the FAO-56 Penman–Monteith equation for cases of limited weather data availability.

The integration of meteorological data with Kc values enables a more accurate estimation of irrigation water demand across cropping seasons. Detailed monthly climatological data and the results of potential evapotranspiration (ETo) calculations, which form the basis for estimating crop water requirements in the Gembolo Watershed, are presented in Table 3. As reported by Allen et al. (1998) in the FAO Irrigation and Drainage Paper No. 56, the use of Kc in combination with the FAO Penman–Monteith method is the global standard for linking local climatic conditions with crop water requirements. Similarly, Pereira et al. (2015b) emphasized that variability in Kc across different crops constitutes a critical factor in designing efficient irrigation planning in tropical regions. Therefore, the combined application of ETo and Kc data forms a fundamental basis for water balance assessments and the development of sustainable cropping patterns in irrigated agricultural systems such as the Gembolo Watershed.

Based on the prevailing meteorological conditions that govern evapotranspiration, the spatiotemporal dynamics of water availability and irrigation demand in the Gembolo Watershed exhibit a distinct seasonal regime. The irrigation water balance analysis demonstrates pronounced fluctuations between supply and demand throughout the year. During the wet season (November–April), water supply reaches its maximum, peaking at over 138,000 m³/day in April, which coincides with a subsequent rise in irrigation requirements exceeding 107,000 m³/day in May. In contrast, during the dry season (July–October), water availability declines sharply to below 37,000 m³/day, while crop water demand remains relatively constant, resulting in a persistent supply–demand gap and potential water deficit. This hydrological imbalance underscores the critical need for the integration of optimization approaches and advanced water management strategies to enhance irrigation efficiency and ensure the long-term sustainability of rice-based agricultural systems in the region.

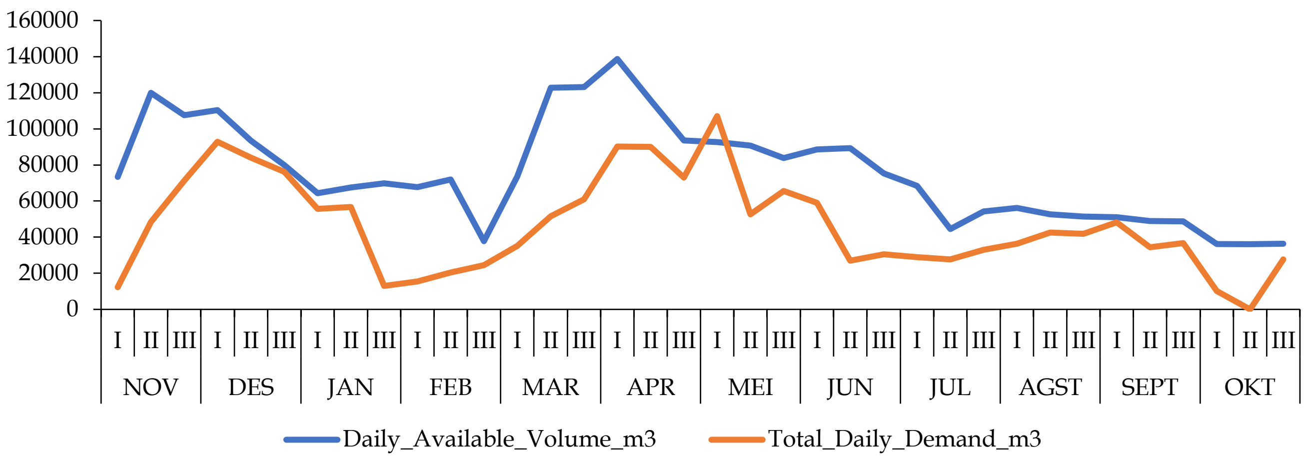

Figure 3. Water balance gembolo (Bidang Sumber Daya Air, Dinas PUPR Kabupaten Mojokerto, 2025)

Formulation of the Optimization Model Using Deterministic Dynamic Programming

Paudyal et al. (1990) introduced a two-step dynamic programming framework combining deterministic and stochastic approaches for optimal water allocation in irrigation projects. This optimization analysis is carried out by considering the irrigation water requirements for the Rice–Rice–Secondary Crop (RTTG) planting pattern during the 2024/2025 cropping season in the Gembolo Watershed. The study is based on the following assumptions: When water allocation exceeds the requirement, the surplus is not utilized and simply passed on to the next irrigation area; When water allocation is below the requirement, only the available volume is used, and profits are calculated accordingly.

The model applied is a deterministic dynamic programming approach, as the irrigation discharge data are definite (non-stochastic). Therefore, probabilistic analysis of the discrepancy between available discharge and crop water demand is not required. The computational process is conducted through recursive approaches: Forward recursive, progressing from the initial stage to the final stage; Backward recursive, serving as control, from the final stage back to the initial stage.

The model consists of nine irrigation structures (stages) as follows:

G1 : Sukosari, Mojokembang, Urung-urung I, Urung-urung II (118 ha)
G2 : Ketidur (214 ha)
G3 : Kandangan, Tumpangsari (146 ha)
G4 : Jambu, Jiyu, Jurukwangi, Jabon, Purworejo (199 ha)
G5 : Dosoermo, Bringin, Jebolkan (297 ha)
G6 : Sidomulyo, Bendungan (157 ha)
G7 : Tempuran (78 ha)
G8 : Mojojejer II, Dlimo (149 ha)
G9 : Ketok, Jabon, Jogodayo (115 ha)

Optimization Model for Irrigation Water Allocation

The decision variable in this optimization model is the water allocation (x) assigned to each irrigation structure. The primary objective is to maximize the annual profit across the three cropping seasons, expressed as:

$$\sum f^* = f^*_{MTI} + f^*_{MTII} + f^*_{MTIII} \tag{1}$$

With the recursive formulation for each cropping season defined as:

$$F^*_{Si-1} = \max\,(R_i + f^*_{Si-1}) \tag{2}$$

Where:

F^*_{Si-1} : Total profit at stage i
R_i : Profit obtained from water allocation at stage i
f^*_{Si-1} : Profit from the previous stage

Constraints

Water Availability:

$$V1 + V2 + V3 + V4 + V5 + V6 + V7 + V8 + V9 \leq A \tag{3}$$

Planting Area per Season:

$$X1 \leq (Lp + Lpl) \leq L1 \tag{4}$$
$$X2 \leq (Lp + Lpl) \leq L2 \tag{5}$$
$$X3 \leq (Lp + Lpl) \leq L3 \tag{6}$$

Land Area Limits per Structure:

$$Y1 \leq 118 \tag{7}$$
$$Y2 \leq 214 \tag{8}$$
$$Y3 \leq 146 \tag{9}$$
$$Y4 \leq 199 \tag{10}$$
$$Y5 \leq 297 \tag{11}$$
$$Y6 \leq 157 \tag{12}$$
$$Y7 \leq 78 \tag{13}$$
$$Y8 \leq 149 \tag{14}$$
$$Y9 \leq 115 \tag{15}$$

Notation:

A : Total water volume available per cropping season
Vi : Water volume allocated to irrigation structure i
Lp, Lpl : Cultivated area for rice and secondary crops (palawija)
Xi : Cultivated area based on allocated water volume
Yi : Cultivated area allocated per irrigation structure

Stages of Irrigation Water Allocation Optimization Modeling

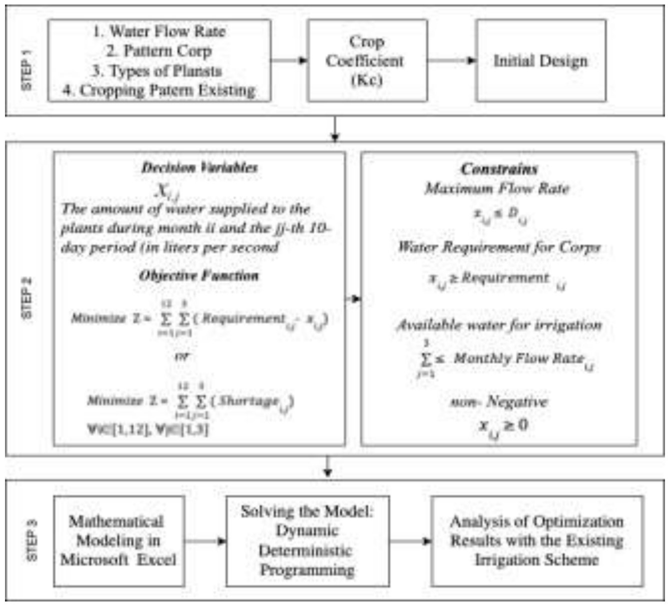

Figure 4. Optimization flowchart of irrigation water allocation

The optimization analysis was conducted by considering the irrigation water requirements for the rice–rice–secondary crop (RTTG) cropping pattern during the 2024/2025 planting period in the Gembolo Watershed. In this study, it was assumed that when water allocation exceeds crop requirements, the surplus is not utilized and is instead conveyed to the subsequent irrigation units. Conversely, when the allocation falls short of the requirements, only the available water is applied, and the resulting benefits are calculated based on the actual utilization. The optimization framework employed a deterministic dynamic programming (DDP) model, given that the irrigation discharge data are certain (non-stochastic), thereby eliminating the need for probabilistic analysis of discrepancies between available and required water. The computational process was performed using recursive procedures, including both forward recursion (from the initial to the terminal stage) and backward recursion (from the terminal to the initial stage), with nine irrigation structures (G1–G9) serving as the decision-making units.

The optimization procedure began with the collection of input data, including streamflow discharge, crop coefficients (Kc), cropping pattern, and crop types, which formed the basis for estimating irrigation water requirements. These data were subsequently formulated into a mathematical model consisting of decision variables representing the volume of water allocated, an objective function aimed at minimizing water deficits, and a set of constraints encompassing maximum discharge limits, minimum crop water requirements, monthly water availability, and non-negativity conditions. The model was implemented and solved using Microsoft Excel through deterministic dynamic programming, and the optimized results were then compared against the existing irrigation scheme to evaluate potential improvements in water distribution efficiency and agricultural productivity.

Result and Discussion

Result

The formulation of the Deterministic Dynamic Programming (DDP) model produced an irrigation water demand pattern that is more consistent with the available discharge throughout the year. Under the existing conditions, irrigation requirements frequently exceeded the available flow, particularly during the dry season (July–September), when river discharge declined sharply to 0.5–0.6 m^3/s. During this period, the actual irrigation demand remained within the range of 0.6–0.7 m^3/s, resulting in substantial water deficits. In contrast, the optimized allocation generated by the DDP model successfully reduced irrigation demand to below 0.1 m^3/s during critical dry months, thereby ensuring that water requirements no longer surpassed the available discharge. This finding highlights the capacity of optimization to alleviate pressure on water resources and prevent imbalances between supply and demand. Liu & Yang (2021) analyzed irrigation scheduling under varying combinations of precipitation (P) and reference evapotranspiration (ET_0) using a spatially distributed crop model.

Table 4. Comparison of farming profit, irrigated area, and cropping intensity before and after irrigation optimization

Cropping Season	Profit (Rp)		Irrigated Area (Ha)		Cropping Intensity (%)	
	Before	After	Before	After	Before	After
MT 1	28,125,107,463	30,536,393,767	1,278.35	1,387.95	92.10	100.00
MT 2	28,125,107,463	30,828,442,465	1,278.35	1,401.22	91.23	100.00
MT 3	7,043,118,595	7,228,765,909	306.40	328.56	93.25	100.00
Total	63,293,333,521	68,593,602,140	2,863.10	3,117.73	276.59	300.00

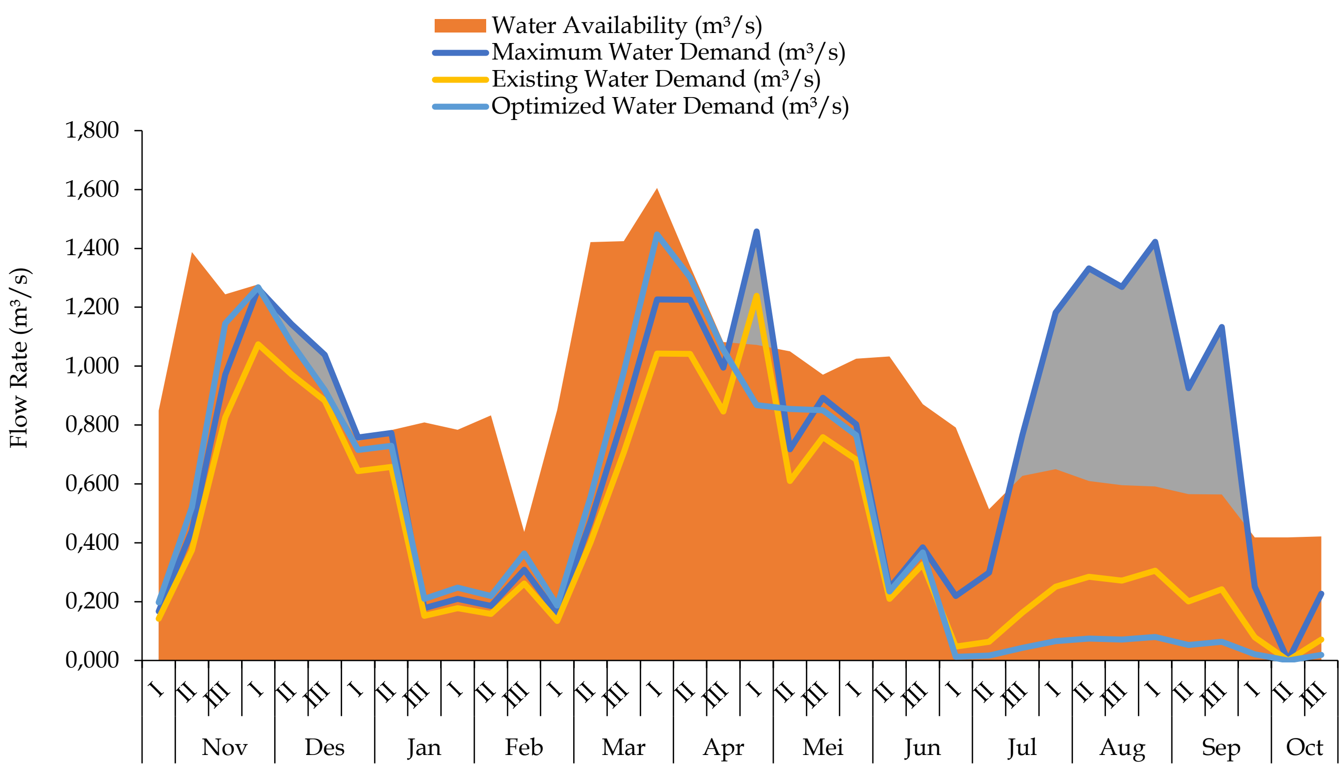

Figure 5. Optimization Results with Deterministic Dynamic Programming (DDP) on Flow Improvement

Furthermore, during periods of relatively high discharge (December–April), the optimized irrigation demand also demonstrated a more efficient pattern compared to existing practices. For instance, in April, the available discharge reached approximately 1.3–1.6 m^3/s, while the existing irrigation demand approached 1.0–1.2 m^3/s. Through optimization, demand could be regulated to remain aligned with water availability, even at levels lower than those observed under the existing scheme. This indicates that the application of DDP is not only effective in addressing water scarcity during the dry season but also enhances efficiency in managing water surpluses during the rainy season. Overall, these results confirm that DDP optimization significantly improves irrigation water-use efficiency and contributes to the sustainability of irrigation systems.

Figure 5 and Table 4 present a comparison of farming profits, irrigated area, and cropping intensity before and after irrigation system optimization across three cropping seasons. A comparison of farming profit, irrigated area, and cropping intensity before and after the implementation of irrigation optimization using the DDP method for each cropping season is presented in Table 4. Overall, there is a notable improvement in all indicators. Total farming profit increased from Rp 63.29 billion to Rp 68.59 billion, reflecting an additional gain of Rp 5.30 billion. This increase is consistent across all seasons, with the most significant improvements observed in MT 1 and MT 2, while MT 3 shows a smaller but still positive growth. These results highlight that irrigation optimization directly enhances agricultural productivity and farmers' income.

The irrigated area expanded from 2,863.10 hectares to 3,117.73 hectares, representing an additional 254.63 hectares of farmland receiving adequate water supply. At the same time, cropping intensity rose from 276.59 to 300%, meaning that land could be fully utilized in all three cropping seasons, each reaching 100%. These outcomes indicate that improved irrigation not only boosts economic benefits but also maximizes land use efficiency and ensures better food security.

Discussion

The results of this study demonstrate that the application of deterministic dynamic programming (DDP) in irrigation water allocation led to a substantial increase in farming profit, irrigated area, and cropping intensity. The total farming profit rose from Rp 63.29 billion before optimization to Rp 68.59 billion after optimization, while cropping intensity improved from 276.59 to 300%. These findings confirm that DDP provides an effective framework for achieving more efficient and equitable water distribution across cropping seasons by prioritizing high-value crop combinations under limited water resources. In the same year, Fan (2023) proposed a model coupling water resource allocation and canal operation for improved distribution efficiency. Santosa et al. (2025) established operational rules for Semantok reservoir to support irrigation-area management in Indonesia, offering local evidence from the Kota Mojokerto region context.

Previous studies also highlighted the effectiveness of DDP in irrigation optimization. For example, a two-stage model developed for seasonal and intraseasonal irrigation management emphasized that deterministic dynamic programming is highly suitable for seasonal allocation decisions, as it ensures optimal cropping patterns before incorporating stochastic variability in intraseasonal water availability (Sunantara & Ramirez, 2017). This aligns with the approach in the present study, where DDP optimized water allocation across three cropping seasons, ensuring full utilization of irrigable land and maximizing returns. Yang et al. (2020) used deep reinforcement learning for irrigation scheduling, representing a novel alternative to classical dynamic programming.

In the Indonesian context, research by Prastyo et al. (2021) demonstrated that dynamic programming could optimize irrigation benefits in Banyuwangi by improving planting intensity in dry-season irrigation areas. Their findings resonate with the present study, showing that DP-based models can significantly improve cropping intensity from suboptimal conditions to full utilization of irrigated land. This reinforces the local relevance and applicability of DDP in addressing water distribution challenges within agricultural systems. Beyond local applications, earlier works have demonstrated the scalability of DDP in complex water resource systems. For instance, an incremental dynamic programming approach applied to the Mahaweli River Basin in Sri Lanka proved capable of handling multi-reservoir and multi-season systems, ensuring optimal allocation at a basin-wide scale (Yakowitz, 1992). Although conducted in a different hydrological setting, the methodological similarities suggest that the deterministic framework adopted in this study could be expanded to larger irrigation networks. Delgoda et al. (2017) presented a generic optimisation method for irrigation scheduling at canal network scale under hierarchical layers and multiple objectives. Li (2020) applied a multistage stochastic programming model to farmland management under uncertainty, suggesting extension beyond two-stage models.

Beyond technical efficiency, the optimized irrigation strategy developed through DDP mirrors broader grassroots adaptations to climate variability, as evidenced by recent findings among horticultural farmers in East Java. Atasa et al. (2024) report that farmers have adopted irrigation adjustments, crop rotation, and input modification as deliberate strategies in response to changing rainfall patterns and temperature fluctuations. Such real-world adaptation aligns with our model's capacity to adjust irrigation demand in line with hydrological variability, demonstrating how algorithmic optimization complements—and potentially scales—farmers' localized experiential adaptations. Fan et al. (2023) developed a canal water distribution optimisation model that couples supply conditions with operational decision-making, relevant for irrigation system redesigns. Guo (2018) developed a multi-objective hierarchical model for irrigation scheduling at network level, incorporating economic, environmental and equity objectives. Handini (2024) proposed an IoT-based micro hydro power integration with irrigation water in rice fields, illustrating technological integration in the Indonesian context.

Moreover, recent developments in hybrid optimization models, such as dynamic dual interval programming, show that deterministic dynamic programming remains a critical foundation for integrating uncertainty in irrigation management (Li et al., 2012). These advancements suggest that while the deterministic approach is powerful for baseline optimization, incorporating uncertainty may further refine decision-making under climate variability and fluctuating water availability. Nonetheless, the current study demonstrates that even a purely deterministic model can deliver significant improvements in agricultural productivity and resource efficiency. Mushthofa et al. (2025) investigated water-spinach variety KK-09 for irrigation optimisation in dry land, offering insights for cropping pattern alternatives in semi-arid regions. Kassing (2020) applied optimal control methods for precision irrigation of large-scale systems, signalling the trend toward high-tech optimisation. Liao et al. (2020) employed Interval-Parameter Two-Stage Stochastic Programming (IPTSP) for ecological water replenishment, illustrating handling of parameter uncertainty. Real-time irrigation scheduling using weather forecasts and data assimilation has been demonstrated by Jamal et al. (2023) as a way to improve responsiveness in irrigation systems.

Conclusion

This study concludes that applying Deterministic Dynamic Programming (DDP) in irrigation management provides an effective way to synchronize water allocation with crop needs. The model enables more efficient use of available resources, ensures full land utilization, and supports higher agricultural productivity. The findings confirm that data-driven optimization can address distribution inefficiencies while reinforcing food security and rural resilience. Moreover, the deterministic framework offers a reliable basis for decision-making in irrigation planning and demonstrates the value of integrating technical models into sustainable agricultural management.

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Author Contributions
M.R.M.: conceptualization, methodology, data curation, formal analysis, writing–original draft; L.M.L.: supervision, validation, methodology, writing–review & editing; P.T.J.: supervision, resources, project administration, writing–review & editing.

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Conflicts of Interest
The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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