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Research Article

Application of an Optimization Model for Water Supply Chain Using Storage Reservoir Operation for Efficient Irrigation System

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The model was created to assist in the appropriate allocation of water to produce crops to optimize net profit through monthly reservoir operation. The model maximizes net crop revenue and determines the type and size of the cultivated crop for each zone, taking into account monthly reservoir water availability. The following factors constrain the optimization model: (1) monthly reservoir water availability; (2) monthly water demand and irrigated farmland for crops; (3) limited crop areas in each zone; (4) projected final storage; (5) proportional sharing rule (PSR) for each zone. The linear programming (LP) algorithm is used to formulate the model, which is then solved using the general algebraic modeling system (GAMS). The model is applied to Hali Dam and validated using two criteria: (1) baseline scenarios (non-PSR) and (2) PSR scenarios in which all zones must have the same amount of water. The results demonstrate that the PSR scenarios give all of these zones identical rights for water delivery, with a total net profit reduction of around 2.6 percent at the planned final storage of 100 Hm^3. As a result, the current model can be utilised to optimize dam water consumption in the future. The methodology is applied to a reservoir of Hali Dam in Saudi Arabia to demonstrate the model's practical application.

1. Introduction

The irregular regional and temporal distributions of rainfall, industrial growth, climate variability, and inefficient management are some of the factors that contribute to water scarcity in many developing countries. Other factors that contribute to water scarcity include population growth, limited surface water resources, and irregular geographical and temporal distributions of rainfalls. Because of this reality, there has been a major decrease in the available water resources, which has further contributed to water-related disagreements among the many stakeholders. The most effective way to alleviate water shortages is to optimize irrigation systems for the regions in which they are being used and enhance water resource allocations by ensuring that multicropping patterns and irrigation time are carried out in the appropriate manner. With rising costs associated with irrigation and a deteriorating water constraint on a worldwide scale, enhancing water productivity in agricultural output is becoming an increasingly important objective. The vast majority of reservoirs were constructed with only a single objective in mind, namely to supply water for a specific application; any other applications were given a secondary or tertiary priority. According to the information found in the ICOLD database, 74% of all certified dams are single purpose dams, with 50% of them serving irrigation. Good irrigation management and high-precision irrigation methods maintain excellent yields and fruit quality [1–5]. Because of the growing demand for irrigation water and the unpredictability of stream flow in arid and semiarid regions, reservoir performance evaluation is critical yet complex [6, 7]. Reservoirs are significant in Saudi Arabia's water resource management since they serve as necessary storage facilities for controlling excess water for subsequent deficit water seasons or, in some cases, drought years [8]. For reservoir-irrigation systems to successfully use water storage, proper reservoir functioning and irrigation timing are required [9–11]. In Saudi Arabia, agriculture accounts for 82.2% of the total water consumption, compared with 13.5% for domestic consumption and 4.3% used by industry [1]. Today, Saudi Arabia has constructed 521 dams for different purposes such as recharging, flood control, drinking, and irrigation, and the current study is to establish 1000 dams by 2030 [8]. The Hali Dam, located in the southern part of Saudi Arabia, is considered the second largest dam in the country after the King Fahad dam. In January 2021, the Hali Dam released $45\,\mathrm{Hm}^3$ to benefit 450 farms [11]. The paper presents a new approach for water allocation from reservoir operations, considering PSR for irrigation zones.

The underlying issues that plague the water supply system give rise to significant research questions (RQs), some of which are discussed in more detail.

RQ1: How realistic are optimization strategies when it comes to filling the gaps in a precarious situation in which technology is more concerned with boosting irrigation systems than with increasing the performance of the entire water-supply chain?

RQ2: How effectively do optimization algorithms handle the diverse physical, chemical, and biological characteristics of the water supply chain?

The proposed model uses monthly reservoir operation and ultimate target storage to help determine the best way to distribute water for crop cultivation in order to maximize the net benefit for each zone. The model takes into account the monthly water availability in the reservoir to predict the type and amount of the farmed crop for each zone while maximizing net crop income. The monthly water availability in the reservoir, the monthly irrigated farmlands for crops, the monthly water demand for crops, and the monthly PSR for each zone are all constraints of the optimization model. We offer two methods for approaching scenarios: (1) examining non-PSR scenarios and (2) examining PSR scenarios with the demand that the water content in each zone be the same. We discover that adopting a PSR scenario when creating a model is crucial, particularly when users or zones are given equal weight. The Hali Dam in Saudi Arabia is used to test the performance of the optimization model. In GAMS, the model is resolved using an LP method [12]. Groundwater, pipeline design, and reservoir operation are just a few of the many optimization challenges that GAMS has successfully solved [13].

1.1. Contribution of the Study. Due to the expansion of the agricultural sector and the new challenges it faces, effective management of agricultural supply chains has become a frequent topic of discussion among academics and industry professionals. Because of this, it is now more important than ever before for managers to take into account uncertain elements when making decisions. Doing so may increase productivity, responsiveness, corporate integration, and ultimately market competitiveness. A growing amount of research is being expressly committed to tackling uncertainty in order to capture the uncertain conjuncture that is present in the vast majority of agricultural applications carried out in the real world. In particular, quantitative modelling approaches have been utilised quite extensively in agricultural supply chain management in order to combat the unpredictability that can occur from managing agricultural supply chains.

(i) The objective of this article is to provide a summary of the most recent developments and enhancements that have been made in the application of operations research methodology

(ii) It aims to provide an overview of the leading research area that highlights the most significant and popular frameworks which discuss the emergence of new operations' research advancements in the agricultural industry

(iii) The wide variety of contributions that have been researched has been organised and presented in accordance with the three characteristics that have been identified as being the most significant: modelling techniques for varying degrees of ambiguity, software development paradigms, and functional application domains

(iv) Finally, the most important findings from the review are summarised and highlighted, and recommendations for new lines of research are offered for the future years

2. Literature Review

Many researchers have developed water allocation models using different aspects of problem techniques and solution approaches [14–16]. Oxley and Mays [17] developed an optimization water allocation model for the Prescott Active Management Area in Arizona, USA, to maximize the sustainable net economic benefit over a long-term planning period. Meng et al. [18] developed and implemented an LP water allocation optimization model based on the sustainability of water resources. The LP approach's ease of formulation and implementation encourages researchers to use it widely [19–23]. However, its failure to deal with nonlinear issues drives the usage of nonlinear programming (NLP). Benli and Kodal [24] determined irrigation water demands and agricultural revenue in Turkey's southeast Anatolian region under a sufficient and constrained water supply based on crop water benefit function through the NLP model. Many researchers adopted NLP, such as [25–27]. Total farm profits on the Havrias River in Northern Greece were maximized using an NLP optimization model that integrated soil water balance [28]. The differences between these two models (LP and NLP) become more pronounced while including more crops. This requires more constraints in the model structure, which may result in computational complexity, though this increase is much less than that for a dynamic model with everything else being equal [29]. Due to the dynamic programming (DP) technique's capacity to represent sequential decision-making processes and integrate the stochasticity of hydrological processes, it has been widely used in irrigation planning and management [30], optimizing dam water resource management through DP. The study by Tran et al. [31], also optimizing the estimated net present value from various uses, proved that the relationship between irrigated area and reservoir capacity should be considered while building a new reservoir.

By 2020, the model expects to increase the advantages of water usage in northern China's Zhangjiakou region. Various agricultural irrigation water allocation optimization models were created, each adopting a different allocation scenario to maximise the net benefit. Tran et al. [31] investigated models for improving agricultural irrigation water allocation, which were implemented using various computer languages to optimize irrigation management. DP was used to give different distributions of agricultural water resources in Yangling, China [32]. Optimal rules to improve the water resource management of Nebhana Reservoir, Tunisia, using stochastic DP developed by [33].

Models were created with the particular motive of supporting water supply decision-makers who are faced with difficult decisions involving a variety of criteria. Bekri et al. [34] used LP approaches for the fuzzy-boundary-interval to construct an optimal model for water allocation optimization. To enhance decision-makers' attitudes, the model incorporated the unpredictability of random water inflows by simulating stochastic equal-probability hydrologic scenarios based on different inflow scenarios utilised in Greece's Alfeios River basin. To give more information to decision-makers, Lu et al. [35] constructed an inexact rough-interval fuzzy linear programming (IRFLP) model for water allocation, which was compared to an interval-valued linear programming model. The results show that the IRFLP can handle the interplay of dual intervals of highly unknown parameters as well as their influence on the system. An integer linear programming (ILP) decision-supporting model for water resources was developed to reduce water treatment, allocation, and environmental costs.

When more than one goal must be addressed, multiobjective programming is used to analyse water allocation. Multiobjective programming was utilised to analyse the Heihe River basin's water deficit by maximising water resource allocation and integrating land use as a constraint [36–39]. They developed a multiobjective water allocation optimization model to optimize agricultural productivity on farms in Iran's Baghmalek plain. Yousefi et al. [40] created a multiobjective crop pattern optimization model to optimize the benefits of reclaimed agricultural water and soil while minimizing the potential negative quantitative-qualitative impacts. In Iran's Varamin irrigation network, the created model maximizes the benefits of crop patterns while lowering nitrogen leaching and enhancing groundwater recharge rates. Another modelling tool that can be used for agricultural applications while allocating water is ant colony optimization (ACO). Ant colony optimization (ACO) was used to create an agricultural crop and water allocation model that allows for dynamic decision variable selection (DDVO) [41]. Near an irrigation district in Loxton, South Australia, the model maximizes the net value of allocating a certain total water volume to produce various crop kinds. Nguyen et al. [41] optimized crop and water allocation using ACO and dynamic decision variable (ACO-DDVO) selection, lowering the search space size and enhancing the computational efficiency of evolutionary algorithm application. Another ACO strategy was employed in eastern Colorado, USA, to boost maize yield by utilizing variable water availability and precise fertiliser application amounts [42]. In a water allocation optimization model, the particle swarm optimization [43] (PSO) approach was utilised [44].

A genetic algorithm (GA)-based agricultural irrigation water allocation optimization model was developed for the Sri Ram Sagar project in India [45]. A water allocation optimization model for agricultural irrigation was developed in Karnataka, India, that optimizes the net benefit from using specified crop types and crop patterns [44]. Sadati et al. [46] used an NLP optimization model with a GA to optimize reservoir releases and cropping patterns around the Doroudzan dam in south-west Iran to maximize agricultural income.

Proportional sharing rules are used by many researchers in the field of water. Salman et al. [47] presented a model that maximizes the overall farming income by reproducing various different crops in Iraq. Anand et al. [48] developed soil and water assessment tool (SWAT) models and a GA model for two reservoirs in the Ganga River basin, India. Aljanabi et al. [49] used proportional sharing rules to develop a mixed-integer nonlinear programming (MINLP) model for Iraq. Therefore, the present model can be used to optimize the utilization of dam water in the future. The methodology is applied to a reservoir of Hali Dam, Saudi Arabia, to demonstrate the model's practical use. With many different methodologies developed for the system, the LP method is quite frequently used for economic impacts and policy [48–51]. The authors of [52] provide a unique mathematical model aiming to build a sustainable mask closed-loop supply chain network in the middle of the COVID-19 pandemic. To handle the locational, supply, production, distribution, collection, quarantine, recycling, reuse, and disposal decisions that occur within a multiperiod, multiechelon, and multiproduct supply chain, a multiobjective mixed-integer linear programming model is employed. The four assessment criteria used in the comparison were the max-spread, spread of nondominance solution, number of Pareto solutions, and mean ideal distance. It was found to be around 25% better in terms of Pareto solution and 2% in terms of quality solution. The authors of [53] have developed a new sustainable-resilient healthcare network associated to the COVID-19 pandemic that blends sustainability features and resiliency ideas. This network is intended to operate under unpredictable conditions. The simulation approach is used whenever there is a need to make an estimate regarding the values of the required demand for medicines. To locate Pareto solutions, they have presented three meta-heuristic methods, which are the multiobjective teaching–learning-based optimization (TLBO), the particle swarm optimization (PSO), and the genetic algorithm (GA). According to the findings, increasing the expenses of transportation led to an increase in both the total cost and the environmental implications of maintaining sustainability. The authors of [54] propose a method for evaluating the countries that offer the greatest medical care for Iranians who wish to seek treatment outside of Iran. The top tourist destinations and top medical tourism destinations were both picked based on criteria related to sustainability. A total of eight countries were identified as the top tourist destinations. The findings of the experiment indicate that efforts made by countries with low Phi values to achieve defined requirements ought to be encouraged by the international community. The configuration of a supply chain network is discussed in [55], which includes closed-loop network design considerations. The objective of the model is to create a distribution network that is tailored to the requirements of the clientele in order to simultaneously cut down on both the overall cost and the total CO_2 emission. The data provide conclusive evidence that the model that was proposed is able to produce effective Pareto solutions. It has also come to light that expanding the capacity of distribution centres brings about a reduction in the number of instances in which products are unavailable.

2.1. Particle Swarm Optimization. Numerous research and application sectors have effectively used particle swarm optimization (PSO). It has been proven that PSO can produce better outcomes more quickly and inexpensively than other approaches. Also possible is parallelization. Additionally, the gradient of the issue being optimized is not used. In other words, PSO does not require that the issue be differentiable, in contrast to conventional optimization techniques. Not to mention, there are not many hyperparameters. These factors don't require complex concepts to grasp and are pretty straightforward. PSO is a mighty and adaptable algorithm that will perform well on a wide range of jobs with the same set of hyperparameters.

2.2. Ant Colony Optimization. In both the scientific and industrial fields, optimization issues are crucial. Time table scheduling, nurse time distribution scheduling, train scheduling, capacity planning, traveling salesman difficulties, vehicle routing challenges, group-shop scheduling problem, portfolio optimization, etc., are real-world examples of these optimization problems. For this reason, several optimization methods are created. One of them is the optimization of ant colonies. A probabilistic method for identifying the best pathways is called ant colony optimization. The ant colony optimization technique is used in computer science and research to address various computing issues. Social insects include ants. They are colony animals. The ant's primary motivation is to find food, which governs their behavior. Ants are scurrying about their hives while looking. To find the food, an ant jumps back and forth frequently. It leaves a pheromone-like organic substance on the ground as it moves. Ants use pheromone trails to communicate with one another. When an ant discovers food, it takes as much as possible. Based on the quantity and quality of the meal, it scatters pheromones on the routes when it returns. Ants have pheromone senses. Other ants will thus follow that trail after smelling it. The likelihood of picking that road increases with pheromone level, and as more ants follow the path, the amount of pheromone will likewise rise on that path.

2.3. Genetic Algorithm. The genetic algorithm is a traditional evolutionary algorithm with a random basis. Random adjustments are made to the existing solutions to discover a solution utilizing the GA to produce new ones. Due to its simplicity when compared to other EAs, GA is also referred to as simple GA (SGA). Darwin's theory of evolution is the foundation of GA. It is a slow, progressive process that functions by changing the sluggish, subtle alterations. Additionally, GA gradually modifies its solutions in little ways until it finds the optimal one. The population size (pop size) of the population on which GA operates is the total number of solutions. We refer to each answer as being unique. There is a chromosome in every individual solution. The chromosome is a collection of characteristics (parameters) that characterize an individual. A group of genes may be found on each chromosome.

2.4. Mathematical Formulation of the Optimization Model. The optimization model aims to find the maximum use of the reservoir during the time seasons. The optimization model can be described by an objective function and is subject to constraints and variables. The model aims to find the maximum profit of irrigated crops in zones z during the time period t. The objective function to maximize profit, (1), is adopted from [43].

$$\mathrm{MaxProfitCrop} = \sum_{c}\sum_{z}\sum_{t}\left[\mathrm{Y}_{c,t}\mathrm{P}_{c}\mathrm{A}_{c,z} - \mathrm{CC}_{c,t}\mathrm{A}_{c,z}\right], \quad (1)$$

where $\mathbf{Y_{c,t}}$ is the crop's c yield in time period t [ton/ha], $\mathbf{P_c}$ is profit in Saudi Riyal (SAR) per hectare [ha] for crop c, $\mathbf{A_{c,z}}$ is the cultivated area [ha] of crop c in zone z, and $\mathbf{CC_{c,t}}$ is production costs in SAR per hectare [ha] for crop c in time period t [Month]. The objective function is subject to constraints on the mass balance in the reservoir, reservoir capacity, diversions flow, crop requirements, area capacity, and PSR.

The mass balance in the reservoir is developed in (2).

$$\mathbf{S_t = S_{t-1} + QIN_t - E_t - R_t \forall t = 1, 2, 3, \ldots T}, \quad (2)$$

where $\mathbf{QIN_t}$ is the inflows [m^3/month] at time period t, $\mathbf{E_t}$ is the evaporation [m^3/month] at time period t. $\mathbf{S_{t-1}}$ is the storage [m^3] in previous time period $\mathbf{t-1}$ [month], $\mathbf{S_t}$ is the current storage [m^3] in time period t [month], and $\mathbf{R_t}$ is the releases [m^3/month] at period time t.

The following constraint, (3), is the maximum and minimum reservoir capacity constraints.

$$\mathbf{S_t \le K_m - K_d \forall t = 1, 2, 3, \ldots T}, \quad (3)$$

where $\mathbf{K_m}$ is representing maximum capacity [m^3] of the reservoir, and $\mathbf{K_d}$ is dead storage [m^3] where the reservoir storage cannot be less.

The constraint (4) is used for target final time period storage that enforcing the model to keep certain storage values in reservoir at the end optimization run (equation (4)). This constraint allows keeping storage volumes in final months.

$$\mathbf{S_{t=12} = K_f}, \quad (4)$$

where $\mathbf{K_f}$ is reservoir storage requirement [m^3] at final period. The constraints can be applied for any month, but in this model, we considered February month only ($t = 12$).

Crop demand constraint defines the diversions for each zone which has to be used to cultivate areas in that practical zone. The constrain (5) is written as follows:

$$\mathbf{D_{z,t}} = \sum_{\mathbf{c}} \mathbf{A_{c,z} CR_{c,z,t}} \left(\frac{\mathbf{10000}}{\mathbf{1000}}\right) \mathbf{\forall t = 1, 2, 3, \ldots T} \wedge \forall z = 1, 2, 3 \ldots Z, \quad (5)$$

where $\mathbf{D_{z,t}}$ is diversion flow [m^3/month] for zone z in time period t, $\mathbf{A_{c,z}}$ is described above, and $\mathbf{CR_{c,z,t}}$ is representing the crop requirements [mm/month] for crop c in zone z in time period t. Number 10 is a conversion factor to [m^3/ha]. The values of crop requirements have been calculated based on crop evapotranspiration, irrigation efficiency, and leaching requirements.

Limitation for area size constraints is described as follows:

$$\mathbf{A_{c,z} \le MA_{c,z} \forall z = 1, 2, 3 \ldots Z} \wedge \forall c = 1, 2, 3 \ldots C, \quad (6)$$

where $\mathbf{MA_{c,z}}$ is the maximum area [ha] for each crop c in each zone z, and $\mathbf{A_{c,z}}$ is described previously.

$$\sum_{\mathbf{c}} \mathbf{A_{c,z} \le AR_{c,z} \forall z = 1, 2, 3 \ldots Z}, \quad (7)$$

where $\mathbf{AR_{c,z}}$ is area limitation [ha] for the summation of crop c in each zone z.

The difference between constraint (6) and (7) is that the area is limited in each zone while in same time is limited for each crop.

PSR for the reservoir operations is written as follows (8):

$$\sum_{\mathbf{t}} \mathbf{PSR}_{\mathbf{z,t}} = \sum_{\mathbf{t}} \frac{\mathbf{D_{z,t}}}{\mathbf{R_t}} = \mathbf{1 \forall z = 1, 2, 3, \ldots Z}, \quad (8)$$

where $\mathbf{PSR_{z,t}}$ is proportional sharing rules for zone z in time period t, and $\mathbf{D_{z,t}}$ and $\mathbf{R_t}$ are described previously. In PSR scenario, it considered each zone must have same quantity of water supplied from reservoir during all time period.

The variables are cultivated areas, $\mathbf{A_{c,z}}$, [ha] for each crop in zone z; reservoir releases $\mathbf{R_t}$ [m^3/month] at time period t; and the diversions flows $\mathbf{D_{z,t}}$ [m^3/month] for each zone z at time period t.

2.5. The Application of Present Model on Hali Dam. The model is applied to the Hali Dam, which is located in Saudi Arabia's southern region at [18° 46′ 4.30″N 41° 34′ 28.29″E] as shown in Figure 1. The system consists of one reservoir and four different zones, as illustrated in Figure 2. Ten different crops can be grown in each irrigation zone: Alfalfa, wheat, maize, tomato, potato, barley, sorghum, cucumber, pepper, and eggplant. These crops are commonly cultivated in the Hali Dam reservoir region because they have been selected.

The yield (ton/ha) for each crop is shown in Table 1 along with maximum crop area. Each crop yields are fluctuation due to soil filtration, water arability and quality, and climate change. Each crop's yield as shown in Table 1 is adopted from [43] and updated from MEWA in Saudi Arabia [51].

The crop water demands ($CD_{c,z,t}$) as shown in Table 2, are updated from adopted from Food and Agriculture Organization (FOD) which includes sowing, growing, and harvesting considering leaching requirement, crop evapotranspiration, and irrigation efficiency for each month. These values can be modified for any updated data available. The selling price in (SAR/ha) for each crop and costs of production have been collected from local markets. The reservoir capacity and dead reservoir are 245 Hm^3 and 49 Hm^3, respectively, and initial storage volume is 110 Hm^3 based on daily reports established by MEWA (2021). The final storage volume at final period (February) is considered as 110 Hm^3 up to 75 Hm^3.

The inflows and evaporation data as shown in Table 3 are secured from [51] which calculated by using average monthly. Infiltration at reservoirs can be performed, obviously but that is not the intent of the model presented herein.

The releases in non-PSR would be distributed through the zones to cultivate the most economical crops, while in the PSR scenario, they are distributed equally. In other words, the PSR scenarios allow the total water supply in all four zones to be the same regardless of any consequences, such as drought. To incorporate proportionality into the model, arbitrary priorities were assigned to these zones. It is to be noted that no standard approach is available for assigning priorities [56]. The corresponding priorities for PSR scenario are as follows: $PSR_{z=1,t} = 25\%$; $PSR_{z=2,t} = 25\%$; $PSR_{z=3,t} = 25\%$; $PSR_{z=4,t} = 25\%$. In this study, our goal is to give each zone right of supplying water based on

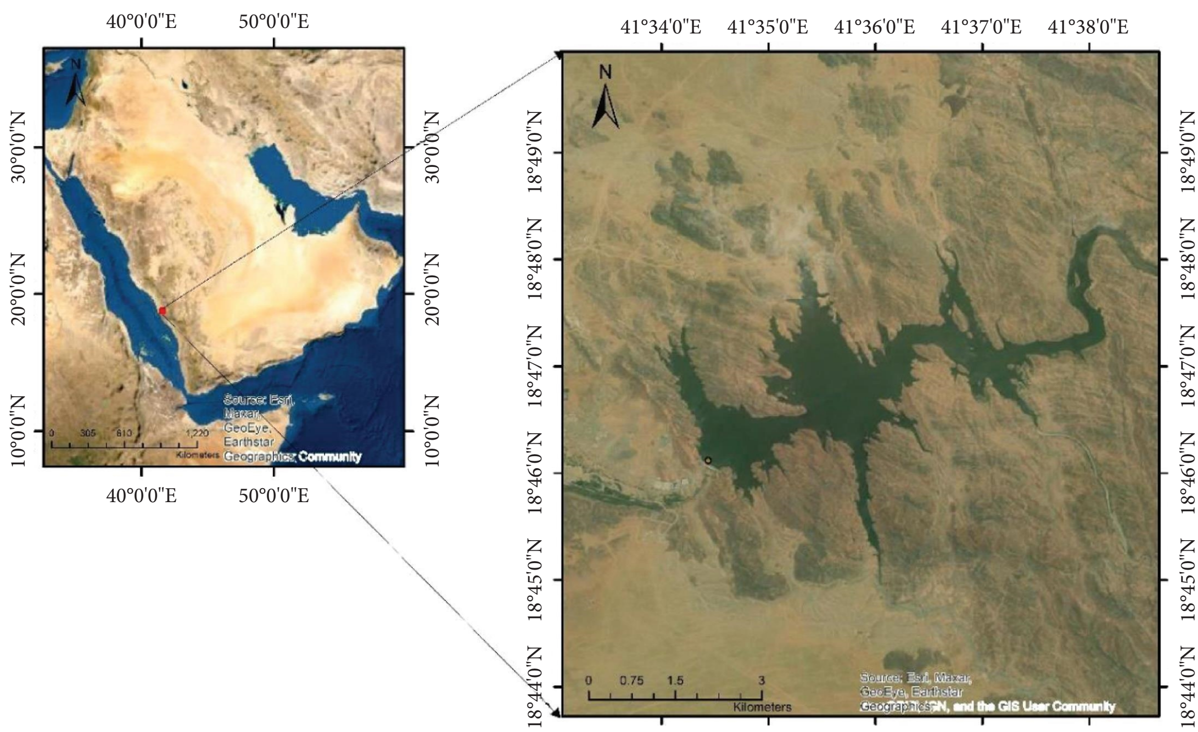

Figure 1: Hali Dam, Saudi Arabia [18°46′4.30″N 41°34′28.29″E].

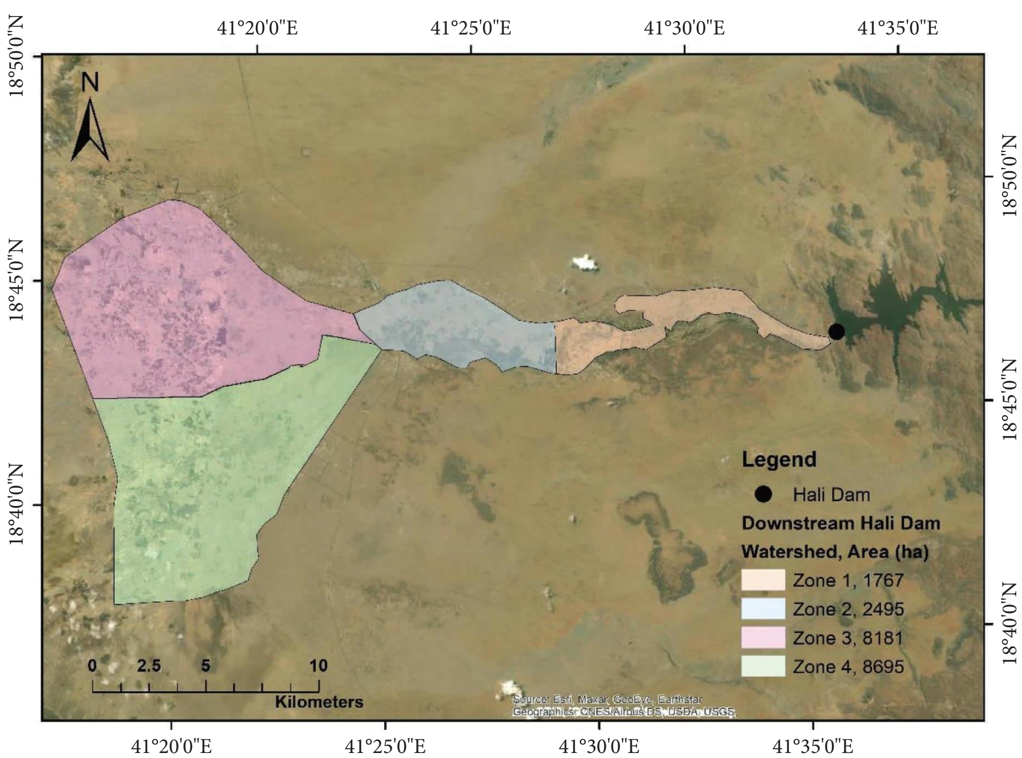

Figure 2: Map showing the reservoir and irrigation zones.

proportional rules. PSR for each zone is somewhat arbitrary, but it may be done by examining the significance and preferences of decision-makers.

In this matter, sometimes, there is no water allocated in certain zones because it is not a good economic choice or extreme drought conditions. However, the purpose of the

Table 1: The yield (ton per ha) for each crop along with maximum crop area (ha) for each zone.

Crop/area	Maximum area (ha)				Yield ton/ha
	Zone 1	Zone 2	Zone 3	Zone 4	
Alfalfa	97.2	137.2	450.0	478.2	22.4[1]
Wheat	79.5	112.3	368.1	391.3	4.6[1]
Maize	312.8	441.6	1448.0	1539.0	1.8
Tomato	547.8	72.4	237.2	252.2	19
Potato	79.5	112.3	368.1	391.3	15.7
Barley	155.5	219.6	719.9	765.2	3.2
Sorghum	51.243	773.5	2536.1	2695.5	2.92
Cucumber	273.9	386.7	1268.1	1347.7	13
Pepper	97.2	137.2	450.0	478.2	26
Eggplant	72.4	102.3	335.4	356.5	17.5
Total	1767.0	2495.0	8181.0	8695.0	

[1]Two seasons per year (August and February).

Table 2: Monthly water demand for each crop in mm.

Months/crop	Water demand for each crop (mm)									
	Alfalfa	Wheat	Maize	Tomato	Potato	Barley	Sorghum	Cucumber	Pepper	Eggplant
March	106.7	42.8	43.3	42.9	60.5	42.8	71.9	46.5	16.1	56.6
April	206.7	94.7	89.6	66.4	104.2	94.7	130.3	72.7	91.9	77.9
May	235.6	124.3	100.6	88.3	147.5	124.3	69.8	96.3	101.7	88.0
June	248.9	112.0	124.6	98.6	147.9	112.0	60.9	85.2	107.1	97.1
July	157.9	40.6	108.3	98.6	110.2	40.6	44.4	55.9	107.1	76.9
August	64.0	25.7	75.8	98.6	96.6	25.7	139.6	83.8	107.1	66.3
September	95.7	42.3	79.0	68.6	151.7	42.3	81.4	116.0	85.7	81.2
October	120.0	55.0	128.4	70.4	206.1	55.0	65.6	97.1	40.5	103.2
November	120.0	55.0	179.4	66.8	63.1	55.0	40.0	0.0	155.6	99.5
December	137.1	70.6	130.3	87.1	0.0	70.6	0.0	0.0	184.3	20.0
January	152.0	84.3	0.0	130.5	0.0	84.3	0.0	0.0	165.0	0.0
February	158.4	34.1	0.0	134.5	0.0	34.1	0.0	0.0	0.0	0.0

Table 3: Average monthly water inflows and evaporation (Hm^3).

Months	Inflows Hm^3	Evaporation Hm^3
March	1.40	1.22
April	15.43	1.28
May	2.21	1.72
June	0.03	1.90
July	0.53	1.99
August	4.24	1.72
September	0.15	1.74
October	0.11	1.45
November	0.22	1.02
December	0.31	0.82
January	4.41	0.68
February	0.65	0.91
Total	29.70	16.44

PSR scenario is to have further flexibility in these optimization models to give each zone a share of water supply.

3. Results

The results of a Hali Dam system are shown in Figures 3 and 4. The model runs for various final storages ranging from 110 Hm^3 to 75 Hm^3 with or without PSR. In non-PSR scenarios, it shows that the cultivated lands of tomatoes, potatoes, and cucumbers are the most economical crop choices in most of the zones. Zone 1 shows the least amount of area cultivated due to the area limitation of the most effective crops. As we expected, the net profit shows a slight increase in total value, roughly up to 5.63 million SAR, when the model is target to reduce the final storage to 75 Hm^3, which means releasing around 35 Hm^3 in total for the year. However, the model shows significant results: if we target the final storage at 100 Hm^3, the total net profit in non-PSR is 5.20 million SAR, which is a reduction of 7.6% of 75 Hm^3, but the saving of total storage is around 25 Hm^3 of storage volume (an increase of 25%).

If the model's target final storage should equal the initial storage, which is 110 Hm^3, it shows a significant reduction in total profits of around 4.86 million SAR (a reduction of 19% of the target final storage of 100 Hm^3) due to the inflows and the evaporation in the reservoir. In PSR scenarios, the total flows should be divided equally among all zones in all time periods. The results show that, rather than large potato crop lands in zones 3 and 4, the model recommends optimal Alfalfa crop lands in zones 1 and 2. In addition, peppers and eggplants grow well in zone 1. However, as shown in Figure 5, these types of pooling laws may have an impact on net earnings; the model successfully

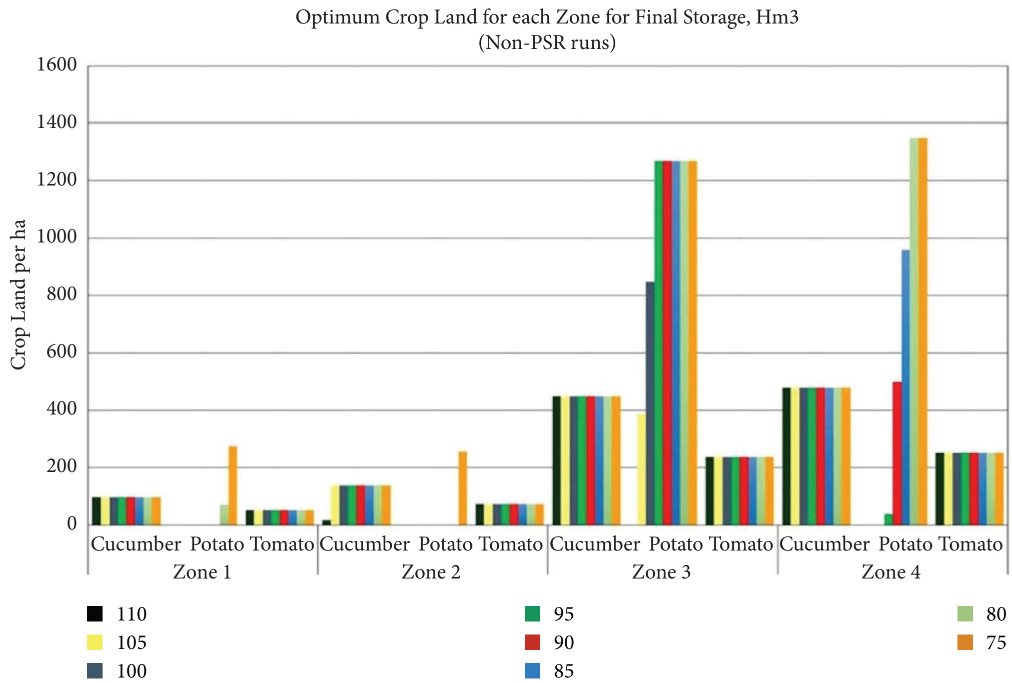

Figure 3: Optimum crop land for each zone using non-PSR scenarios.

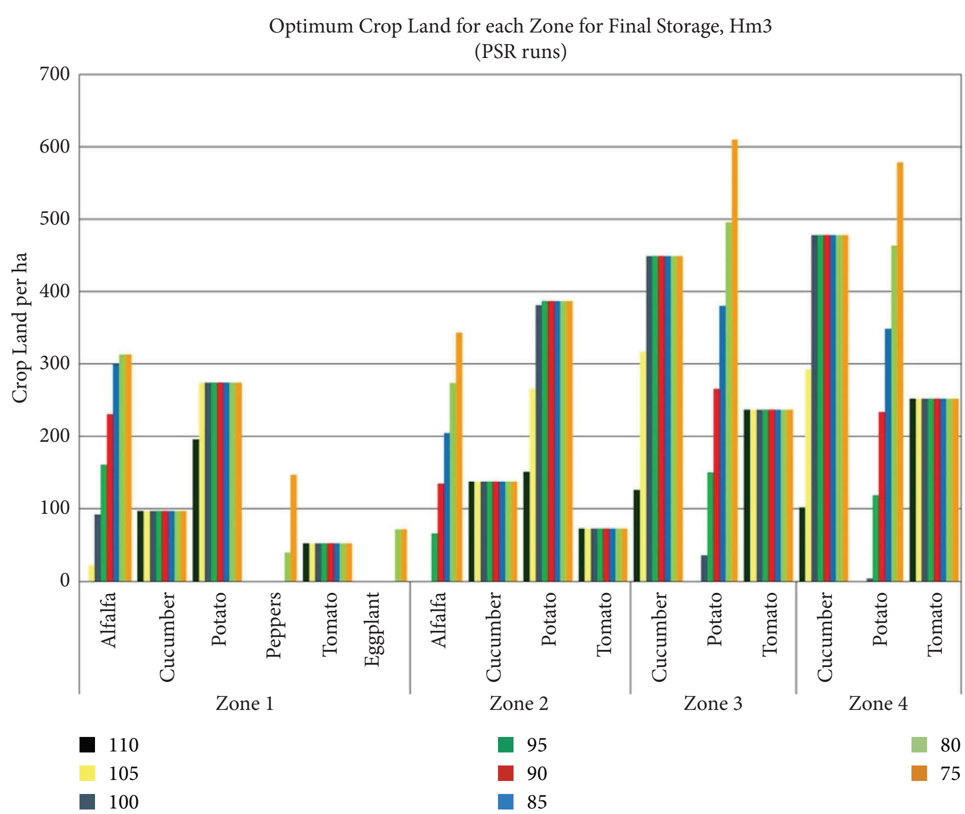

Figure 4: Optimum crop land for each zone using PSR scenarios.

guarantees the proportional rule among all zones. Interestingly, the PSR scenarios show that releasing large amounts of water (Target final storage of 75 Hm^3) is not sufficient in the system provided herein. Also, it shows that if the target final storage is 100 Hm^3, the total net profit is 5.06 million SAR, which is close to the non-PSR scenario at the same target final storage (5.20 million SAR). Figure 6 shows the total flows into each zone with and without

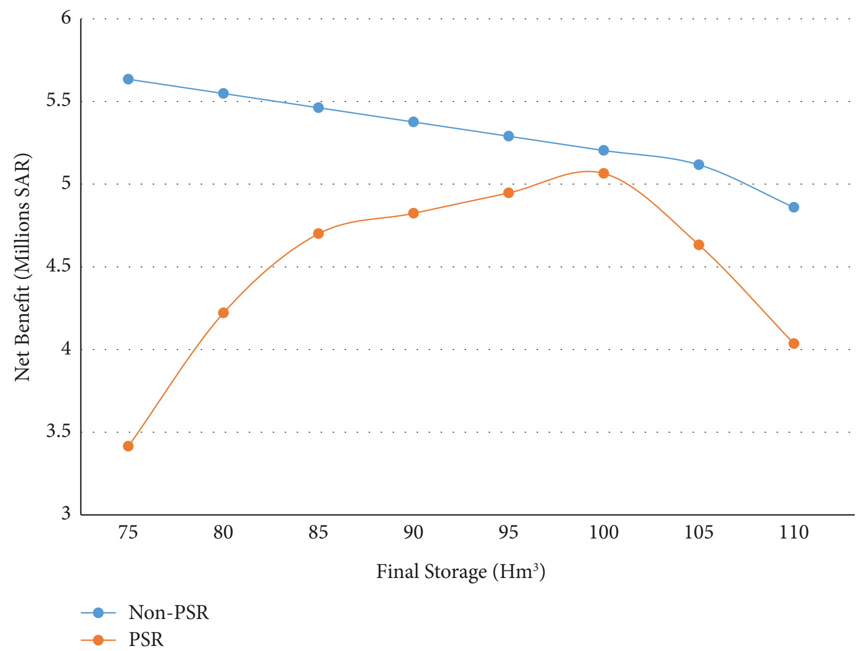

Figure 5: Net benefit using non-PSR and PSR scenarios for different final storages.

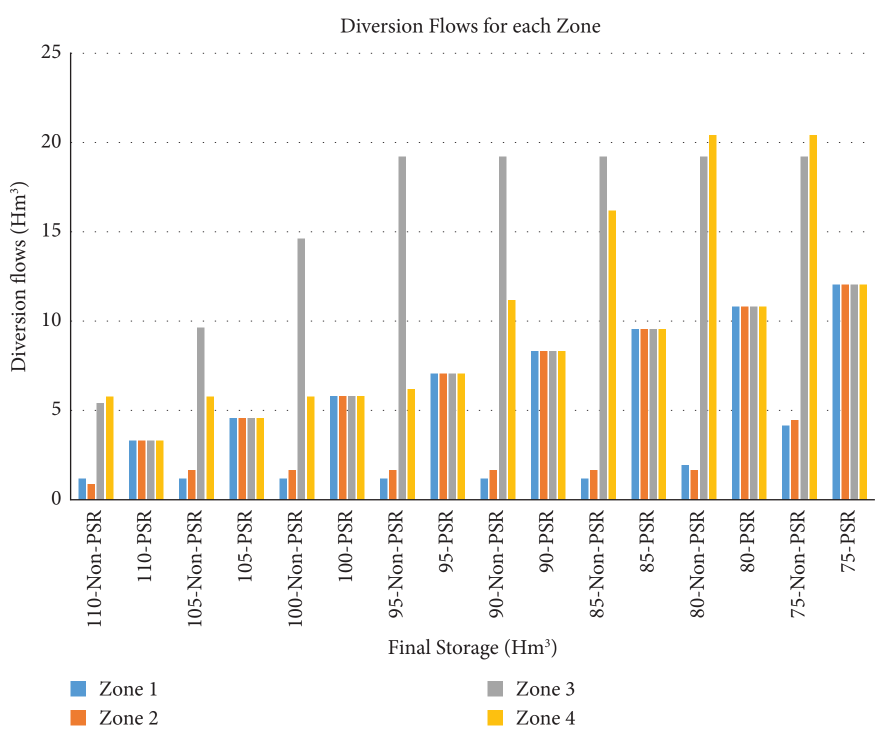

Figure 6: The diversions for each zone considering non-PSR and PSR scenarios.

considering PSR. Clearly, the PSR shows that the total flows are evenly distributed among all zones. On the other hand, the non-PSR shows that zone 3 would take total flows (19.2 million Hm^3) more than any zone at target final storage (100 Hm^3 to 85 Hm^3) while at target final storage (80 Hm^3 and 75 Hm^3), zone 4 takes more total flows than any zone (20.4 Hm^3). Interestingly, the total profit in PSR scenarios is decreasing when it is compared with non-PSR scenarios. However, at target final storage, it can reduce these differences as it occurs on 100 m^3. The PSR scenario of target end storage to 75 Hm^3 shows that Zone 4 has the most croplands with 1308 ha, which are considered tomato, cucumber, and potato crops, which have a significant impact on total profits and the type of crop demand.

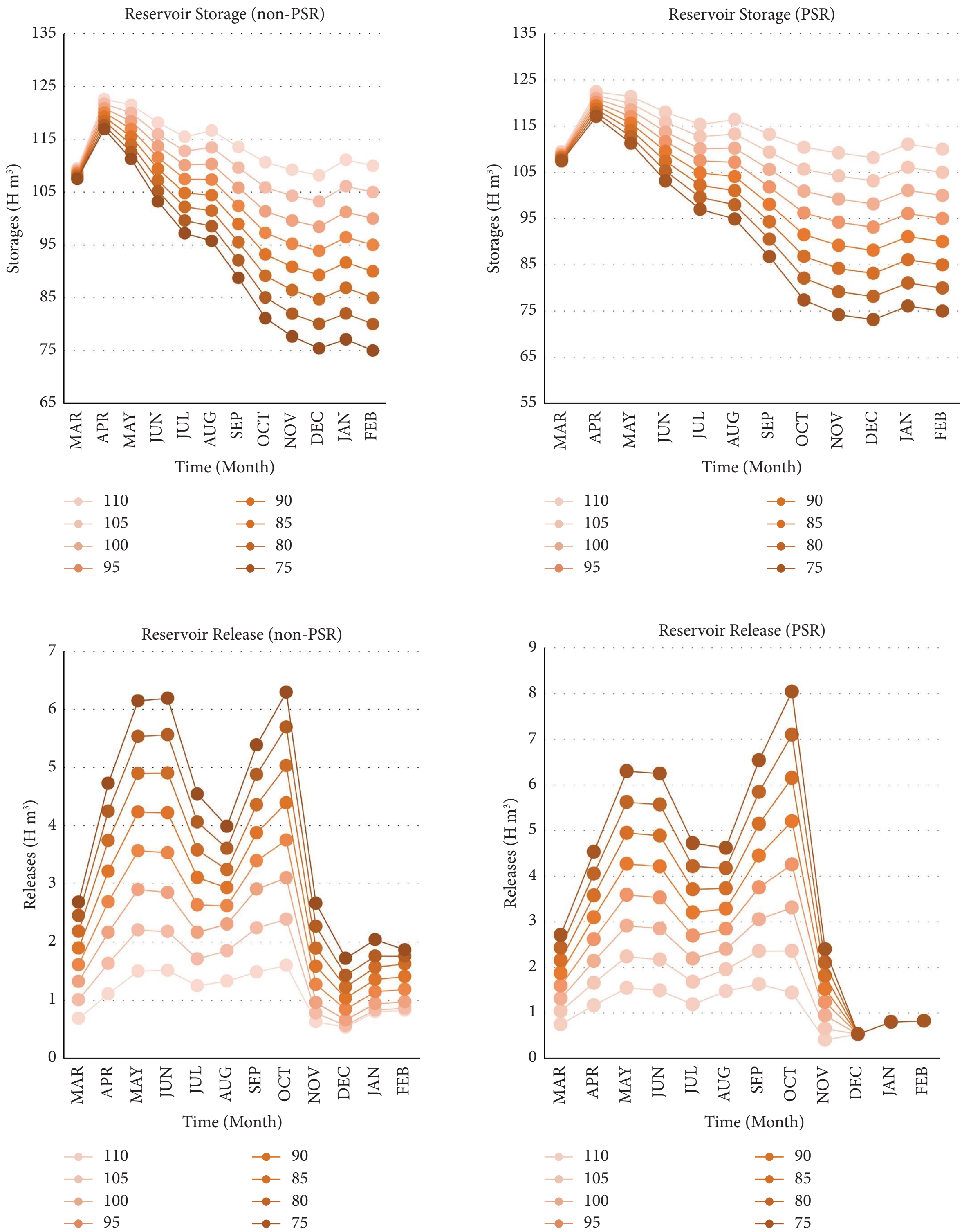

Figure 7: Reservoir storages and releases considering non-PSR and PSR scenarios.

3.1. Releases and Diversions. In terms of reservoir operation, the values of storage and releases show the performance in great mode and can be satisfied with minimum, maximum, and final storage requirements. A key finding in the Hali Dam system is that the most economical crops, such as tomatoes, cucumbers, and potatoes, can increase the zone's profit and the system's profit. The diversion for each zone is shown in Figure 6. In non-PSR of target final storage of 100 m^3, the diversion for zone 1 is 1.18 m^3, while in the other zones, there are significant values, which means that zone 1 does not give profit for cultivating any type of crop. In other zones, mainly, we are not allowing to cultivate tomato crops, which is the most profitable crop to cultivate in large areas. In the PSR scenario, the total diversion is the same in each zone because we apply PSR in the model to have the same quantity of released water be given to each zone. It is shown that as an optimization solution, the total diversion flow for each zone at the target final storage of 110 Hm^3 is 3.32 Hm^3 and increases dramatically to 12.1 Hm^3 at the target final storage of 75 Hm^3. In non-PSR scenarios, the diversions are different based on the most optimal choice. For example, at target final storage of 100 Hm^3, the total diversions flow for Zone 1 is 1.18 Hm^3, Zone 2 is 1.67 Hm^3, Zone 3 is 14.6 Hm^3, and Zone 4 is 5.77 Hm^3. In PSR scenarios, the maximum diversion of zone 1 is from starting in April until July, which is considered the maximum crop demand of the tomato crop. While the maximum diversions for zones 3 and 4 start in August and end in October to meet the demands of potato and cucumber crops, Zone 2 in PSR shows that the maximum diversions are similar to zone 1, while in non-PSR, they are similar to zone 3 or 4. The maximum release of the dam that is shown in PSR (Target final storage 75 Hm^3) is around 8.04 Hm^3 on October while the storage volume at that time is 7.73 Hm^3. However, PSR scenario gives each zone the same right of supplying water. The interesting point, the PSR shows can be helpful tool for cultivate crops that do not give the most profitable crops such as tomato.

The reservoir storage and releases for each month are shown in Figure 7. Clearly, reservoir releases have been reduced in the last three months (less than 2 Hm^3) in order to keep the storage volume at the target final storage level.

4. Conclusions and Recommendations

This work presents an optimization model for the operation of reservoirs that makes use of proportionate sharing rules in order to improve the effectiveness of irrigation systems. The storage reservoir water allocation model, often known as the LP problem, was utilised in order to distribute water across four distinct zones, both with and without taking PSR into account. Decision-makers and water authorities are able to better evaluate the early cost-benefit analysis of reservoir-irrigation systems when they make use of fundamental tools such as linear optimization models. These fundamental tools allow for a better evaluation of the early stages of the cost-benefit analysis. In order to optimize the net benefit for each zone, the suggested model leverages monthly reservoir operation and ultimate target storage to assist decide the optimal way to allocate water for crop production. In order to forecast the type and quantity of the farmed crop for each zone while maximising net crop revenue, the model takes into account the monthly water availability in the reservoir. The optimization model is constrained by the monthly PSR for each zone, the monthly irrigated farmlands for crops, the monthly water demand for crops, and the monthly water availability in the reservoir. We provide two strategies for handling scenarios: considering both non-PSR and PSR scenarios with the requirement that the water content in each zone be the same. We find that while building a model, adopting a PSR scenario is critical, especially when users or zones are given equal weight. Performance of the optimization model is evaluated using the Hali Dam in Saudi Arabia. According to the findings, the PSR had a considerable influence on the outcomes for each distinct zone, making it one of the most important factors to consider when formulating policy regarding reservoirs. In every scenario, the non-PSR scenarios among the zones had more profitable aims. According to the findings, the most optimal PSR scenario for the Hali Dam was provided at a target final storage of 100 Hm^3, which demonstrates a net profit that is comparable to that of the non-PSR scenario (2.6%). The optimization model that is proposed in this article is successful in achieving water allocation across all zones while simultaneously taking into consideration PSR and non-PSR scenarios for target final storage. The model that was established in this article, on the other hand, offers the greatest potential for financial gain in circumstances in which PSR is required for equitable distribution of water across all zones.

The suggestions that could be taken into account for future development are that the model has the capability of including a vast assortment of reservoirs, zones, and crops in its simulations. It may be altered by the incorporation of recharge zones and reservoir features such as in-filtrations and gate operations. It is also possible to incorporate into the model the costs associated with water drawn from a reservoir. In certain areas, crop production may be discontinued, and a reordering of priorities may be instituted. This kind of modelling not only enhances engineering practises and research methods but it also has the potential to be utilised in the future for the purpose of optimising the water that is drawn from enormous reservoirs.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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