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An Integrated Framework for Optimal Allocation of Land and Water Resources in an Agricultural Dominant Basin

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Abstract

The water deficit is one of the primary challenges faced by developing countries, stemming from several factors such as limited water resources, population growth, and climate change. Optimal allocation of water resources represents a comprehensive strategy for water resource management, acknowledging the intricate connections between water systems and their repercussions on the environment, society, and economy. It serves as a means of integrating diverse elements of development plans into a cohesive approach for land and water planning and management. In the current study, we undertook the optimal allocation of land and water resources across different sectors for the water years 2016-17, 2017-18, and 2018-19. The study area chosen was the Munneru basin, situated in the lower section of the Krishna River Basin in India. This basin is predominantly agricultural, covering 63.17% of the area, and was selected to validate the proposed framework concept. Within the study area, we identified six distinct water-demanding sectors and calculated their sectoral water demands at a basin level. To assess water availability in the basin, we conducted hydrological modeling employing the Soil and Water Assessment Tool (SWAT). Furthermore, we determined the crop water requirements for various crops using CROPWAT. For the optimal allocation of water resources, we applied the Non-dominated Sorting Genetic Algorithm-II (NSGA – II) optimization model, considering two different objectives that account for social and economic aspects. To identify superior solutions from the Pareto front, we employed the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Compromising Programming (CP) methods. Through this methodology, we achieved maximum utilization of water and land resources and maximized returns from the agricultural sector. Following the optimal allocation of land and water, we observed an average annual increase of 3.61% in agricultural sector returns. These outcomes demonstrated a substantial enhancement in the water use efficiency across all pertinent water use sectors. As a result, decision-makers may contemplate the implementation of this framework in large-scale regions, with potential expansion to encompass a national sustainable development strategy at the country level.

Keywords Basin · CROPWAT · IWRM · Munneru · NSGA-II · Optimization

Extended author information available on the last page of the article

1 Introduction

Water and land resources constitute pivotal elements in national planning and development, playing a dual role in both sustaining ecosystem equilibrium (Ren et al. 2021; Gong et al. 2020; Huang 2022; Kalhori et al. 2023; Chu et al. 2024) and serving as the backbone of socio-economic progress. The intricate dynamics of water and land systems have grown increasingly complex, driven by the twin challenges of water scarcity and climatic variability. This complexity necessitates a holistic research approach that integrates disciplines such as climatology, hydrology, and socioeconomics, especially when addressing basin-level issues (Shirmohammadi et al. 2020). The relentless expansion of the economy and population serves as a perennial catalyst for the ongoing tension between the supply and demand of water resources across various sectors. Consequently, there arises an imperative for the judicious and sustainable allocation of both land and water resources.

Before embarking on the optimal allocation of water resources, it is imperative to quantify water availability at the basin level. Hydrological models have emerged as indispensable tools for comprehending the intricacies of hydrological processes and assessing water availability within a basin. Among these models, the Soil and Water Assessment Tool (SWAT) has gained widespread adoption, facilitating a nuanced understanding of hydrological aspects and water balance components at the basin level (Yang et al. 2008; Guo et al. 2002; Devkota and Gyawali 2015; Zhang et al. 2015; Iskender and Sajikumar 2016; Samavati et al. 2023). To ascertain the water requirements of crops, various tools such as FASSET, CROPWAT 8.0, DSSAT, and WOFORST have been employed. The calculation of irrigation water hinges on factors including soil type, crop type, and prevailing weather conditions. Notably, CROPWAT has garnered widespread global usage among researchers for estimating both crop water needs and irrigational water requirements (Chowdhury et al. 2016; Boonwichai et al. 2018; Moseki et al. 2019; Elbeltagi et al. 2020; Gabr and Fattouh 2021).

Efficient water resource management hinges upon the pivotal role played by multi-objective optimization. Various algorithms, including Non-dominated Sorting Genetic Algorithm - II (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO), have been extensively employed in such applications to generate a representative set of Pareto optimal solutions. For instance, Hojjati et al. (2018) employed MOPSO and NSGA-II to tackle the critical issue of optimizing reservoir system operation within the context of water resource management in the Ozan River catchment in Iran. Their findings distinctly favored NSGA-II over MOPSO in optimizing reservoir operation, offering a more comprehensive coverage of the genuine Pareto front, thereby presenting alternative solutions. In another study, Chakraei et al. (2021) combined the Water Evaluation And Planning (WEAP) model with NSGA-II algorithms to develop a simulation-optimization model. This model provided a Pareto front for reservoir operations and water allocations while simultaneously minimizing environmental consequences. A distinct approach was taken by Zhang and Zhang (2021), who employed a swarm intelligence approach to enhance water resource utilization in the Yu-Shen Mining Area, Shaanxi Province, China. Their results provided valuable insights for regulating economic, social, and ecological water consumption, striking a balance between in-stream flow and net benefits.

Globally, the optimal allocation of water resources to various sectors, considering diverse objectives encompassing social, economic, and environmental aspects, has been pursued through integrated approaches employing various optimization algorithms (Hoekema and Sridhar 2013). Babamiri and Marofi (2021) explores the optimal operation of surface water resources in Iran's Dez river-basin using the NSGA-II algorithm and a WEAP-QUAL2K coupling model to address both water quality and quantity. In a different vein, Abdulbaki et al. (2017) introduced an innovative integer linear programming model designed to optimize resource treatment and allocation. This model takes into account various water sources, qualities, and demands. Meanwhile, Sridhar et al. (2021) developed an integrated modeling framework for the Mekong River basin, underscoring the importance of considering climate-water-human society feedback in systems modeling to address societal and ecological challenges. Furthermore, Al-Jawad et al. (2019) optimized investment policies and community welfare through an Optimum Integrated Water Resources Management (OP-IWRM) approach. Lastly, Tian et al. (2021) devised a cascade model chain to assess the impacts of projected climate change and human activities on water resources allocation. Their work offers valuable insights for the management of water resources and the enhancement of water availability and demand assessments on a regional or national scale. Muronda et al. (2021) assessed reservoir operations for effective water allocation under uncertainty using the WEAP model and the PSOA, with inflow and evaporation forecasts based on ARIMA and SARIMA models for Iran's AmirKabir dam. Results showed that the WEAP model was better at meeting water demands during low inflows, while PSOA performed better during high inflows, with both models exhibiting varying levels of uncertainty across different months.

In the Indian context, there is a notable scarcity of comprehensive studies focusing on Integrated Water Resources Management (IWRM) at the basin level. While some localized efforts have been made, such as the "Local IWRM" applied to the Ur river watershed in Madhya Pradesh's Tikamgarh district, which integrated land, water, and natural resources with considerations for local vulnerabilities and livelihoods (Goyal et al. 2020). Additionally, Jaiswal et al. (2014) utilized the MIKE BASIN as a decision support tool for effectively managing irrigation and water allocation in the Rangawan interstate reservoir, a shared resource between Madhya Pradesh and Uttar Pradesh, India. Their developed models were designed to be adaptable for real-time reservoir operation, irrigation planning, and the accommodation of variable conditions and efficiencies. However, despite these localized efforts, there remains a significant gap in knowledge regarding the establishment of a comprehensive framework for the optimal allocation of land and water resources in an integrated manner, particularly within an agriculturally dominant basin. In the current study, we aim to address this gap by developing a holistic framework.

Our study focuses on the calculation of water demand for various sectors on an annual scale, spanning three consecutive water years (2016-17, 2017-18, and 2018-19). To assess water availability, we employ the Soil and Water Assessment Tool (SWAT) model (Setti et al. 2020). Furthermore, for each district within the basin, we calculate the irrigation requirements specific to particular crops using the CROPWAT tool. Importantly, our study incorporates objective functions that take into account both social and economic factors. Specifically, we seek to maximize the utilization of water and land resources to optimize returns from the agricultural sector, presenting a multi-objective function tailored to our research objectives. To achieve these goals, we utilize the NSGA-II algorithm for the optimal allocation of water and land resources. Additionally, we employ multi-criteria decision-making techniques, such as Technique for Order of Preference by Similarity to Ideal

Solution (TOPSIS) and Compromising Programming (CP), to identify superior solutions among the Pareto optimal solutions generated by the NSGA-II algorithm. The primary objective of this study is to bridge the existing gap in knowledge by establishing a comprehensive framework for the integrated and optimal allocation of land and water resources within an agriculturally dominant basin, with a specific focus on maximizing returns from the agricultural sector while considering social and economic factors. The novelty of this work lies in the integrated framework it proposes for the optimal allocation of both land and water resources across multiple sectors, specifically in a predominantly agricultural region such as the Munneru Basin. By combining hydrological modeling (SWAT), crop water requirement assessment (CROPWAT), and multi-objective optimization (NSGA-II) with solution selection methods (TOPSIS and CP), the study achieves a unique, holistic approach to enhancing water use efficiency and maximizing returns in agriculture. This comprehensive strategy aligns sectoral water demands with social and economic objectives, offering potential scalability for national sustainable development planning, which sets it apart from other studies that might focus on isolated components. Thus, the application of advanced algorithms and decision-making techniques is expected to contribute valuable insights to the field of water resource management in India.

2 Study area and data preparation

The Munneru River is a tributary of the Krishna River comes under lower region of it. Its catchment area covers the districts of Khammam, Warangal Rural, Mahabubabad, Jangaon, Hanumakonda, Bhadradri Kothagudem (Telangana State) and NTR (Andhra Pradesh State). The Munneru River Basin encompasses a total drainage area of approximately 10,392 square kilometers. Its source can be traced to the Warangal district of Telangana, and it ultimately merges with the Krishna River near Vijayawada, Andhra Pradesh. Within the basin, the prevailing soil types consist predominantly of red soils, followed by black soils. The principal crops cultivated in this region include paddy, cotton, and maize. The ecosystem surrounding the Munneru River sustains a diverse range of aquatic and avian species. The river's waters serve various purposes, including irrigation, domestic consumption, industrial use, and the provision of drinking water, significantly benefiting the agricultural sector in the area. However, sustainable water management remains a critical challenge in the basin.

Figure 1 depicts the geographical location map of the Munneru River Basin, India, along with its sub-basins and major water bodies. Figure S1 provides an overview of the districts encompassed within the basin. For reference, Table 1 presents data on the sources of various crops grown in the basin, organized by mandal-wise distribution, and includes population datasets. Table S1 details the percentages of Land Use and Land Cover (LULC) categories across sub-basins within the region. These categories include Built-up Area, Agricultural Land, Plantations, Forest Area, Barren Land, and Waterbodies. Figure S2 offers a spatial representation of groundwater levels (measured in meters below ground level) within the basin for the years 2016, 2017, and 2018. This data is instrumental in assessing groundwater consumption for domestic and irrigation purposes, discerning variations in groundwater levels between the pre-monsoon and post-monsoon seasons. Furthermore, spatial maps depicting the principal crops grown during the Kharif and Rabi seasons in 2017-18 are illus-

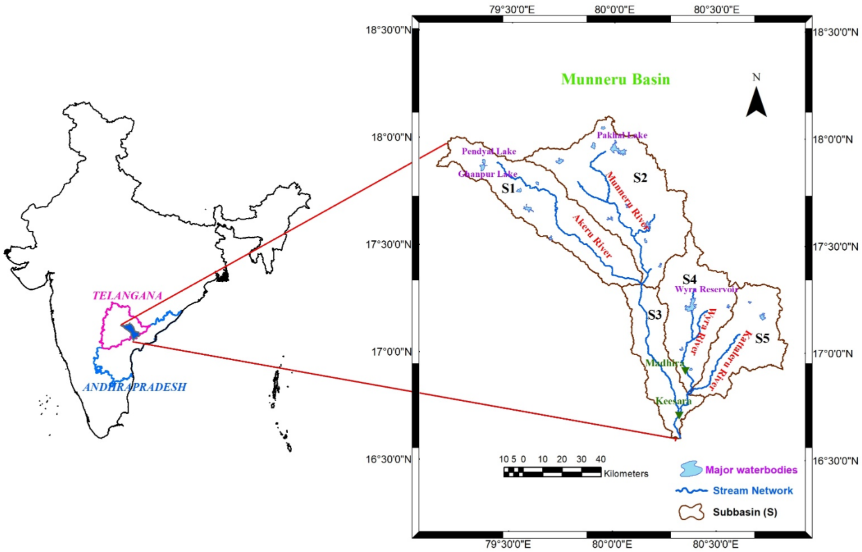

Fig. 1 Location map of the Munneru basin, India with sub-basins and major water bodies

Table 1 Different data sets used in the study area and their sources

Sl. No.	Data Set	Data Source
1	Agricultural Data in Telangana State	http://agri.telangana.gov.in/content.php?U=19
2	Crops data of Khammam District	https://data.telangana.gov.in/dataset/khammam-district-mandal-wise-crop-areas
3	Crops data of Mahabubabad District	https://data.telangana.gov.in/dataset/mahabubabad-district-mandal-wise-crop-areas
4	Khammam District data	https://khammam.telangana.gov.in/district-glance-2021/
5	Agricultural Data in Andhra Pradesh State	https://www.apagrisnet.gov.in/weekly_report.php
6	Krishna District data	https://krishna.ap.gov.in/
7	Observed precipitation and temperature datasets	https://www.imdpune.gov.in/Clim_Pred_LRF_New/Grided_Data_Download.html
8	Wind speed and Relative humidity	https://power.larc.nasa.gov/data-access-viewer/

trated in Figs. S3 and S4, respectively. These maps reveal that paddy cultivation dominates during the Kharif season, while pulses take precedence in the Rabi season.

The district-wise crop extents in hectares for the Munneru River Basin during the Kharif seasons of the water years 2016-17, 2017-18, and 2018-19 are presented in Table S2. This table includes both normal and actual crop extents for all the crops cultivated in the area. 'Normal area' represents the ten-year average extent for each respective crop, while 'actual area' reflects the extent for the specific year. Similarly, Table S3 provides district-wise crop extents in hectares for the Munneru River Basin during the Rabi seasons of the water years 2016-17, 2017-18, and 2018-19. The Kharif season in the study area witnesses the cultivation of crops such as Paddy, Maize, Pulses, Chillies, Cotton, Groundnut, Sugarcane, Vegetables, Turmeric, and Sesamum. In contrast, during the Rabi season, crops including Paddy, Maize, Pulses, Groundnut, Chillies, Jowar, Sesamum, Vegetables, and Sugarcane are grown.

2.1 Agricultural Seasons

There are essentially two main agricultural seasons in India due to the country's close ties to its meteorological conditions: Kharif and Rabi. Kharif begins with the arrival of the monsoon, typically in June, and lasts until September or October. The main crops grown during the Kharif season include rice, maize, millets (such as jowar and bajra), cotton, groundnut, soybean, and sugarcane. The Rabi period usually starts in October or November and continues until March or April, following the Kharif season. These crops are typically cultivated in cooler and relatively drier regions. Since they are sown after the monsoon has passed, they are not entirely dependent on rainfall. Important Rabi crops include wheat, barley, oats, mustard, chickpeas (gram), and peas. In addition to the Kharif and Rabi seasons, there is a third agricultural season known as the Zaid season. It takes place during the summer months, usually from March to June. Zaid crops are short-duration plants that can be grown in the summer with irrigation. Examples of Zaid crops include vegetables like cucumber, watermelon, bitter gourds, and muskmelon. The returns of crops in the Kharif and Rabi seasons in the study area are presented in Table S4. District-wise total area and population within the basin have been interpolated and are tabulated in Table S5.

3 Methodology

The methodology of the present study involves finding the water availability in the basin through hydrological modeling, determining sectoral water demands, including crop water requirements using CROPWAT, and optimizing the allocation of land and water resources. The overall methodology used in the present study is represented in Fig. 2.

3.1 Hydrological Modeling

For determining water availability within the basin, to allocate it among various sectors, and to simulate water balance components such as surface runoff, lateral flow, evapotranspiration, deep aquifer recharge, return flow, etc., we employed the calibrated and validated Soil and Water Assessment Tool (SWAT) model for the Munneru River Basin (Buri et al. 2022b,

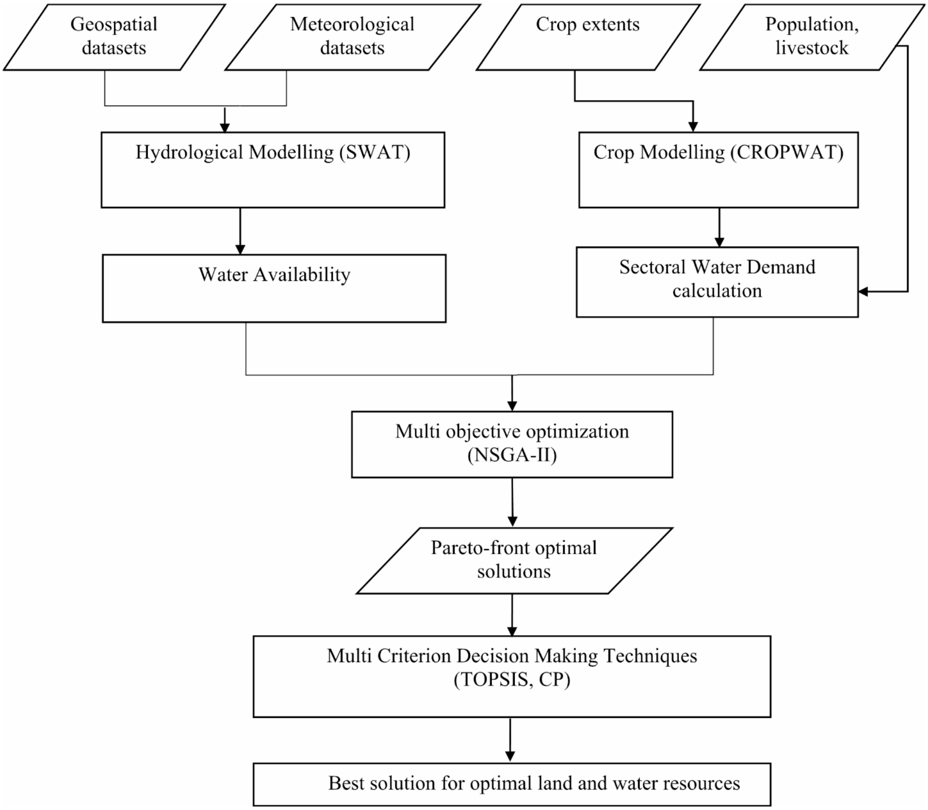

Fig. 2 Comprehensive framework for optimal allocation of land and water resources in an integrated approach for the study area

Loukika et al. 2022) in this study. Streamflow data collected from the Krishna Godavari Basin Organization (KGBO) at the basin outlet were utilized for calibration and validation. The R2 and NSE values were 0.85 and 0.88 during calibration and 0.82 and 0.83 during validation, respectively. Additionally, evapotranspiration losses from each Land Use and Land Cover (LULC) class were considered when calculating the available water in the basin for distribution among various sectors.

3.2 CROPWAT

CROPWAT is a decision support tool developed by the Land and Water Development Division of the Food and Agriculture Organization of the United Nations (FAO). Its purpose is to estimate the water requirements of different crops under varying climatic and soil conditions. Agricultural experts, researchers, and policymakers widely use this tool to make informed decisions related to irrigation planning, water management, and crop selection. CROPWAT 8.0 for Windows is a computer program designed for the calculation of crop water requirements (CWR) and irrigation requirements. This tool allows users to develop irrigation schedules for different management conditions and calculate scheme water supply for various crop patterns. Moreover, it can be employed to evaluate farmers' irrigation practices and estimate crop performance under both rainfed and irrigated conditions (https://www.fao.org/land-water/databases-and-software/cropwat/en/).

CROPWAT utilizes the Penman-Monteith method, which is considered one of the most accurate methods for calculating potential evapotranspiration (ET_0). Evapotranspiration is the combined loss of water from the soil through evaporation and transpiration by plants. By estimating ET_0, CROPWAT helps in determining the irrigation water needs of various crops and guides users on when and how much water should be applied to achieve optimal crop growth. The model has five input data modules, namely climate/ET_0, Rain, Crop data Soil data and Crop Pattern. Maximum and Minimum temperature, humidity, wind speed, sunshine hours and solar radiation, to calculate reference evapotranspiration (ET_0) for a specific location were the meteorological inputs for the seven districts present in the study area. The monthly rainfall data for each district were given and effective rainfall calculated by USDA soil conservation formula. Crop parameters provides a database of specific parameters of different crops like crop description, planting date, rooting depth, crop factor, critical depletion factor, etc. for each crop. The soil parameters like soil moisture availability, maximum rooting depth, maximum infiltration rate, yield response factor, etc., for soils like red loamy, black clayey were given based on the district. Using selected crop and climate data, CROPWAT determines crop water requirement (CWR) and irrigation requirement (IR), considering factors such as crop stage, effective rainfall, and irrigation efficiency.

By providing all the input data to the tool, we were able to determine the Crop Water Requirement (CWR) and Irrigation Requirement (IR) necessary for different crops in specific areas or districts. In our study area, which comprises seven districts, we considered crops from two seasons, Kharif and Rabi. In the 2017-18 season, there were 10 different crops in Kharif and 9 in Rabi. Information about the areas where these crops are grown in the districts was collected from the agricultural department websites of both Andhra Pradesh and Telangana state governments. We gathered data on both normal areas and the actual areas cultivated in a particular year. Additionally, we collected data on the returns in Rupees per hectare for different crops in the two seasons. Population datasets, as per the census, were gathered on a district-wise basis. This data collection process was repeated for the remaining water years.

3.3 NSGA (Genetic Algorithm for Non-Dominant Sorting-II)

The genetic algorithm, as a global optimisation probability technique, does not have too many mathematical prerequisites for solving optimization issues (Feng et al. 2013). This concept can be used to solve water resource optimisation models (Hu et al. 2013; Monadjemi 1994). Srinivas and Deb (1994) created the popular NSGA-II algorithm in 2002 to address non-convex and non-smooth single and multi-objective optimisation problems. In comparison to NSGA, NSGA-II features an enhanced mating mechanism based on crowding distance and executes constraints without penalty functions. As before, the population is initialised. At first, all non-dominated individuals are assigned a level of zero. The recently non-dominant solutions are assigned level one during population elimination. This process is repeated until all solutions have been assigned a non-domination level. The parents are chosen using a binary tournament system based on their lower rank and larger crowding distance. The next stage is to generate offspring from the selected population using crossover and mutation operators, as detailed below. Finally, the current offspring and population are sorted once more based on non-domination and only the best individuals with the population size (P). The parameters for NSGA-II include population size, number of offspring generated in each generation, sampling procedure for generating initial solution in the population, crossover probability, and mutation rate. In this study, the population size of 400, number of offsprings to be 100, crossover probability as 90%, distribution index as 20 and distribution operator as 20.

3.4 Multi Objective Optimization

Multi Objective Optimization consists of the following two different objectives:

- Maximize water distribution between water demanding sectors based on availability of water (Z_1 - Social).
- Maximize returns from Agriculture sector (Z_2 - Economic).

The following equations represents the objective functions and the constraints used for the multi-objective optimization problem. The objective function (Z_1) for maximizing the water distribution between water demanding sectors based on the availability of water is shown in the following equation:

$$Max\ Z_1 = \sum_{k=1}^{6} Q^k \tag{1}$$

Constrained to:

$$Q^k = Q^{Kh} + Q^R + Q^D + Q^L + Q^I + Q^E \tag{2}$$

$$0.9 \times KhD \leq Q^{Kh} \leq KhD \tag{3}$$

$$0.9 \times RD \leq Q^R \leq RD \tag{4}$$

$$0.9 \times DD \leq Q^D \leq DD \tag{5}$$

$$0.9 \times LD \leq Q^L \leq LD \tag{6}$$

$$0.9 \times ID \leq Q^I \leq ID \tag{7}$$

$$0.8 \times ED \leq Q^E \leq ED \tag{8}$$

$$Q^{kh} + +Q^R + Q^D + Q^L + Q^I + Q^E \leq WA \tag{9}$$

Where, Q^k indicates total water allocated for all the sectors optimally, WA indicates total water availability in the sub-basin. Q indicates optimal allocated water and D indicates demand of each sector respectively. $Kh,\ R,\ D,\ L,\ I\ and\ E$ represents kharif, rabi, domestic, livestock, industrial and ecological demands, respectively. The decision variable would be the amount of water allocated to each sector.

The objective function (Z_2) for maximizing returns from agriculture sector is shown in the following equations:

$$Max\ Z_2 = \sum{}_{j=1}^{m} \sum{}_{i=1}^{n} B_{ij} \tag{10}$$

$$B_{ij} = [R_{ij}] * A_{ij} \tag{11}$$

Where, *B* indicates returns, *i* indicates crop, *j* indicates season, *n* indicates number of crops, *m* indicates number of seasons, R indicates net returns in thousands per hectare and *A* indicates extent of crop area in square Kilometres. In the second objective, two methods were considered for maximizing the returns in Kharif and Rabi seasons i.e., total area under irrigation to be utilized and total water under irrigation sector has to be utilized. A indicates area of the crop and the suffix 1 and 2 indicates Kharif and Rabi seasons, respectively and the other suffixes *r*, *m*, *p*, *ch*, *gn*, *s*, *v se*, *j* indicate the crops grown in the study area i.e. rice, maize, pulses, chillies, groundnut, sugarcane, vegetables, turmeric, cotton, sesamum and jowar, respectively. In other words, this objective function focuses on maximizing the economic returns from agricultural crops. The returns are typically a function of water allocation, crop type, and other agricultural inputs. The relationship between water uses and crop returns is based on agricultural productivity functions, which correlate water usage to yield and income.

Kharif :

$$\begin{aligned} &65.05 * A_{r1} + 82.65 * A_{m1} + 23.62 * A_{p1} + 424.62 * A_{ch1} + 56.34 * A_{c1} \\ &\quad +83.72 * A_{gn1} + 121.84 * A_{v1} + 130.73 \ * A_{s1} + \ 411.1 \ * A_{t1} \\ &\quad + 30.16 * A_{se1} \end{aligned} \tag{12}$$

Rabi :

$$\begin{aligned} &62.95 * A_{r2} + 73.82 * A_{m2} + 23.1 * A_{p2} + 73.92 * A_{gn2} + 116.76 * A_{v2} \\ &\quad +460 * A_{ch2} + 29.87 * A_{se2} + 22.61\ A_{j2} + 125.04 \\ &\quad *A_{s2} \end{aligned} \tag{13}$$

Constrained to :

$$\begin{aligned} &0.163 * A_{r1} + 0.063 * A_{m1} + 0.009 * A_{p1} + 0.038 * A_{ch1} + 0.255 * A_{c1} \\ &\quad +0.033 * A_{gn1} + 0.494 \ * A_{s1} + \ 0.027 \ * A_{t1} + \ 0.017 \\ &\quad *A_{se1} \end{aligned} \tag{14}$$

$$\begin{aligned} &0.834 * A_{r2} + 0.442 * A_{m2} + 0.235 * A_{p2} + 0.328 * A_{gn2} + 0.158 * A_{v2} \\ &\quad +0.191 * A_{ch2} + 0.202 * A_{se2} + 0.115\ A_{j2} + 0.148 \\ &\quad *A_{s2} \end{aligned} \tag{15}$$

In NSGA- II algorithm, the maximization functions need to be written as a minimization function. For that the objective function (Z_1) shown in Eq. 3 and the objective function (Z_2) is shown in Eq. 4.

$$Min\ Z_1 = \left(\frac{1}{\sum_{k=1}^{6} Q^k} \right) \tag{16}$$

$$Min\ Z_2 = \left(\frac{1}{\sum_{j=1}^{m} \sum_{i=1}^{n} B_{ij}} \right) \tag{17}$$

3.5 Optimal Land and Water Allocation

The water-demanding sectors identified in the basin were domestic, livestock, industrial, ecological, CWR of kharif and rabi seasons. The surface runoff, deep percolation and evapotranspiration losses were collected from calibrated SWAT model for the basin. In agricultural systems, evapotranspiration, soil moisture (Sridhar et al. 2006) and water allocation are tightly coupled. Subsequently, the total water available in the basin was determined for optimal allocation of water to meet the crop water demand as well as different sectors and optimal areas to maximize returns by using a multi-objective optimization model.

3.6 Best Solution for land and Water Allocation

After obtaining a set of solutions in the form of a pareto front, the selection of the best solutions among them is accomplished using stablished multi-criterion decision-making techniques like CP and TOPSIS (Buri et al. 2022a).

4 Results and Discussions

The water availability in the basin was calculated for the water years 2016-17, 2017-18, 2018-19, excluding losses such as discharge at outlet, dep aquifer recharge and evapotranspiration. Water demand for each sector, including irrigation, domestic, livestock, ecological, industrial was calculated. The runoff simulation diagram using the SWAT model was represented in Fig. S5. From the CROPWAT tool, we obtained data on evapotranspiration (ET) and irrigation requirement (IR) for crops in the Munneru basin during the Kharif and Rabi seasons for the years 2016-17, 2017-18, and 2018-19, as presented in Tables S6 and S7, respectively. It is worth noting that sugarcane requires a large amount of water compared to other crops, and paddy cultivation demands more water during the rabi season in comparison to the kharif season.

For the water year 2017-18, the total precipitation received was 10,610 Mm^3. Losses due to deep aquifer recharge, evapotranspiration, and discharge at the outlet amounted to 8779.8 Mm^3. The total water used by all sectors, considering both surface and groundwater sources, was calculated as 2225 Mm^3. Groundwater pumped from all sources was estimated to be 394.73 Mm^3. Similarly, for the years 2016-17 and 2018-19, the water used was calculated as 2740 Mm^3 and 3320 Mm^3, respectively, with groundwater pumping estimated at 181.6 Mm^3 and 96.79 Mm^3, respectively. It should be noted that in the year 2017-18, the rainfall received was less compared to other years, leading to higher groundwater usage. Lower rainfall in 2017-18 led to greater reliance on groundwater for irrigation. This finding aligns with hydrological behaviour in water-scarce basins where farmers resort to groundwater pumping when surface water availability decreases. The results from CROPWAT provided calculated crop water requirement (CWR) and irrigation requirement (IR) data for each crop in all districts within the basin. Both normal and actual areas were considered to establish the upper and lower bounds for each individual crop area. Similarly, Moseki et al. (2019) suggested that Jatropha had an evapotranspiration rate (ET_c) of 955.4 mm per growing season and an irrigation requirement of 665.4 mm suggesting that it needed supplementary irrigation.

The results for the water year 2017-18 are explained as follows. Through the multi-objective optimization process, 11 solutions were generated in the Pareto front, consisting of optimal crop areas for various crops in both Kharif and Rabi seasons in that particular year, as well as the optimal allocation of water to the mentioned sectors. Out of the 11 Pareto optimal solutions obtained from the NSGA-II algorithm, Multi-Criteria Decision-Making (MCDM) techniques such as CP and TOPSIS were applied to select the best solution from each technique. The optimal crop area extents in square kilometres for kharif and rabi seasons using CP and TOPSIS techniques are presented in Table S8. Optimal water allocation to the sectors (in million cubic meters) using CP and TOPSIS techniques is shown in Table 2.

After the optimal allocation of water and area extents to the kharif and rabi seasons, the total revenue generated was Rs. 6149 crores using the TOPIS technique, and Rs. 6042 crores using CP technique. The maximum water utilization was also observed with the TOPSIS technique. By comparing the solutions, it becomes evident that the TOPSIS technique achieved both the maximum water utilization and the highest returns in the agricultural sector. The visualization of the Pareto front and the best solutions from both methods is presented in Fig. S6.

The actual returns generated from the agricultural sector for the water year 2017-18 were Rs. 5987 Crores, with a total available water volume in the basin of 2225 Mm^3. However, with the best solutions obtained from TOPSIS, the returns increased to Rs. 6005 Crores, while still utilizing a maximum of 2225 Mm^3 of water. Naghdi et al. (2021) addressed the joint allocation of surface and groundwater among various sectors and the optimal water supply of $16.84\times10\hat{}6$ m^3 and a groundwater table reduction of 0.63 m, improving the current situation by 30% in Najaf-Abad sub-basin in Iran. It should be noted that there was an increase in crop extents for both Kharif and Rabi seasons compared to the actual extents in that particular year, indicating the maximum utilization of land was also achieved. Similarly, the actual returns for the year 2016-17 were Rs. 7037 crores, whereas the optimal

Table 2 Optimal water allocation to the sectors (in million cubic meters) by CP and TOPSIS techniques for the year 2017-18

Sector	TOPSIS	CP
Kharif	926.20	926.20
Rabi	859.76	859.99
Domestic	184.88	184.88
Livestock	68.17	68.25
Industrial	90.64	90.64
Ecological	95.35	95.03
Total Water Allotted (Mm3)	2225.00	2224.80

returns were Rs. 7469 crores. In the year 2018-19, the actual returns generated were 5554 crores, while the optimal returns reached Rs. 5799 Crores for maximum utilization. The actual and optimal extents of each crop in Kharif and Rabi seasons in square Kilometers for 2017-18 are shown in Fig. S7. Significant changes in crop allocation after optimization were observed, with notable shifts in paddy and vegetables during Kharif, and maize and pulses during Rabi.

The actual and optimal water allocation for different sectors in million cubic meters for the years 2016-17, 2017-18 and 2018-19 are represented in Fig. 3. It was observed that more water allocated to kharif and rabi seasons than the actual usage in the 2017-18 year. However, this allocation compromised the water allocation for domestic purposes.

5 Conclusions

The Munneru Basin in India faces a significant water deficit, primarily due to factors such as limited water resources, population growth, and the impacts of climate change. To address this challenge, the optimal allocation of water resources necessitates a comprehensive and well-thought-out strategy for effective water resource management. This basin is predominantly devoted to agriculture, encompassing a substantial 63.17% of its total area. Our approach involved the implementation of hydrological and crop water requirement model-

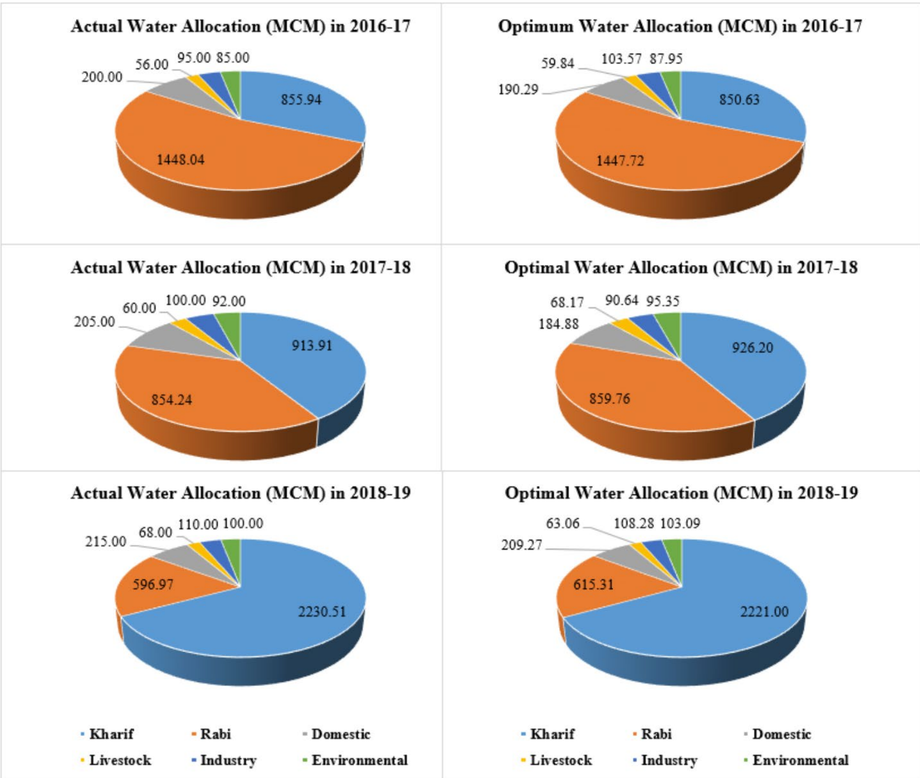

Fig. 3 The actual and optimal water allocations for different sectors in million cubic meters

ing, utilizing the Soil and Water Assessment Tool (SWAT) and CROPWAT, respectively. In our pursuit of optimizing water resource allocation, we employed the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) optimization model. This model considers two distinct objectives, taking into account both social and economic aspects.

Data acquisition played a pivotal role in establishing a comprehensive framework for the optimal allocation of land and water resources in an integrated manner. This involved gathering data on crop extents, population datasets, livestock information, and industrial water demand from reliable sources. With our objectives in mind, we successfully achieved the maximization of water utilization across all sectors, adhering to constraints defined by lower and upper bounds for the three respective water years. Furthermore, by optimizing the allocation of land to different crops, we observed a significant increase in returns – Rs. 432 Crores, Rs. 18 Crores, and Rs. 245 Crores for the years 2016-17, 2017-18, and 2018-19, respectively, following the optimal allocation of both water and land resources.

While our study primarily focused on two objective functions related to social and economic elements on a seasonal basis, it's important to note that additional objective functions could be incorporated. These could encompass factors such as government regulations, the conjunctive use of ground and surface water, and considerations related to reliability. Our study was conducted at both seasonal and annual scales, but potential improvements could be achieved by increasing the temporal resolution, possibly considering monthly assessments. As this approach represents a crucial tool for sustainable development at the basin level, it provides a solid foundation for further extension to other basins in India. The research results presented in this paper offer valuable insights for sustaining water resource management, particularly in agriculturally dominant basins. Given that agriculture serves as a primary source of revenue in many developing countries, the study of optimal land and water resource allocation remains a critical endeavour. Furthermore, this work offers the potential for future research into the impacts of climate change and land use/land cover changes on water allocation over various timeframes, without compromising crop yields. In conclusion, the framework developed in this study quantitatively illustrates the optimal allocation of water and land resources within a basin. These results may serve as valuable references for guiding water resource allocation decisions and enhancing our understanding of water availability and demand assessments at the basin scale.

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Declarations

Ethical Approval All authors accept all ethical approvals.

Consent to Participate The authors agree to participate in any survey or feedback task.

Consent to Publish All authors agree to provide manuscript for publication.

Conflict of Interest The authors declare no conflict of interest.

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