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# Revitalization of Irrigation Area Based on Optimization and Risk of Land Failure

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**Abstract** Water availability significantly impacts rice cultivation in paddy fields, especially during land preparation when irrigation demand is the highest. Imbalances between water supply and demand can result in technical and social challenges. Hence, revitalizing irrigation areas is critical for improving agricultural productivity and profitability. This study was performed in the Cimulu Irrigation area, Tasikmalaya, West Java, Indonesia. The research employed the Land Failure Risk Assessment (LFRA) to determine the optimal irrigation area based on the water balance (k-factor), representing the ratio of available irrigation water to demand. Discharge data from 1984 to 2073, representing an 80% dependable discharge, were used as a reference for water availability. This was compared with existing data under the same discharge conditions. Linear programming (LP) optimization of irrigation areas often prioritizes "safety", potentially leading to suboptimal benefits. However, higher risks may yield more significant profit potential. This study integrated LP and LFRA to maximize benefits. The results indicated good discharge validity. LP optimization revealed that the highest profit was achieved with early cropping on Nov-1, generating Rp 61.96 billion with an 80% existing and IDR 67.24 billion with a Q80% generation. Utilizing the LFRA Model at the same cropping time resulted in profits of IDR 71.24 billion (k = 0.62) and IDR 96.16 billion (k = 0.72). Recommendations include modifying the cropping pattern to incorporate paddy-paddy-palawija in one cropping season, potentially generating a substantial profit of IDR 71.11 billion. This practice also allows for a "cropping break period" for soil health and risk mitigation.

**Keywords** Revitalization, Optimization, Linear Programming, Land Failure Risk Assessment

## 1. Introduction

Water imbalance in irrigation areas can cause technical and social problems. Reducing land is the easiest way to deal with it. However, it is risky because farmers' land ownership is not evenly distributed, so it is impossible to reduce land evenly. The best way to optimize water balance is the regulation of schedules and cropping patterns. The regulation of schedules and cropping patterns depends on the climate, which can affect the parameters of water availability, irrigation water demand, and cropping schedule [1]. Precipitation usually can meet irrigation water demands or occurs in only a few areas. Failure to fulfill this can impact the smaller irrigation water supply [2].

The revitalization of irrigation areas is indispensable for cost efficiency and the use of irrigation water so that maximum profits can be achieved, and this requires particular expertise [3]. Revitalization of irrigation areas in water resources engineering must be done periodically and iteratively. Irrigation water distribution problems usually occur in irrigation areas farthest from the intake water [4]. The connection between crop failures and land failures due to imbalances in water availability has not been extensively addressed. That is possible because simulated irrigated land generally needs to have a crucial interaction between the crop water requirements and the water supply of irrigation systems [5]. But besides that, the water deficit clearly affects crops [6]. Revitalization of irrigation areas is basically the irrigation water optimum management to achieve maximum economic profit [7-9]. This research focuses on strategies to enhance agricultural productivity by considering water availability and the risk of water shortages that may cause crop failure. It explores irrigation demand management through planting schedules and crop selection. Ten planting schedule scenarios were examined for two main crops, rice and secondary crops. The previous calculation of rice and secondary crop profitability per hectare in the study area served as the basis for evaluating farming returns under different planting schedules. Factors such as market changes and socio-economic variables that fluctuate over time were not analyzed separately, as they were deemed incorporated into the profit calculations.

In general, efforts to revitalize often prioritize “safety” in terms of sufficient irrigation water rather than maximizing profits. Linear Programming (LP) models tend to produce a constant factor (k = 1) as they focus on reducing land or regulating crop types, which does not lead to maximum profits. Continuous water use does not necessarily result in increased production [10-12]. LP can optimize and improve the efficiency of water use [13]. However, higher profits can be achieved by managing the risk of land failure. By modifying the LP model into a Land Failure Risk Assessment (LFRA) model, it can better accommodate varying water availability conditions, even when it approaches zero. LFRA can also incorporate the wisdom of local farmers. When local wisdom is compromised with knowledge, the abilities of farmers will increase [14]. Monitoring and mitigating risks using LFRA can lead to higher benefits compared to conventional optimization methods. The LFRA method produces the same results as LP when water availability is sufficient. However, in cases of zero water availability for specific periods, LP fails due to its constraints requiring values greater than zero, a challenge that LFRA, developed in this study, can effectively address.

# 2. Methodology

## 2.1. Detailed Case Study

The research was conducted in the area of Cimulu Irrigation with a water source from the Cimulu Weir intake, which can be seen in Fig. 1. The Cimulu weir is located on the Ciloseh river, which the Citanduy River Region UPTD PSDA manages in Tawangsari Village, Tawang District, Tasikmalaya City, precisely at the coordinates 7° 19’ 14.6” South Latitude and 108° 13’ 17.4” East Longitude. The Cimulu Irrigation Area covers 1546.20 ha and is divided into three UPTDs: Cimulu (1008 ha), Dalemsuba (316.20 ha), and Cihanjang (222 ha).


**Figure 1.** Research Location

## 2.2. Irrigation Water Availability

The water availability in the analysis of irrigation water is a dependable discharge. The dependable discharge is obtained with the Weibull ranking using the following equation [15].

$$P(X \geq X_m) = \frac{m}{n+1} \tag{1}$$

Where $P$ is a probability expressed as a percentage, $X$ is a random variable, $Xm$ is the probability distribution linked to rank $m$, $m$ is the serial number of discharge data, and $n$ is the total number of discharge observance data.

Measured discharge data is generated first so the value can be used longer. Data generation was analyzed using the Thomas-Fiering method with the following equation [16].

$$q_{i+1,j} = \hat{q}_{i+1,j} + b_{i+1}\left(q_{i,j} - \hat{q}_i\right) + t_i s_{i+1}\left(1-\left(r_{i+1}\right)^2\right)^{1/2} \tag{2}$$

Where: $q_{i+1,j}$ and $q_{i,j}$ denote the nonhistoric monthly flow for month $i+1$ and month $i$, respectively, during year $j$; $\hat{q}_{i+1,j}$ and $\hat{q}_i$ represent the average monthly flow for month $i+1$ and month $i$, respectively, based on the historic irrigation record; $b_{i+1}$ signifies the regression coefficient used to estimate flow during month $i+1$ from the flow during month $i$; $t_i$ refers to a random deviation drawn from a normal distribution with zero variance; $s_{i+1}$ stands for the standard deviation of the historic irrigation record for month $i+1$; and $r_{i+1}$ denotes the correlation between flow for month $i+1$ and month $i$.

## 2.3. Irrigation Water Requirements

The demand for irrigation water for agricultural land and its paddy production is affected by climate change [17].

Formulas used for analysis include:

- Water requirement during land preparation,

$$IR = \frac{M.e^k}{e^k - 1} \tag{3}$$

- Clean water requirement in paddy fields,

$$NFR = ET_c + P - R_e + WLR \tag{4}$$

$$ET_c = K_c \times ET_o \tag{5}$$

- Clean water requirement in paddy fields for palawija,

$$NFR = ET_c + P - R_e \tag{6}$$

Where: *IR* stands for the paddy field irrigation water requirement (mm/day), *M* represents the water needed to replenish or compensate for losses due to evaporation and saturated paddy field percolation (mm/day), *e* corresponds to the mathematical constant approximately equal to 2.7182. *NFR* signifies the net field water requirement (mm/day), $ET_c$ denotes plant evapotranspiration (mm/day), P indicates percolation (mm/day), $R_e$ refers to effective rainfall (mm/day), and *WLR* is the water layer replaced (mm/day).

- Irrigation water requirement at the intake gate,

$$DR = f(IR, loss, eff) \tag{6}$$

$$IR = NFR \times A \tag{7}$$

Where: *DR* is the water requirements for irrigation retrieval (lt/s), *IR* is the irrigation discharge (lt/s/ha), *A* represents the paddy field area (ha), *loss* accounts for water losses in the canal, and *eff* stands for irrigation efficiency.

### 2.4. Irrigation Area Pre-Failure Detection

2.4.1. Linear Programming Method

Optimization procedures are performed using linear programming and POM-QM for Windows 5.3 software. The mathematical model equations used are as follows [18]:

Objective function,

$$z = P_1X_1 + P_2X_2 + P_3X_3 + \dots + P_nX_n \tag{8}$$

$$P_1X_1 = P_{pd} \cdot X_{1a} + P_{sc} \cdot X_{1b}$$
$$P_nX_n = P_{pd} \cdot X_{na} + P_{sc} \cdot X_{nb} \tag{9}$$

Constraint function,

$$V_{m1}X_1 + V_{m2}X_2 + \dots + V_{mn}X_n \le b_m \tag{10}$$

$$X_{1a} + X_{1b} \le X_n,\ X_{2a} + X_{2b} \le X_n,\ X_{3a} + X_{3b} \le X_n \tag{11}$$

$$V_{1,pd} \cdot X_{1b} + V_{1,sc} \cdot X_{1b} \le V_1,\ V_{2,pd} \cdot X_{1b} + V_{2,sc} \cdot X_{1b} \le V_2$$
$$V_{3,pd} \cdot X_{1b} + V_{3,sc} \cdot X_{1b} \le V_3 \tag{12}$$

Where: z is function of an objective (IDR or ha); $P_n$ represents the agricultural production profit. (IDR/ha) or $P_{pd}$ is the paddy farmers profit (IDR/ha) and $P_{sc}$ is the palawija farmers profit (IDR/ha); $X_n$ is the area of agricultural land (ha) or $X_{1a,2a,3a}$ is paddy field area for the 1st, 2nd, and 3rd cropping seasons respectively (ha) and $X_{1b,2b,3b}$ is palawija field area for the 1st, 2nd, and 3rd cropping seasons respectively (ha); $V_{mn}$ denotes the water demand for each crop type n during the cropping season m (lt/s), $V_{1pd,2pd,3pd}$ is paddy field water requirements for the 1st, 2nd, and 3rd cropping seasons respectively ($m^3$/ha), $V_{1sc,2sc,3sc}$ is palawija field water requirements for the 1st, 2nd, and 3rd cropping seasons respectively ($m^3$/ha), $V_{1,2,3}$ is dependable discharge during the 1st, 2nd, and 3rd cropping season ($m^3$); and $b_m$ represents the function of a constraints related to either water or land availability.

2.4.2. Land Failure Risk Assessment (LFRA)

This research faces more than one objective function that must be optimized simultaneously (multiobjective optimization), including the area of irrigated land and the advantages of agricultural production. LFRA schematically can be seen in Fig. 2 and the objective function is formulated as follows [1, 4]:

$$P_{max} = \sum P_{ijT} \cdot D_{ijT} - LFR_{ijT} \tag{13}$$

$$LFR_{ijT} = \Phi \cdot WFR \cdot \left(1 - (R)^{\frac{DR}{Q_{80\%}}}\right) \cdot A \cdot P \tag{14}$$

Where: $P_{max}$ represents the highest achievable profit from agricultural production (IDR). $D_{ijT}$ stands for the decision variable, $LFR_{ijT}$ indicates the cost associated with evaluating the risk of land failure in irrigation (IDR), $P_{ijT}$ or *P* signifies the profit from agricultural production (IDR/ha), where *i* refers to the crop type, *j* is associated with the cropping schedule, and *T* represents a specific cropping season. *Φ*, which falls within the range of 0 to 1, signifies the irrigation failure risk index, while *WFR* denotes the risk of water failure, *R* represents the level of reliability, and Q80% is the 80% dependable discharge ($m^3$/s).

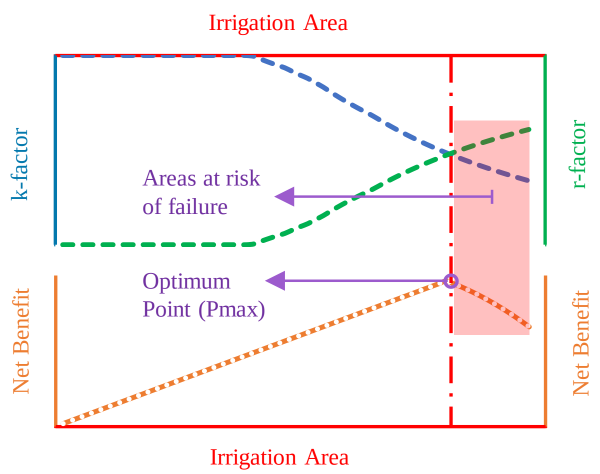


**Figure 2.** Land Failure Risk Modeling Scheme

The k-factor highly depends on water requirements, while water availability is a given nature. The k-factor (worth 0 - 1) is a function of $Q_{80\%}$, $IR$, and $R_e$. Meanwhile, failure risk of irrigation represents the k-factor inverse and can be understood as a failure factor (1 - k-factor).

### 2.5. Details of the Research Process

The water balance or k-factor is the ratio between the availability and requirements for irrigation water. The k-factor plays a vital role in the irrigation, and when the k-factor is less than 1, it signifies a potential risk of failure in the irrigation area. The research flow is reflected in Fig. 3.

## 3. Results and Discussion

### 3.1. Dependable Discharge Analysis

Dependable discharge information is derived from actual discharge measurements. Discharge data is projected until 2073 using the Thomas-Fiering method, with the findings presented in Fig. 4. Furthermore, to obtain a dependable discharge, the Weibull ranking is used. The recapitulation of dependable discharge analysis results from 1984-2073 are presented in Fig.5.

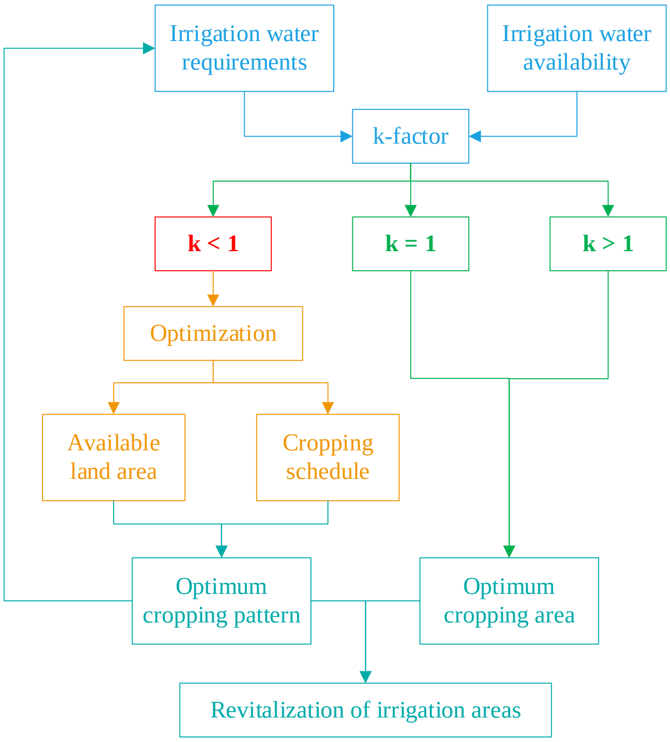


**Figure 3.** Flow Chart of Methodology Research

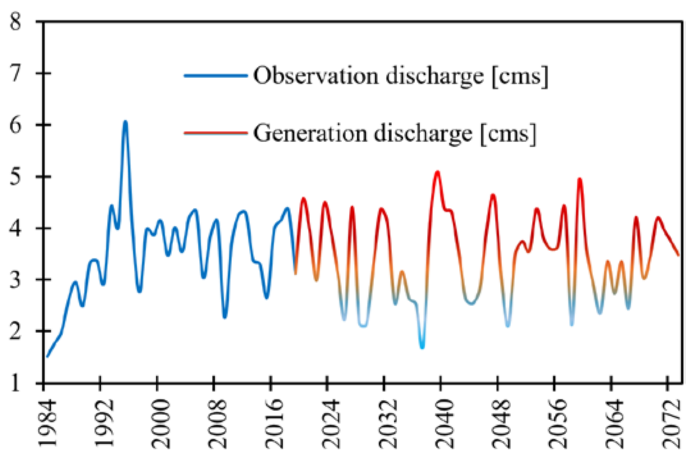


**Figure 4.** Historical Discharge Graph and Generated from 1984 – 2082

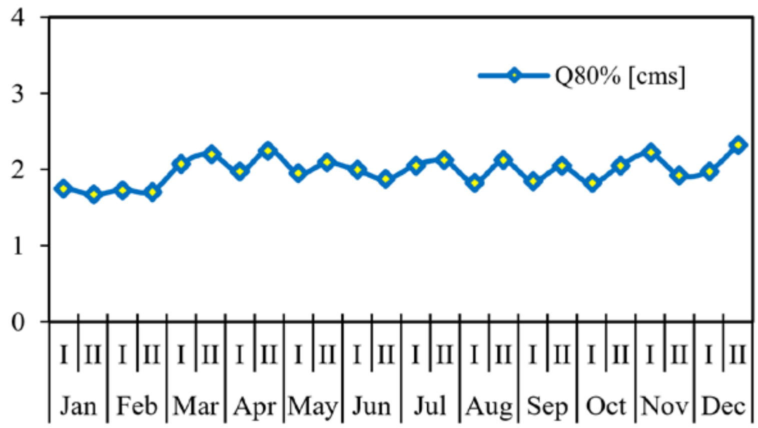


**Figure 5.** Graph of Dependable Discharge (Q-80%) Weibull Ranking Results from 1984 – 2073

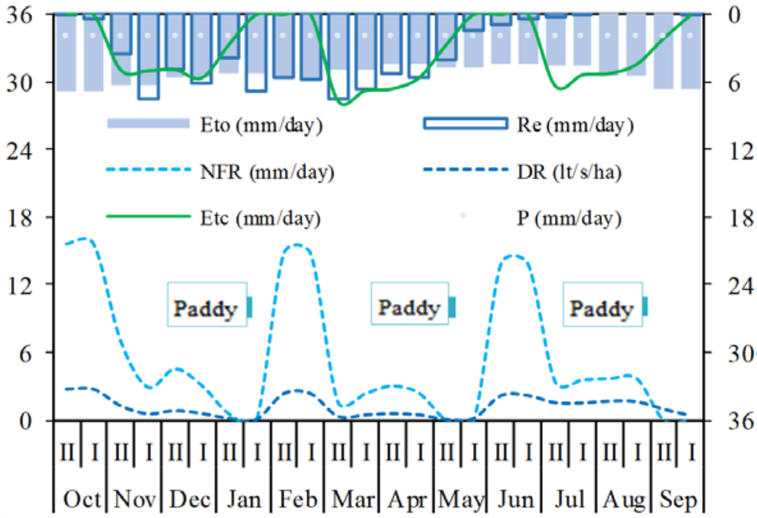


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**Figure 6.** Irrigation Water Requirements for Paddy Plants Based on RTTG ECS in Oct-II

### 3.2. Irrigation Water Requirements and Water Balance

Irrigation water requirements depend on crop evapotranspiration, percolation, inundation requirements, and effective rainfall. Evapotranspiration, commonly called consumptive use, depends on crop coefficients and references, which are ultimately influenced by planting schedules. The planting schedule was made for ten scenarios, including a scenario based on the Global Cultivation Plan (RTTG) with ECS Oct-II and a scenario based on local community habits (existing) with ECS May-II. Furthermore, forward and backward simulations are each made of two periods, so the total becomes 5+5 scenarios. Simulations of paddy and palawija water demands were carried out for ten scenarios which would generate ten variations of irrigation water requirements. An example of analysis results can be seen in Fig. 6.

### 3.3. Reliable Land Area Optimization Results of Linear Programming (LP)

Optimization is carried out in two categories, including optimization based on meeting water requirements and profit yields. Analysis was performed using POM QM for Windows 5.3. An example of the analysis results can be seen in Tab 5. Then, the complete recapitulation results for each cropping season are presented in Tables 1, 2, 3, and 4.

**Table 1.** Optimization Irrigation Area Based on Fulfilled Water Requirements of Q80% Existing

| Early Cropping | 1st ECS (ha) | | 2nd ECS (ha) | | 3rd ECS (ha) | |
|---|---|---|---|---|---|---|
| | Pd | Sc | Pd | Sc | Pd | Sc |
| **Apr-II** | 0.000 | 1487.04 | 0.000 | 902.74 | 729.19 | 817.01 |
| **May-I** | 0.000 | 1446.85 | 0.000 | 928.17 | 811.23 | 734.97 |
| **May-II** | 0.000 | 1209.76 | 0.000 | 1126.50 | 1053.48 | 492.72 |
| **Jun-I** | 0.000 | 1128.46 | 0.000 | 1432.61 | 1099.28 | 446.92 |
| **Jun-II** | 0.000 | 847.14 | 224.17 | 1322.03 | 1151.86 | 394.34 |
| **Sep-I** | 0.000 | 928.17 | 918.88 | 627.32 | 0.000 | 1446.85 |
| **Sep-II** | 0.000 | 1126.50 | 1053.48 | 492.72 | 0.000 | 1209.76 |
| **Oct-I** | 0.000 | 1432.61 | 1099.28 | 446.92 | 0.000 | 1128.46 |
| **Oct-II** | 194.13 | 1352.07 | 1151.86 | 394.34 | 0.000 | 847.14 |
| **Nov-I** | 870.24 | 675.96 | 1232.38 | 313.82 | 0.000 | 817.93 |

Note: ECS is Early Cropping Seasons. Pd is paddy. Sc is secondary crops.

**Table 2.** Optimization Irrigation Area Based on Fulfilled Water Requirements of Q80% Generated

| Early Cropping | 1st ECS (ha) | | 2nd ECS (ha) | | 3rd ECS (ha) | |
|---|---|---|---|---|---|---|
| | Pd | Sc | Pd | Sc | Pd | Sc |
| **Apr-II** | 493.23 | 1052.97 | 0 | 1274.65 | 768.4 | 777.8 |
| **May-I** | 327.56 | 1218.64 | 0 | 1343.66 | 846.51 | 699.69 |
| **May-II** | 0 | 1435.68 | 162.21 | 1384.00 | 1260.12 | 286.09 |
| **Jun-I** | 0 | 1379.59 | 303.79 | 1242.41 | 1431.62 | 114.58 |
| **Jun-II** | 0 | 1092.86 | 550.13 | 996.07 | 1538.09 | 8.11 |
| **Sep-I** | 0 | 1343.66 | 958.84 | 587.36 | 327.56 | 1218.64 |
| **Sep-II** | 162.21 | 1384.00 | 1260.12 | 286.09 | 0 | 1435.68 |
| **Oct-I** | 275.85 | 1270.35 | 1443.03 | 103.17 | 0 | 1379.59 |
| **Oct-II** | 476.43 | 1069.77 | 1538.09 | 8.11 | 0 | 1092.86 |
| **Nov-I** | 973.24 | 572.96 | 1241.13 | 305.07 | 0 | 1055.17 |

Note: ECS is Early Cropping Seasons. Pd is paddy. Sc is secondary crops.

**Table 3.** Optimization Irrigation Area Based on Profits using Q80% Existing

| Early Cropping | 1st ECS (ha) | | 2nd ECS (ha) | | 3rd ECS (ha) | |
|---|---|---|---|---|---|---|
| | Pd | Sc | Pd | Sc | Pd | Sc |
| **Apr-II** | 794.10 | 487.06 | 447.55 | 0.000 | 729.19 | 817.01 |
| **May-I** | 667.34 | 611.17 | 441.51 | 0.000 | 811.23 | 734.97 |
| **May-II** | 753.33 | 0.000 | 493.67 | 0.000 | 1053.48 | 492.72 |
| **Jun-I** | 753.33 | 0.000 | 493.67 | 0.000 | 1053.48 | 492.72 |
| **Jun-II** | 658.20 | 0.000 | 549.17 | 0.000 | 1151.86 | 394.34 |
| **Sep-I** | 441.51 | 0.000 | 918.88 | 627.32 | 898.15 | 0.000 |
| **Sep-II** | 441.51 | 0.000 | 1053.48 | 492.72 | 852.83 | 0.000 |
| **Oct-I** | 485.07 | 0.000 | 1099.28 | 446.92 | 835.81 | 81.99 |
| **Oct-II** | 491.79 | 0.000 | 1151.86 | 394.34 | 689.53 | 0.000 |
| **Nov-I** | 870.24 | 675.96 | 1232.38 | 313.82 | 670.06 | 0.000 |

Note: ECS is Early Cropping Seasons, Pd is paddy, Sc is secondary crops or palawija.

**Table 4.** Optimization Irrigation Area Based on Profits using Q80% Generated

| Early Cropping | 1st ECS (ha) | | 2nd ECS (ha) | | 3rd ECS (ha) | |
|---|---|---|---|---|---|---|
| | Pd | Sc | Pd | Sc | Pd | Sc |
| **Apr-II** | 794.44 | 673.67 | 577.36 | 0 | 768.4 | 777.8 |
| **May-I** | 854.22 | 559.13 | 577.36 | 0 | 846.51 | 699.69 |
| **May-II** | 776.44 | 0 | 695.36 | 0 | 1260.12 | 286.09 |
| **Jun-I** | 776.44 | 0 | 695.36 | 0 | 1260.12 | 286.09 |
| **Jun-II** | 740.98 | 0 | 795 | 0 | 1538.09 | 8.11 |
| **Sep-I** | 577.36 | 0 | 958.84 | 587.36 | 1009.15 | 365.12 |
| **Sep-II** | 621.89 | 0 | 1260.12 | 286.09 | 878.99 | 0 |
| **Oct-I** | 675.37 | 0 | 1443.03 | 103.17 | 798.52 | 387.68 |
| **Oct-II** | 711.94 | 0 | 1538.09 | 8.11 | 837.04 | 0 |
| **Nov-I** | 973.24 | 572.96 | 1241.13 | 305.07 | 837.04 | 0 |

Note: ECS is Early Cropping Seasons, Pd is paddy, Sc is secondary crops or palawija.

**Table 5.** Optimization results based on meeting water requirements in ECS May-II using POM QM for Windows 5.3

| | X1a | X1b | X2a | X2b | X3a | X3b | | RHS | Dual |
|---|---|---|---|---|---|---|---|---|---|
| Maximize | 20731500 | 4530000 | 20731500 | 4530000 | 20731500 | 4530000 | | | |
| May-II | 2.44 | 0.29 | 0 | 0 | 0 | 0 | <= | 1940 | **0** |
| Jun-I | 2.4 | 0.67 | 0 | 0 | 0 | 0 | <= | 1808 | **8638125** |
| Jun-II | 1.36 | 0.83 | 0 | 0 | 0 | 0 | <= | 1846 | **0** |
| Jul-I | 1.41 | 1.09 | 0 | 0 | 0 | 0 | <= | 1606 | **0** |
| Jul-II | 1.43 | 1.11 | 0 | 0 | 0 | 0 | <= | 1600 | **0** |
| Aug-I | 1.54 | 1.23 | 0 | 0 | 0 | 0 | <= | 1488 | **0** |
| Aug-II | 0.78 | 0.78 | 0 | 0 | 0 | 0 | <= | 1388 | **0** |
| Sep-I | 0.36 | 0.36 | 0 | 0 | 0 | 0 | <= | 1186 | **0** |
| Sep-II | 0 | 0 | 2.37 | 0.62 | 0 | 0 | <= | 1170 | **8747469** |
| Oct-I | 0 | 0 | 2.4 | 0.92 | 0 | 0 | <= | 1300 | **0** |
| Oct-II | 0 | 0 | 1.78 | 1.17 | 0 | 0 | <= | 1318 | **0** |
| Nov-I | 0 | 0 | 1.07 | 0.82 | 0 | 0 | <= | 2308 | **0** |
| Nov-II | 0 | 0 | 0.34 | 0.85 | 0 | 0 | <= | 3226 | **0** |
| Dec-I | 0 | 0 | 0.63 | 0.71 | 0 | 0 | <= | 2522 | **0** |
| Dec-II | 0 | 0 | 0 | 0.27 | 0 | 0 | <= | 2494 | **0** |
| Jan-I | 0 | 0 | 0 | 0 | 0 | 0 | <= | 2078 | **0** |
| Jan-II | 0 | 0 | 0 | 0 | 2.2 | 0.09 | <= | 2362 | **7678436** |
| Feb-I | 0 | 0 | 0 | 0 | 2.24 | 0.29 | <= | 2904 | **0** |
| Feb-II | 0 | 0 | 0 | 0 | 0.4 | 0.49 | <= | 2592 | **0** |
| Mar-I | 0 | 0 | 0 | 0 | 0.06 | 0.49 | <= | 2806 | **0** |
| Mar-II | 0 | 0 | 0 | 0 | 0.27 | 0.51 | <= | 2666 | **0** |
| Apr-I | 0 | 0 | 0 | 0 | 0.41 | 0.57 | <= | 1967 | **0** |
| Apr-II | 0 | 0 | 0 | 0 | 0 | 0.22 | <= | 2290 | **0** |
| May-I | 0 | 0 | 0 | 0 | 0 | 0.1 | <= | 2186 | **0** |
| Area GS-1 | 1 | 1 | 0 | 0 | 0 | 0 | <= | 1546.2 | **0** |
| Area GS-2 | 0 | 0 | 1 | 1 | 0 | 0 | <= | 1546.2 | **0** |
| Area GS-3 | 0 | 0 | 0 | 0 | 1 | 1 | <= | 1546.2 | **3838941** |
| **Solution** | **753.33** | **0** | **493.67** | **0** | **1053.48** | **492.72** | | **49924500000** | |

Profit per hectare serves as a vital variable in this research's optimization process. The profit analysis indicates that the net income from rice and secondary crop farming in Tasikmalaya in 2022 amounts to IDR 20,731,500 and IDR 4,530,000, respectively. This income is computed by subtracting the expenses (e.g., production facilities, labor costs, etc.) from the revenue generated from crop sales. The results, available in Tables 6 and 7, detail the profitability for various cropping schedules, categorized by both the existing and generated discharge. These are ranked from the highest to the lowest. The area of irrigation resulting from optimization based on profits must be controlled against the irrigation water requirements so that water balance remains. An example of an optimized water balance based on fulfilling water requirements and the benefits for ECS May-II (existing) and ECS Oct-I (RTTG) can be seen in Fig. 7. The results of the water balance analysis at ECS in May II show the significant impact of optimization on water flow over several months. Although the peak water intensity occurred in October, the biggest changes were seen in May and June, indicating that the optimization of river flow management in irrigation canals affected the water flow from the early cropping and had an impact on the next few months.

**Table 6.** Profits and Cropping Intensity Based on Early Cropping using Q80% Existing

| Order Number | Early Cropping | Cropping Intensity (%) | Profit x billion (IDR) |
|---|---|---|---|
| 1 | Nov-I | 243 | 61.965 |
| 2 | Oct-I | 191 | 52.569 |
| 3 | Sep-II | 184 | 50.905 |
| 4 | Jun-II | 178 | 50.696 |
| 5 | Oct-II | 176 | 50.156 |
| 6 | May-II | 181 | 49.924 |
| 7 | Jun-I | 181 | 49.92 |
| 8 | Sep-I | 184 | 49.664 |
| 9 | Apr-II | 212 | 46.765 |
| 10 | May-I | 211 | 45.904 |

**Table 7.** Profits and Cropping Intensity Based on Early Cropping using Q80% Generated

| Order Number | Early Cropping | Cropping Intensity (%) | Profit x billion (IDR) |
|---|---|---|---|
| 1 | Nov-I | 254 | 67.237 |
| 2 | Oct-II | 200 | 64.036 |
| 3 | Jun-II | 199 | 63.766 |
| 4 | Oct-I | 220 | 62.695 |
| 5 | Sep-II | 197 | 58.535 |
| 6 | Jun-I | 195 | 57.932 |
| 7 | May-II | 195 | 57.932 |
| 8 | Sep-I | 226 | 57.083 |
| 9 | May-I | 229 | 52.930 |
| 10 | Apr-II | 232 | 50.944 |

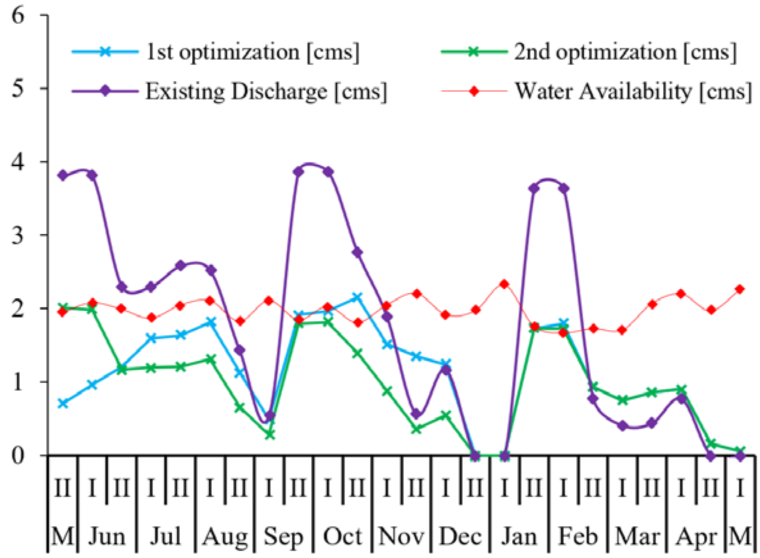



**Figure 7.** Water Balance Graph of ECS in May-II for 1st and 2nd Optimization

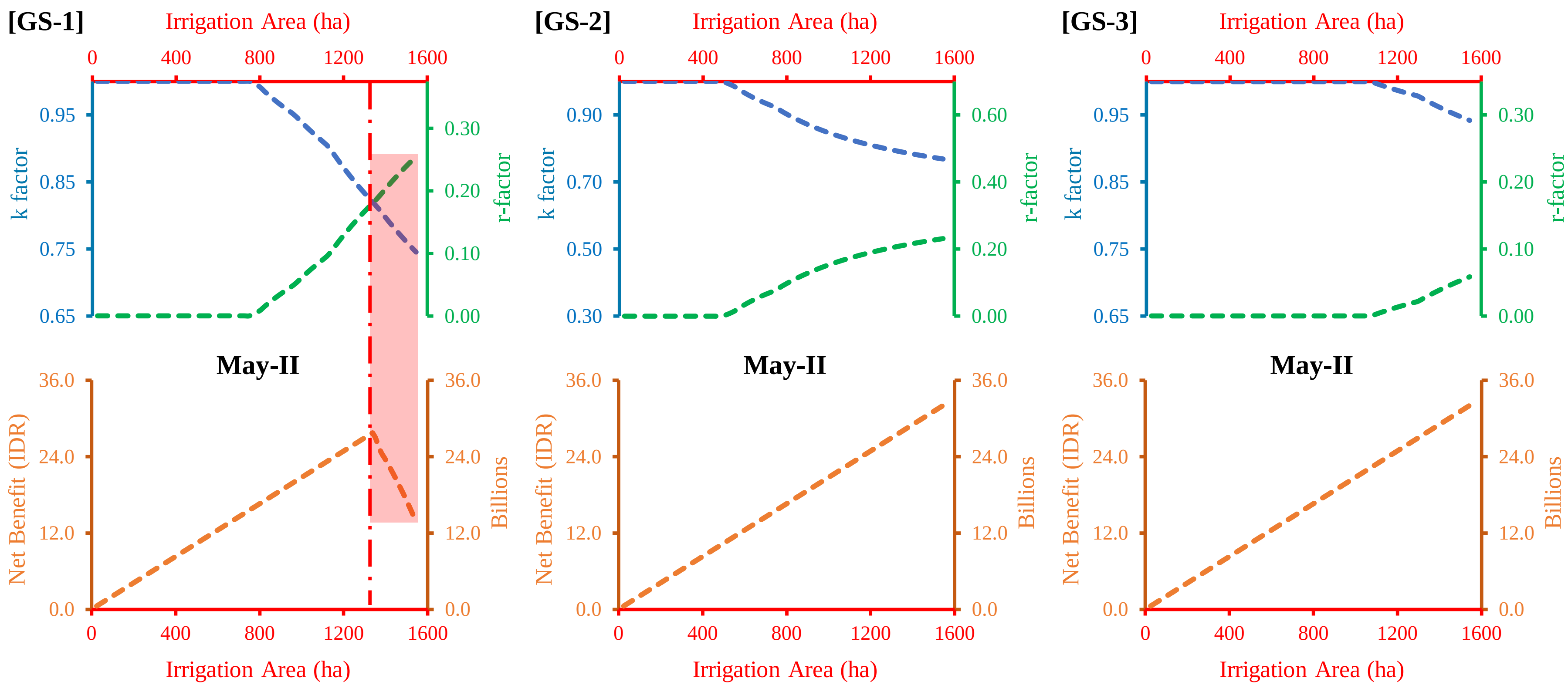
### 3.4. Based-LFRA Reliable Land Area Optimization

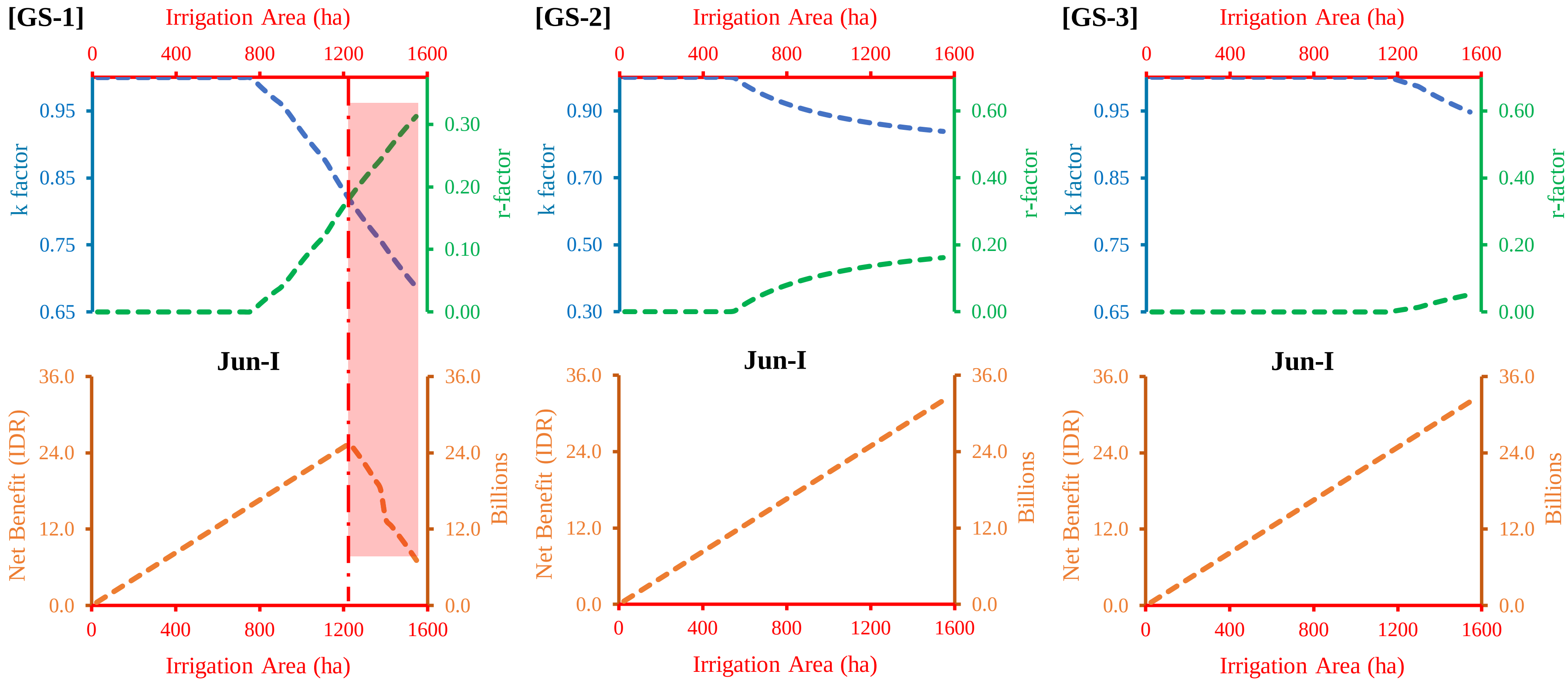
The cropping pattern for each growing season (GS) consists of the 1st GS (paddy and palawija combination), the 2nd GS (paddy and palawija combination), and the 3rd GS-only paddy. The water balance condition in Fig. 7 shows that the water requirement is always fulfilled. In specific periods, water availability is excess. As a result, there is still much that needs to be utilized. It is reasonable because water availability is a limitation in the linear programming (LP) formula. Therefore, an approach is taken using the LFRA method so that the water balance of each growing season (GS) can be utilized while maintaining the k-factor value. The optimization results show that at Q50%, no land is at risk of failure, allowing the irrigation area to be planted according to the existing cropping patterns and schedules and RTTG. However, for Q80% existing, out of 40 scenarios (including 10 ECS scenarios, two cropping pattern scenarios, and two alternative flows), 14 ECS are at risk of land failure. The results are presented in Table 8. An example of the graph can be seen in Fig. 8, and the profit is presented in Tables 9 and 10.

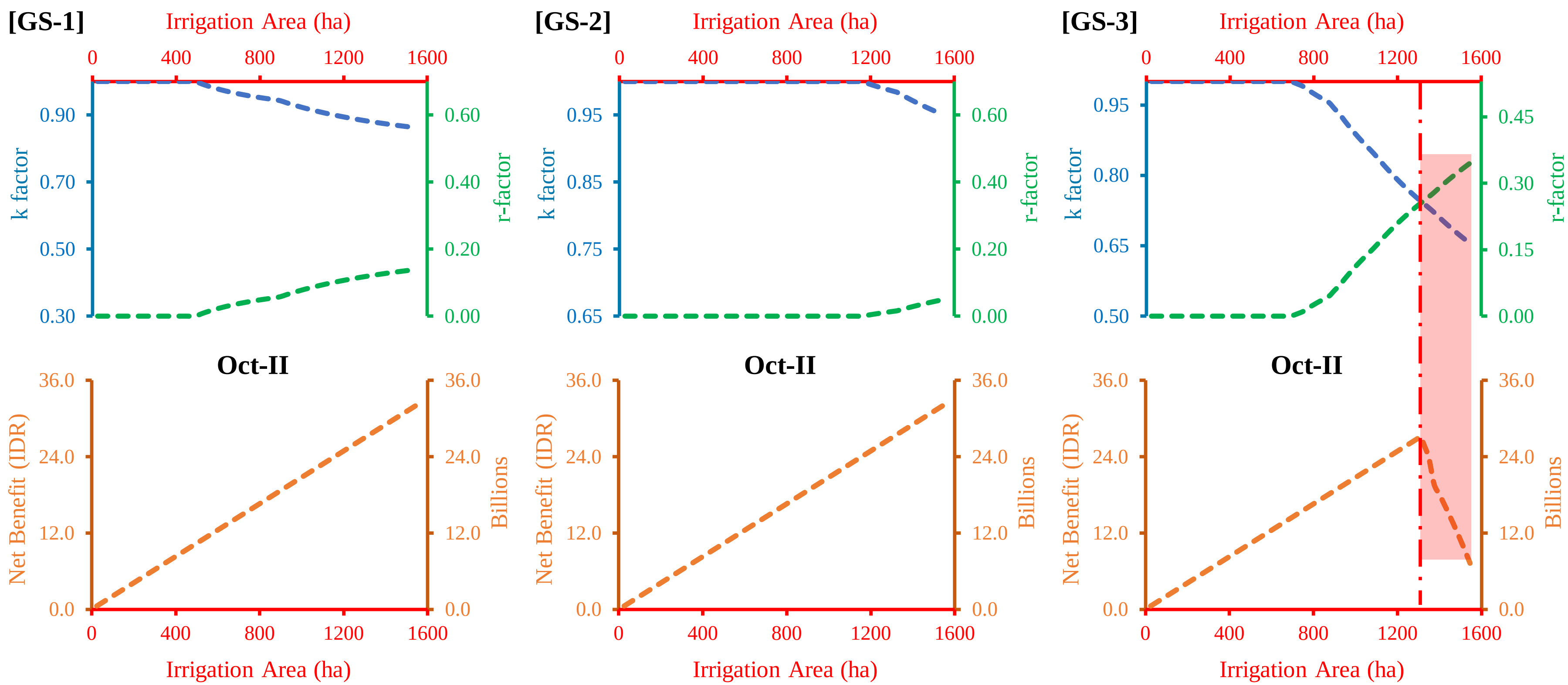
**Table 8.** Distribution of Land Failures for Growing Season (GS) using Dependable Discharge of 80%

| Early Cropping | Cropping Patterns | | | |
|---|---|---|---|---|
| | WLF | | RTTG | |
| | Q80% Existing | Q80% Generated | Q80% Existing | Q80% Generated |
| May-I | GS-1 | - | GS-1 | - |
| May-II | GS-1 | - | GS-1 | - |
| Jun-I | GS-1 | GS-1 | GS-1 | GS-1 |
| Jun-II | GS-1 | - | GS-1 | - |
| Sep-II | GS-3 | - | - | - |
| Oct-I | GS-3 | - | - | - |
| Oct-II | GS-3 | - | - | - |
| Nov-I | GS-3 | - | - | - |

Note: WLF is Wisdom of Local Farmers., RTTG is The Global Cultivation Plan, and GS is Growing Season.


[GS-1]
Irrigation Area (ha)
0
400
800
1200
1600
k factor
0.95
0.85
0.75
0.65
r-factor
0.30
0.20
0.10
0.00
May-II
Net Benefit (IDR)
36.0
24.0
12.0
0.0
Billions
Irrigation Area (ha)
[GS-2]
Irrigation Area (ha)
k factor
0.90
0.70
0.50
0.30
r-factor
0.60
0.40
0.20
0.00
May-II
Net Benefit (IDR)
Billions
Irrigation Area (ha)
[GS-3]
Irrigation Area (ha)
k factor
0.95
0.85
0.75
0.65
r-factor
0.30
0.20
0.10
0.00
May-II
Net Benefit (IDR)
Billions
Irrigation Area (ha)


[GS-1]
Irrigation Area (ha)
k factor
r-factor
Jun-I
Net Benefit (IDR)
Billions
Irrigation Area (ha)
[GS-2]
Irrigation Area (ha)
k factor
r-factor
Jun-I
Net Benefit (IDR)
Billions
Irrigation Area (ha)
[GS-3]
Irrigation Area (ha)
k factor
r-factor
Jun-I
Net Benefit (IDR)
Billions
Irrigation Area (ha)


[GS-1]
Irrigation Area (ha)
k factor
r-factor
Oct-II
Net Benefit (IDR)
Billions
Irrigation Area (ha)
[GS-2]
Irrigation Area (ha)
k factor
r-factor
Oct-II
Net Benefit (IDR)
Billions
Irrigation Area (ha)
[GS-3]
Irrigation Area (ha)
k factor
r-factor
Oct-II
Net Benefit (IDR)
Billions
Irrigation Area (ha)

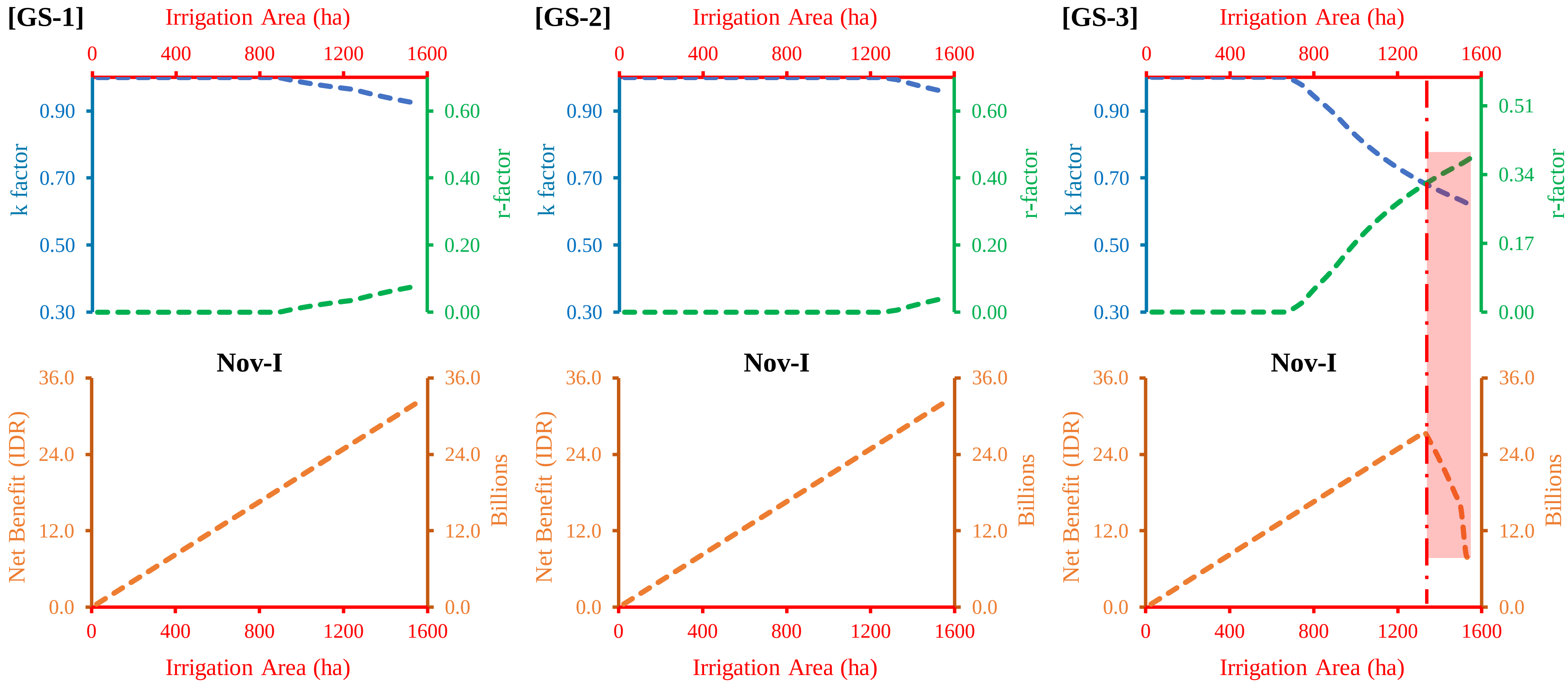



**Figure 8.** Graph of Analysis Results for ECS in May-II, Jun-I, Oct-II, and Nov-I Based on the LFRA Method

Based on existing and generated data, the optimization results in Tables 9 and 10 using the Land Failure Risk Assessment (LFRA) method for an 80% dependable discharge exhibit contrasting outcomes on the early cropping season that yields the highest profit.

**Table 9.** Profits and k-Factors Based on Early Cropping using Q80% Existing

| Early Cropping | k-factor | Profit *x* billion (IDR) |
|---|---|---|
| Apr-II | 0.80 | 96.165 |
| Sep-I | 0.81 | 96.165 |
| May-I | 0.80 | 77.984 |
| Sep-II | 0.82 | 77.955 |
| May-II | 0.82 | 77.728 |
| Oct-I | 0.82 | 71.394 |
| Oct-II | 0.82 | 71.365 |
| Nov-I | 0.83 | 71.245 |
| Jun-I | 0.82 | 71.223 |
| Jun-II | 0.82 | 71.205 |

**Table 10.** Profits and k-Factors Based on Early Cropping using Q80% Generated

| Early Cropping | k-factor | Profit *x* billion (IDR) |
|---|---|---|
| Nov-I | 0.88 | 96.165 |
| Oct-II | 0.88 | 96.165 |
| Oct-I | 0.88 | 96.165 |
| Jun-I | 0.88 | 96.165 |
| Jun-II | 0.88 | 96.165 |
| Mei-II | 0.87 | 96.165 |
| Sep-II | 0.87 | 96.165 |
| Sep-I | 0.86 | 96.165 |
| May-I | 0.86 | 96.165 |
| Apr-II | 0.87 | 78.106 |

### 3.5. Discussion

Dependable discharge data can be more accurate with extended discharge data, and dependable future discharges can be predicted using measured result data. Visually, the discharge data does not indicate anomalies. However, to obtain reliable results must be tested for reliability and homogeneity [19]. Table 11 summarizes the validity test at a 10% significance level ($\alpha = 0.1$), confirming their usability.

**Table 11.** Validity Testing of Discharge Data Generated from 1984 to 2073

| Type of Testing | Type of Method | Statistic Test Result | Critical Significance | Accept. |
|---|---|---|---|---|
| **Consistency** | RA PS | Q = 8,48 | 11,04 | ✓ |
| | | R = 8,25 | 15,14 | ✓ |
| **Homogeneity** | **Test-F** | F = 0,69 | 1,47 | ✓ |
| | Z-Test | Z = -1,29 | 1,64 | ✓ |

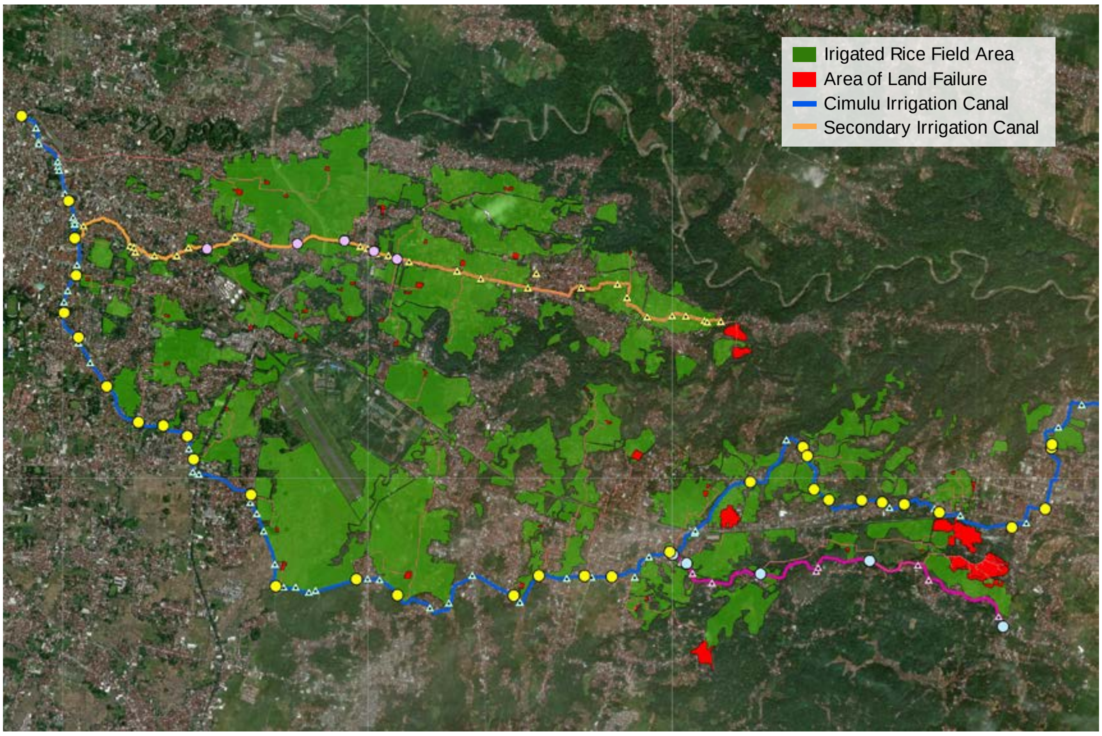



**Figure 9.** Mapping of the Cimulu Irrigation Area

The requirements for irrigation water in existing conditions are more significant than the water availability in Fig. 7, so there is an irrigation water deficit from Jan-I to Feb-II, May-II to Aug-I, and Sep-II to Oct-II. It corresponds to the mapping in Fig. 9. The irrigation water deficit underscores the immediate requirement for comprehensive and sustainable water resource management strategies.

The LP optimization involved ten scenarios for Q80% existing and Q80% generated discharge. The dependable irrigation area ranged from 176% to 243% for Q80% existing and 195% to 254% for Q80% generated. Maximum profits of IDR 61.97 billion and IDR 67.237 billion were attained at intensities of 243% and 254%, respectively, during the early Nov-I cropping. These profits were based on the optimal land area determined by the 2022 Tasikmalaya farming analysis. Notably, LFRA demonstrates that farmers can achieve even higher profits, and some farmers in the field are already implementing this approach. The comparison is presented in Tables 12 and 13.

The LFRA method provides significantly more benefits, with an average k factor of 0.80 to 0.90 for each Growing Season (GS), which is relatively safe. Conversely, Linear Programming is safe, but much available water is not utilized. A modification proposal is needed from these analysis results, namely the Land Failure Risk Assessment (LFRA) Model with a paddy-paddy-palawija cropping pattern. This practice also allows for a “cropping break period” for soil health and risk mitigation. Therefore, the recommendation for revitalizing the Cimulu irrigation land is early cropping in Nov-I with a paddy-paddy-palawija pattern. The profit obtained is less significant than the other early cropping periods, but the soil fertility can be maintained. Table 14 compares the analysis results and the suggestions given in this study.

**Table 12.** Profits Based on Early Cropping Results of LP and LFRA using Q80% Existing

| Early Cropping | Linear Programming | | LFRA Method | |
|---|---|---|---|---|
| | Cropping Intensity (%) | Profit x billion (IDR) | k-factor | Profit x billion (IDR) |
| Nov-I | 243 | 61.97 | 0.82 | 71.24 |
| Oct-II | 191 | 52.56 | 0.90 | 96.17 |
| Sep-I | 184 | 50.90 | 0.90 | 96.17 |
| Jun-II | 178 | 50.69 | 0.82 | 77.98 |
| Apr-II | 176 | 50.16 | 0.82 | 77.96 |
| Sep-II | 181 | 49.92 | 0.82 | 77.73 |
| May-II | 181 | 49.92 | 0.82 | 71.39 |
| Oct-I | 184 | 49.66 | 0.83 | 71.36 |
| Jun-I | 212 | 46.76 | 0.82 | 71.24 |
| May-I | 211 | 45.90 | 0.82 | 71.21 |

**Table 13.** Profits Based on Early Cropping Results of LP and LFRA using Q80% Generated

| Early Cropping | Linear Programming | | LFRA Method | |
|---|---|---|---|---|
| | Cropping Intensity (%) | Profit x billion (IDR) | k-factor | Profit x billion (IDR) |
| Nov-I | 254 | 67.24 | 0.88 | 96.17 |
| Oct-II | 200 | 64.04 | 0.88 | 96.17 |
| Jun-II | 199 | 63.77 | 0.88 | 96.17 |
| Oct-1 | 220 | 62.70 | 0.88 | 96.17 |
| Sep-II | 197 | 58.54 | 0.87 | 96.17 |
| Jun-1 | 195 | 57.93 | 0.88 | 96.17 |
| May-II | 195 | 57.93 | 0.87 | 96.17 |
| Sep-I | 226 | 57.08 | 0.87 | 96.17 |
| May-I | 229 | 52.93 | 0.86 | 96.17 |
| Apr-II | 232 | 50.94 | 0.87 | 78.11 |

**Table 14.** Comparison of the Linear Programming, LFRA, and RTTG-Modification in Nov-I Early Cropping

| Method | 1st ECS (ha) | | 2nd ECS (ha) | | 3rd ECS (ha) | | Profit x billion (IDR) |
|---|---|---|---|---|---|---|---|
| | Pd | Sc | Pd | Sc | Pd | Sc | |
| LP | 870.2 | 675.9 | 1232.4 | 313.8 | 670.1 | 0.0 | 61.97 |
| LFRA | 1546 | 0.0 | 1546 | 0.0 | 1546 | 0.0 | 96.17 |
| LFRA- Mod-RTTG | 1546 | 0.0 | 1546 | 0.0 | 0.0 | 1546 | 71.11 |

Note: ECS is Early Cropping Seasons, Pd is Paddy, Sc is Secondary Crops or Palawija, LP is Linear Programming, LFRA is Land Failure Risk Assessment, LFRA-Mod-RTTG is Modification - The Global Cultivation Plan. The difference between LFRA and LFRA-Mod-RTTG is that LFRA: Growing Season-1 (GS-1): paddy, Growing Season-2 (GS-2): paddy and Growing Season-3 (GS-3): paddy, whereas LFRA-Mod-RTTG: Growing Season-1 (GS-1): paddy, Growing Season-2 (GS-2): paddy and Growing Season-3 (GS-3): secondary crops (palawija).

## 4. Conclusions

Linear Programming (LP) and LFRA are two different methods used for irrigation and farming. LP focuses on meeting irrigation water needs, with water availability as a constraint, and aims to generate the maximum cropping intensity that can be irrigated. The results of LP analysis provide the Irrigation Area that can be planted, and the cropping pattern or crop type as planned. However, it can be challenging to implement this model in the field and socialize it with the community.

On the other hand, LFRA focuses on planting patterns to determine the value of the k-factor, which indicates the risk of land failure. The existing conditions, such as the early cropping, cropping pattern, and planted areas, are the input into the system. The results of LFRA analysis are k-factors and land failure risk. This method is easier to implement in the field as it aligns with the conditions and habits of the community. LFRA is particularly useful in Irrigation Areas with dry conditions, as it allows for early detection of failure risk.

Both models consider the planting schedule an essential parameter for obtaining optimal profits. For instance, LP analysis shows that the planting schedule at the early Nov-1 cropping season for the Q80% existing is optimal. Meanwhile, LFRA analysis presents many options for obtaining optimal results with the same k-factor, as shown in Tables 12 and 13. Considering the "cropping break period" is crucial in achieving maximum profit. Therefore, the recommendation for revitalizing the Cimulu irrigation land is to choose the early Nov-I cropping season with a paddy-paddy-palawija pattern, both for the Q80% existing or Q80% generated.

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