

Final Report
(PDS NO: SP-56/2021-2022/NIH(CIHRG))

**Integrated Reservoir Operation Studies for Mahanadi Reservoir
Project Complex in Chhattisgarh**



**National Hydrology Project
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Development and Ganga
Rejuvenation,
Ministry of Jal Shakti, New Delhi**



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PREFACE

Mahanadi Reservoir Project (MRP) is a multipurpose project situated in the state of Chhattisgarh, India for supplying water for irrigation, power generation, domestic, and industrial uses. Under the MRP project, four reservoirs including Ravi Shankar Sagar (RS Sagar), Maramsilli, and Dudhawa reservoirs were built on the Mahanadi River and the Sondur reservoir on the Pairi basin comes under the Mahanadi River Basin. The system has a Rudri barrage from where water is transferred from RS Sagar after power generation is transferred to the Mahanadi main canal for irrigation and domestic purposes. The Mahanadi feeder canal (MFC) was constructed to supply water for irrigation, domestic supply to Raipur City, and Industrial water to Bhilai Steel Plant (BSP). The Dudhawa and Sondhur reservoirs have their commands besides transferring extra water to the RS Sagar dam, however, the Murumsilli reservoir transfers its stored water to RS Sagar whenever required. This complex system is managed by the Water Resources Department of the Chhattisgarh government and is a vital contributor to the economic growth and development of the region. The study aims to develop a reservoir operation plan and examine this system's performance, status, challenges, and potential under present and future climatic scenarios. The water storage infrastructure of Chhattisgarh has faced various challenges due to climate change, increasing water demand, and poor water management practices. The WRD, Govt of CG, and the NIH Roorkee have jointly studied the development reservoir operation plan for efficient management of resources in the MRP system, which is the backbone for social, industrial, and economic development of the Chhattisgarh state.

The Special Study (SP) titled “Integrated Reservoir Operation Studies for Mahanadi Reservoir Project Complex in Chhattisgarh (SP-56/2021-2022)” has been awarded to NIH, Regional Center Bhopal, and WRD, Govt. of Chhattisgarh under NHP with the objectives to estimate the revised capacity & revised demand with future projection, development of a long-term hydrological series using balance approach, development of a model for the integrated

operation of the reservoirs, and optimization of reservoir operation for maximization of benefits from MRP complex. Adopting a demand-based reservoir operation approach can increase water use efficiency and maximize revenue from hydroelectric power. An integrated reservoir operation model has been developed in NIH ReSyp software for the Mahanadi Reservoir Project to revise reservoir rule levels to optimally utilize the resources and minimizing the deficit of water for different users. The final report contains the various aspects of hydrological interaction in the catchments and commands, review of literature, GIS database, existing database and analysis, field data collection and survey results, water balancing, hydrological modeling, assessment of climate change impact on demand and supplies, development of rule curves for present and under climate change scenarios, etc. The developed rule curves under the study will be helpful to Water Resource Department, Govt of CG for planning reservoir operation and maintaining releases under complex water transfer scenarios in MRP.

The report was prepared by Dr. R.K. Jaiswal, Scientist-F as P.I. and Dr. Ravi Galkate, Scientist-F and Mrs. Shashi Indwar, Scientist D as Co-PIs, Sri Shivendra Jaiswal, Sri Shohrat Ali & Ms Varnika as JRF from Regional Centre Bhopal of NIH Roorkee, Dr. A. K. Lohani, Scientist-G, Dr. M.K Goel, Scientist- G and Dr. Vishal Singh, Scientist-C, Mr. Sumit Saini, Research Scientist & Dr. Deepti Rani, RA as Co-PIs from National Institute of Hydrology, Roorkee, Mr. Jayant Bisen, Deputy Director (WRD Chhattisgarh) as PI, and Mr. Ananya Gupta, Assistant Engineer & Mr. Prince Awadhiya, Sub Engineer Co-PI's From WRD Chhattisgarh, and Dr. Surnedra Chandina, Asstt. Professor (Co-PI) From IGKV, Raipur (Collaborative Institute). This report is the results of the research work conducted by all organizations under this PDS.

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Integrated Reservoir Operation Studies for Mahanadi Reservoir Project Complex in Chhattisgarh

(No: SP-56/2021-2022/NIH(CIHR))

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Efficient reservoir operation is of utmost importance for the timely and prompt supply of water for different uses. Various demands on reservoirs have conflicts of interest in time and space, due to which managers must keep balance in supplies and upkeep reservoir storages in such a way that most of the demand can be met. The operation of multipurpose reservoirs with multi-reservoir systems becomes more complex due to variations in inflows, demands, priorities, and operational difficulties. The Mahanadi River is one of the major Rivers in Peninsular India that caters to irrigation, domestic, industrial, and recreational demands in the eastern states of Chhattisgarh Odisha. Presently, the reservoirs of the MRP complex are being operated without any scientific assessed studies, and this special study was designed to develop individual operation curves for different reservoirs for integrated operation for present and future scenarios. In the present study, Inflow was estimated for all reservoirs using a water balancing-based Excel sheet including Reservoir levels, Spillway release, water spread area, evapotranspiration, inflow-outflow, and change in storage. From the analysis, it has been observed that percentage errors in water balance varied in the range of -6.38 to -7.21 % for the Sondhur reservoir, -6.09 to 6.40 %, for Dudhawa reservoir for Murumsilli reservoir -1.98 to 0.425 and -7.72 to 8.36 % for Ravishankar Sagar reservoir. The results of water balance for reservoirs indicated the average annual inflow may be 272.58 ± 188.629 MCM from Sondhur, 522.52 ± 214.95 MCM from Dudhawa, 216.74 ± 112.65 MCM from Murumsilli catchment, and 2995.74 ± 1980.76 from Ravishankar Sagar reservoir. The estimated inflow from the water balance of these reservoirs was used in	

the MIKE-11 NAM model as input discharge data. The MIKE-11NAM for Sondhur, Dudhawa, and Murumsilli reservoir catchment up to the dam site was set up and the model was calibrated and validated for the period from 2003 to 20015 and validated from 2016 to 2020 for RS Sagar from 1991 to 2011 for calibration and 2012 to 2020 for validation. The coefficient of determination (R^2) found during calibration and validation for daily modeling was 0.73, 0.76, 0.70, and 0.74 for Sondhur, Dudhawa, Murumsilli, and Ravishankar Sagar respectively, and 0.73, 0.69, 0.69 and 0.83 respectively which was a good match between observed and simulated runoff. The revised water spreads computed using the GEE application was further used to calculate the revised volume and, in turn, the revised cumulative capacities at different levels. The analysis indicated that RS Sagar had lost 17.65% of its dead storage (118.26 MCM from 143.00 MCM), and 9.25% of its gross storage (85.26 MCM from 910.52 MCM) in 42 years (1978 to 2020) due to sedimentation. Similarly, the gross capacity of Murumsilli, Sondhur, and Dudhawa reservoirs had decreased by 10.33%, 13.12%, and 12.37% respectively due to sedimentation from catchments. These results were found to be comparable with the bathymetric survey results of three reservoirs. The study also predicts significant changes in land use from 2005 to 2025 and 2050, with some land uses experiencing increases while others are decreasing areas. Urbanization and infrastructure development are rapidly taking place in the region, leading to both positive and negative impacts on the environment and communities. While there is a slight increase in barren land and water area, the decrease in forest area is a cause for concern. It is crucial to monitor these changes closely and take appropriate measures to promote sustainable land use practices. This may include reforestation and afforestation programs, promoting agroforestry, and implementing sustainable urban planning strategies to ensure the long-term well-being of both the environment and the communities living in the region.

For reservoir operation, Rule curves have been derived for all reservoirs using NIH_ReSyP. The domestic supply is considered as priority demand, environmental flow is the second priority, irrigation is third and hydropower is considered as fourth priority demand. Integrated operation of the MRP system was carried out using NIH_ReSyP with Standard Operating Policy (SLOP) and Rule Curve. Month-wise reliability suggests that Sondhur, Dudhawa, and Murumsilli reservoirs maintain perfect reliability for each month for all relevant demands using both SLOP and rule curves. A significant improvement in

meeting irrigation demands under rule curves compared to SLOP, especially during non-monsoon months. The reliability analysis suggests that irrigation supply can be considerably enhanced using rule curves, making them a more promising option for agricultural needs in drier periods. The use of rule curves for the integrated operation of the Ravishankar Sagar reservoir generally leads to better outcomes for minimum flow, domestic, industrial, and irrigation demands, particularly in non-monsoon months. The improvement comes at the expense of reduced reliability in meeting power demands during the same period, although power reliability improves during the monsoon months. The results suggest that while rule curves provide a more balanced and flexible approach overall, specific adjustments might be needed to better manage power generation, especially during non-monsoon months.

The study examines the best GCM for future climate projection over the study area, the performance of 13 Global Climate Models (GCMs) of CMIP6 during 1991-2014 was evaluated against the observed dataset to identify the best climate model to reproduce rainfall and temperature time series. The BCC-CSM2-MR was selected as the model for projecting future rainfall and temperature. The future rainfall and temperature of BCC-SCM2-MR were applied over the MRP complex to identify the impact of climate change on rainfall, temperature, inflow, and irrigation water requirements under SSP scenarios.

Maximum and minimum temperatures are showing an increasing trend under all scenarios of SSPs over all the catchments. Rainfall is increasing in all scenarios of SSPs scenario over the Sondhur, Dudhawa, and Murumsilli catchments, and In Ravishankar Sagar catchment rainfall increasing in SSP126 and SSP245 and decreasing in SSP370 and SSP585 respectively. Inflow is decreasing in all of the SSPs scenarios over the Ravishankar and Sondhur catchments. Murumsilli and Dudhawa are showing a decreasing trend in SSP126, SSP370, and SSP585 and increasing in SSP245. The future projection indicated an increase in average irrigation water requirement by +20.2%, +26.9%, +26.6% & +26.7% in different SSP scenarios. The domestic water supply is projected to increase by 1.92 times in the future. The computed inflow, Irrigation water requirement, domestic water supply, projected rainfall, and projected evapotranspiration have been used in NIH_ReSyP to develop future rule curves for all reservoirs under SSP126, SSP245, and SSP585 scenarios. The analysis of the three climate scenarios (SSP126, SSP245 & SSP585) reveals a decline in reservoir performance as climate change intensifies.

Murumsilli and Dudhawa remain highly reliable across all scenarios. Sondhur and Ravishankar show increasing vulnerability, particularly in meeting full irrigation and power demands. The worsening performance under SSP585 highlights the growing challenges that reservoirs will face in maintaining operational efficiency, especially under severe climate impacts.

The findings of the study have significant implications for various applications, including water resource planning, reservoir operation, and irrigation scheduling. The future projections based on the selected GCMs and SSP data can be utilized for informed decision-making and improved utilization of available resources. The results can be used to optimally operate the reservoirs under present and future climate conditions.

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1.1 General

The utilization of water resources efficiently and sustainably is crucial for addressing the growing demands of agriculture, urbanization, and industrialization. In this context, reservoir complexes play a pivotal role in water management, especially in the realms of irrigation planning and industrial demand management. A reservoir complex comprises a network of interconnected reservoirs, dams, and associated infrastructure designed to store and regulate water flow. This intricate system serves as a lifeline for ensuring water availability for agricultural activities, meeting the water needs of burgeoning urban populations, and sustaining industrial processes.

Reservoir complexes are indispensable components of comprehensive water resource management strategies, providing a reservoir of benefits that extend beyond mere storage. They facilitate precise control over water release and distribution, enabling optimized irrigation planning for agricultural lands. By harnessing the potential of reservoir complexes, planners can implement efficient water allocation systems, mitigating the impact of water scarcity and enhancing crop yields. Moreover, these complexes play a crucial role in meeting the escalating industrial demands for water, ensuring a reliable supply to support manufacturing processes, energy generation, and other industrial activities.

The complexities of reservoir systems necessitate a holistic approach to their planning, operation, and management. With the integration of advanced technologies such as remote sensing, data analytics, and modeling tools, stakeholders can achieve enhanced precision in assessing water availability, predicting demand patterns, and optimizing reservoir operations. This integration is particularly pertinent in the face of climate variability, where reservoir complexes become pivotal in adapting to changing precipitation patterns and mitigating the impacts of droughts or floods.

In this multifaceted landscape, the effective management of reservoir complexes requires a balance between meeting the needs of agriculture, urban areas, and industries while also safeguarding the ecological integrity of the surrounding ecosystems. This necessitates the formulation and implementation of robust policies, collaborative decision-making

frameworks, and innovative water management strategies that account for the diverse and often competing interests of various stakeholders.

This introduction sets the stage for a comprehensive exploration of reservoir complex systems, delving into their critical role in irrigation planning and industrial demand management. As we navigate through the intricacies of these systems, we will uncover the challenges, opportunities, and innovative solutions that contribute to sustainable water resource management in the face of a rapidly changing world.

1.2 Water Availability in India

India exhibits considerable geographical diversity, ranging from the arid regions of Rajasthan to the high rainfall areas of the Western Ghats and north-eastern states. This diversity leads to uneven spatial distribution of water resources, impacting water availability across different regions. Rivers such as the Ganges, Brahmaputra, and Indus contribute significantly to surface water availability. Himalayan glaciers, acting as natural reservoirs, further augment River flows during the dry season. Groundwater plays a crucial role in augmenting water availability, especially in regions with erratic rainfall. Over-extraction and declining groundwater levels pose a significant challenge, requiring sustainable management practices. The Indian subcontinent relies heavily on the monsoon for replenishing water resources. Variability in monsoon patterns leads to fluctuations in water availability, impacting both agriculture and water supply. Dams and reservoirs contribute to water storage and regulation, crucial for managing water availability throughout the year. Issues such as sedimentation and siltation affect the efficiency of these storage structures. Changing climate patterns, including altered precipitation and temperature, impact water availability. Increased frequency of extreme weather events, such as floods and droughts, adds complexity to water resource management. While focusing on water availability, it is imperative to consider water quality issues, including contamination from industrial discharge and agricultural runoff. Ensuring both quantity and quality is crucial for sustainable water management. Agriculture is a major consumer of water, and efficient irrigation practices are essential to optimize water use. Adopting modern irrigation technologies and promoting water-efficient crops can contribute to sustainable agriculture. Rapid urbanization leads to increased water demand for domestic and industrial purposes. Integrated urban water management and wastewater treatment are critical to ensuring adequate water availability in urban areas. Disputes over shared River basins among states highlight the complex socio-political dimension of water

availability. Effective inter-state water-sharing agreements and River basin management are essential for equitable water distribution. The interdependence between water and energy sectors underscores the importance of considering water availability in energy planning and vice versa. Hydropower generation, for instance, is directly linked to water availability in Rivers.

Understanding water availability in India requires a comprehensive assessment of various factors, including geographical features, climate patterns, human activities, and sustainable management practices. Addressing the complex demand-supply scenarios of water in India requires a holistic approach that combines technological innovations, policy reforms, and community engagement. Sustainable water management practices, coupled with awareness and conservation efforts, are key to ensuring a resilient and balanced water future for the country.

1.3 Water Availability in Chhattisgarh

Chhattisgarh is blessed with a network of Rivers, the prominent one being the Mahanadi. These Rivers contribute significantly to surface water availability. The state's geographical layout, featuring multiple River basins, enhances its resilience to water scarcity. The construction of reservoirs and dams across key Rivers is a strategic move to harness and regulate water flow. Bhakhra Reservoir, Ravi Shankar Reservoir, and other dam projects play a pivotal role in ensuring water availability for various purposes. The state's agrarian economy heavily relies on water for irrigation. Both surface water from Rivers and stored water in reservoirs contribute to agricultural needs. Efficient water management practices are crucial to sustain the agricultural sector. Chhattisgarh's aquifers contribute to the availability of groundwater, serving as an essential resource for irrigation and domestic use. Monitoring groundwater levels and promoting sustainable extraction practices are vital for long-term availability. The state experiences a tropical climate with distinct wet and dry seasons. The monsoon, from June to September, plays a pivotal role in replenishing water sources, impacting agriculture and overall water availability. Rapid urbanization in cities like Raipur and Bilaspur has increased the demand for water in urban areas. Balancing urban water needs with sustainability and efficient supply infrastructure is a key challenge. Chhattisgarh's industrial hubs, especially in sectors like steel and power, contribute to heightened water demand. Sustainable water management practices are essential to support industrial growth without compromising water availability for other sectors. Changing climate patterns,

including temperature variations and altered precipitation, pose challenges to water availability. Adapting to these changes through resilient water management strategies is imperative. The health of Riverine ecosystems, including wetlands and riparian zones, is interconnected with water availability. Conservation efforts are necessary to maintain ecological balance and sustain biodiversity. As the state progresses, adopting sustainable water management strategies becomes crucial for long-term water security. Technological advancements, community involvement, and policy reforms are key components in ensuring a balance between demand and supply.

Understanding the scientific intricacies of water availability in Chhattisgarh involves a comprehensive analysis of the state's hydrological, climatic, and geological factors. As the state strives for sustainable water management, ongoing research, and data-driven decision-making are paramount to addressing current challenges and adapting to future dynamics. Reservoir complexes in Chhattisgarh are primarily designed to support agricultural activities through efficient irrigation planning. Besides agriculture, water from these reservoirs is allocated for urban and industrial needs, ensuring a balanced distribution among different sectors. The reservoir complexes contribute significantly to hydroelectric power generation in the state. During the monsoon, excess water is stored in reservoirs, acting as natural buffers against floods and ensuring a regulated release throughout the year. Stored water is crucial during dry seasons, sustaining agricultural needs and maintaining River flows. Over time, sedimentation can reduce the storage capacity of reservoirs. Therefore, periodic sedimentation management is employed to maintain operational efficiency. The operation of reservoir complexes involves precise control over the release of water to downstream areas, considering agricultural demand, environmental needs, and downstream water users. Advanced technologies, including real-time monitoring and modeling tools, aid in data-driven decision-making for optimized water release. Modern technologies like remote sensing and Geographic Information System (GIS) tools are integral for monitoring, assessing, and optimizing reservoir complex operations and help in predicting water availability.

1.4 Importance of Reservoir Operation

Reservoir operation is necessary for India to ensure sustainable water management, meet the diverse needs of its growing population, and support economic development while minimizing environmental impacts. Effective reservoir management strategies are essential to address water scarcity, floods, energy demand, and other challenges facing the country.

Reservoir operation is essential for India due to several reasons:

- Water Management
- Irrigation
- Hydropower Generation
- Flood Control
- Drinking Water Supply
- Navigation
- Recreation and Tourism
- Environmental Benefits

Integrated reservoir operation refers to the coordinated management of multiple reservoirs within a River basin or water system to optimize water allocation, meet diverse water demands, and enhance overall water resource management. This approach recognizes that reservoirs are interconnected components of a larger hydrological system and aims to maximize the benefits of reservoir operation while minimizing negative impacts on the environment and downstream users.

For reservoir operation, the development of rule curves is a critical aspect of water resource management, particularly in regions where reservoirs play a significant role in meeting various demands such as irrigation, hydropower generation, flood control, and water supply. Rule curves, also known as operating curves or operating policies, are predefined guidelines that dictate how reservoir water levels should be managed over time based on factors such as inflow, demand, and seasonal variability.

The operation of the Mahanadi Reservoir Complex is a complex and multi-faceted endeavor that requires careful planning, coordination, and management. By optimizing water allocation, ensuring flood control, supporting hydropower generation, irrigation, and environmental sustainability, the complex plays a vital role in the socio-economic development and ecological health of the Mahanadi River basin. The main purpose of developing rule curves for the Mahanadi Reservoir Complex is to ensure future sustainability and proper functioning of the reservoir system. Rule curves serve as guidelines for managing water levels within the reservoirs, dictating when water should be stored, released, or allocated for various purposes. By developing rule curves tailored to the specific hydrological, environmental, and socio-economic conditions of the Mahanadi River basin, several key objectives can be achieved:

1. **Optimized Water Allocation:** - Rule curves enable the efficient allocation of water resources, ensuring that water is allocated equitably among different sectors such as agriculture, urban water supply, industry, hydropower generation, and environmental conservation. This helps maximize the socio-economic benefits derived from the reservoirs while minimizing conflicts over water use.
2. **Hydropower Generation:** - Rule curves play a crucial role in optimizing hydropower generation by coordinating the release of water from the reservoirs to meet electricity demand while ensuring environmental sustainability. By following rule curves, hydropower operators can maximize electricity production while maintaining adequate water levels for downstream users and ecological needs.
3. **Irrigation Management:** - Rule curves facilitate the effective management of irrigation water by ensuring that water is available when needed for agricultural activities. By aligning reservoir operations with crop water requirements and seasonal demand patterns, rule curves can enhance agricultural productivity and support the livelihoods of farmers in the region.
4. **Flood Control:** - Rule curves are designed to mitigate the risk of floods by regulating the release of water from the reservoirs during periods of heavy rainfall or cyclonic events. Properly developed rule curves can help reduce flood peaks downstream, minimizing the potential for inundation and damage to lives, property, and infrastructure.
5. **Environmental Sustainability:** - Rule curves incorporate ecological flow requirements to maintain the health of River ecosystems and support biodiversity conservation. By ensuring minimum flow levels downstream, rule curves help sustain ecosystem services, aquatic habitats, and the overall ecological integrity of the River basin.
6. **Adaptation of Climate Change:** - Rule curves can be designed to incorporate climate change projections and adaptive management strategies. By considering future changes in hydrological patterns, such as altered precipitation regimes and increased frequency of extreme events, rule curves can help build resilience to climate change impacts and ensure the long-term sustainability of the reservoir system.

The development of rule curves for the Mahanadi Reservoir Complex is essential for guiding reservoir operations in a manner that promotes sustainability, resilience, and equitable

water management. By adhering to well-designed rule curves, water managers can optimize the functioning of the reservoir system while balancing the needs of multiple stakeholders and safeguarding the ecological health of the River basin.

1.5 Origin of the Project

With the ever-increasing population, municipal and irrigation demands have increased. Also due to climate change, uncertainty in the extreme hydro-meteorological events such as floods and droughts has increased. This has increased the possibility of conflicts of interest among the users and stakeholders. Presently, MRP Complex does not have a firm reservoir operation policy to operate the reservoirs in an integrated manner. In the case of a multipurpose reservoir, which mainly serves hydropower and irrigation as key purposes, the water resource managers wish to maximize benefits from hydropower generation, while releasing sufficient water for irrigation to meet the demands. If there are multiple reservoirs in a water resources system then the operation of reservoirs becomes more complicated. In such a situation, multi-objective optimization becomes imperative to harness maximum benefits. The scarcity of water is now an important issue in many parts of the world and more so in tropical countries. The countries situated in the tropical region are characterized by arid and semi-arid conditions are supporting a majority of the population of the world (more than 3 billion), and are witnessing the increasing water demand. Apart from drinking water demand, the demand for industrial, agriculture is steadily increasing over the years.

1.6 Objectives

The report is a part of the R & D Project entitled "Integrated Reservoir Operation for Mahanadi Reservoir Project Complex in Chhattisgarh", sponsored by the Ministry of Water Resources, Govt. of India under the World Bank aided "National Hydrology Project". The main

objectives envisaged for the PDS study are:

- Estimation of revised capacities of the reservoirs and revised demand with future projection.
- Development of long-term hydrological series for the reservoirs using a water balance approach.

- Development of a model for the short-term/long-term integrated operation of the reservoirs in the Mahanadi Reservoir Project Complex.
- Optimization of reservoir operation for maximization of benefits from the Mahanadi Reservoir Project Complex

The reservoir operation is an important aspect of the optimal use of water resources and maintaining the balance of supplies for different conflicting demands. Poor reservoir operation may lead to water deficit or flooding despite sufficient water available in the reservoir. The present study has been taken for the Mahanadi Reservoir Project complex (MRP complex) with the objective of the estimation of revised capacities of the reservoir using different techniques, water balancing of reservoir, hydrological model application for computation long term hydrological series, development of a model for integrated operation of the reservoir, optimization of reservoir using management tools, application of remote sensing data for irrigation planning, Irrigation water requirement and development of the management model for optimal utilization of resources. A detailed literature review of different aspects has been presented below.

2.1 Water Balance of Reservoir

The water balance can be used as an efficient tool to correlate local climate, geology, land use, hydrology, and soil with the availability of surface water for storage and groundwater for recharge. The water resource assessment is a crucial tool for the sustainable development of water resources projects. The water balance equation, which employs the principle of conservation of mass to compute inflows and long-term availability of water in the reservoir, is a useful tool for the assessment of source sustainability, current status, and long-term trend of water availability in the reservoir over a specific period. The water balance study of the catchment, reservoir, lake, and groundwater basin can be used for allocation, controversy, and decision-making. The availability of water in a reservoir enables managers to take appropriate decisions regarding the releases and suggest farmers and other users adopt suitable measures for water conservation or change practices.

Cancelliere et al. (2002) used a neural network approach to develop operating rules for an irrigation supply reservoir. The process involves a dynamic programming technique to minimize the sum of squared deficits, subject to various constraints. The resulting releases are then expressed as a function of significant variables by neural networks. The rules are trained over a long period, including severe drought events, and validated over a shorter period. The behavior of different rules is assessed by simulating reservoir operation and computing performance indices through a soil-water balance model. Results show that optimizing

operating rules with real system operation criteria leads to good performance in both normal and drought periods, reducing maximum deficits and water spills.

Mouelhi et al. (2005) developed a new two-parameter rainfall-flow model using a stepwise approach, based on a sample of 410 basins from semi-arid to tropical humid climate conditions. The model, compared to several well-known models, is efficient and offers valuable insights into rainfall-flow transformation at a monthly time-step, demonstrating the parsimonious structures of monthly water balance models. The model's efficiency is demonstrated through comparisons with existing models.

Raes et al. (2005) used the soil water balance model to estimate the relative yield decline expected under specific levels of water stress at different moments in the growing period. The model tracks incoming and outgoing water fluxes at its boundary, determining the soil water content in the root zone and determining the corresponding crop water stress. The yield decline is estimated using the FAO Ky approach, which describes the relationship between water stress in a particular growth stage and the corresponding expected yield. The model incorporates multiplicative, seasonal, and minimal approaches to account for the effect of water stresses in various growth stages. The simulated yields for two crops under various levels of water stress in two different environments were compared with observed yields. The simulated yields agreed well with observed yields using the multiplicative approach, with a correlation value (R^2) between observed and simulated yields ranging from 0.87 to 0.94 with high modeling efficiencies. The minimal and seasonal approaches performed significantly less accurately in both study areas. Estimation of yields based on relative transpiration performed better than estimations based on relative evapotranspiration in Burkina Faso. A sensitivity analysis showed the model's robustness, making it useful for designing deficit irrigation strategies. BUDGET is public domain software, freely available with an installation disk and manual.

Batelaan and Smedt (2007) developed a water balance model to simulate long-term average recharge based on land cover, soil texture, topography, and hydro-meteorological parameters. The model was iteratively connected to a groundwater model, influencing recharge estimates by groundwater depth. Parameter estimation is based on literature values from Belgium and The Netherlands. The model was applied to 17 catchments and successfully tested. The recharge has a spatial complex pattern, largely influenced by soil texture and land cover. Shallow groundwater levels in valleys cause negative recharge conditions due to

evapotranspiration by abundant phreatophytic vegetation. GIS analysis reveals strong variations in recharge for different land cover and soil texture classes. This analysis provides better insight into groundwater resource sustenance and management.

Komorníková et al. (2008) carried out the flow forecasting problem for the Liptovská Mara reservoir using a hybrid modeling approach. The nonlinear hybrid modeling framework was applied under specific physiographic conditions in the High Core Mountains of Slovakia. The Rivers used in the study are predominantly fed by snowmelt in the spring and convective precipitation in the summer, exhibiting two clear seasonal patterns. The hydrological regime of the mean monthly discharge time series in this area may differ due to differences in geology, slope orientation, and atmospheric circulation. A deterministic water balance scheme was set up to estimate reservoir inflow from left and right-sided tributary flows separately. The contributions of ungauged catchments were estimated from flows from gauged tributaries with similar physiographic conditions. Separate nonlinear regime-switching time series models were identified for each gauged tributary, and the forecasts of the tributaries were combined into a hybrid forecasting model. The combined forecast was compared with the single forecast of the overall reservoir inflow in several combinations.

Wale et al. (2009) used simple pragmatic approaches to estimate runoff from ungauged catchments of Lake Tana, but this study emphasizes more advanced approaches based on regionalization and spatial proximity principles. The regionalization approach transfers model parameters from the conceptual HBV rainfall-runoff modeling of gauged catchments to ungauged catchments for runoff simulation. Lake areal rainfall is estimated using interpolation of rain gauges around the lake, and open water evaporation is estimated using the Penman-combination equation. The water balance closure term is established by comparing measured lake levels with calculated levels. Results show that runoff from ungauged catchments is around 880 mm per year for the simulation period 1995-2001 with a 5% water balance closure error.

Wang et al. (2009) used the annual time series of observed streamflow data to divide the data into two study periods, 'before' and 'after' of the Chaobai River basin in northern China, consisting of the Chao River and Bai River. There was significant anthropogenic alteration and land use changes over the past 35 years. The distributed time-variant gain model (DTVGM) was used to evaluate the water resources of the area, while the Bayesian method was used to evaluate uncertainty sources. The study found that the annual precipitation

means decreased by 5.4% and 4.9% in the Chao River and Bai River basins over 13 years, while the related annual runoff decreased by 40.3% and 52.8%. The decreases in runoff between the two periods can be attributed to 35% (31%) from climate variations and 68% (70%) from human activities in the Chao River (Bai River). This study enhances the understanding of the relative roles of climate variations and human activities on runoff.

Beek et al. (2011) Carried out the global water availability using the global hydrological model PCR-GLOBWB and daily global meteorological fields from 1958-2001. A prognostic reservoir operation scheme was included to produce a monthly time series of global River discharge modulated by reservoir operations. The model was used to specify green water availability for irrigated areas, using actual transpiration from the model. The computed water availability reflects climatic variability over 1958-2001 and is contrasted against monthly water demand using the year 2000 as a benchmark. The paper evaluates model performance for three regimes reflecting different degrees of human interference: natural discharge, discharge regulated by reservoirs, and modified discharge. Results show that model simulations of monthly River discharge compare well with observations from most large Rivers, except for basins subject to large extractions for irrigation purposes. The prognostic reservoir operation scheme results in a mixed performance, with a poorer approximation of peak flows but a marginally better simulation of low flows and persistence. A comparison of simulated actual evapotranspiration with that from the ERA-40 reanalysis shows similar patterns over nonirrigated areas but substantial deviations over major irrigated areas. The simulation provides adequate fields of water availability to assess water stress at the monthly scale, with a separate validation provided.

Li et al. (2012) investigated the impact of the three Gorges Reservoir (TGR) on hydrological droughts at the downstream Yichang hydrological station from 2003-2011. A two-parameter monthly water balance model was used to generate monthly discharges at the Yichang station, representing the unregulated flow regime. A naturalized monthly discharge series was constructed to provide a reference series for the entire study period of 1951-2011. The hydrological drought index series were calculated using the standardized streamflow index method. The results show that the initial operation of the TGR from 2003 to 2011 slightly aggravated the hydrological droughts at the downstream Yichang station. The River flow reduction at the Yichang station after TGR impoundment may account for the downstream drought aggravation.

Domfeh et al. (2015) assessed water balance using an integrated Remote Sensing and GIS approach for surface runoff estimation of the Barekese Reservoir, located across the Offin River. The SCS-CN model, calibrated against observed discharges, produced an R-value of 0.84 and an efficiency of 82.68%. The water balance model, calibrated against monthly reservoir levels, produced an R-value of 0.84 and an efficiency of 81.9%. The monthly water budget revealed that total catchment runoff and direct precipitation constituted 94.32% and 5.68% of inflows, while spilled water, water withdrawal, and evaporation accounted for 72.19%, 20.85%, and 6.96% of outflows. The reservoir is underutilized, with an average production of treated water of 109,000m/day.

Senay et al. (2015) discussed methods for estimating basin scale ET and its applications in understanding basin water balance dynamics. The basin scale water balance approach is used to calculate ET as a residual on longer time scales, where net storage changes are assumed to be negligible. Direct estimation methods, such as soil moisture balance modeling, satellite-based vegetation index methods, and satellite land surface temperature measurements, use remotely sensed data to estimate spatially explicit ET and basin-wide averaging. The review also highlights the need to compare and evaluate different ET approaches using standard data sets in basins covering different hydro-climatic regions of the world.

Deng et al. (2016) developed a model for predicting reservoir water levels, combining the Xinjiang model and a reservoir routing model. The model calibrates hydrologic parameters based on observed water levels, compared to the conventional method which uses estimated reservoir inflows. The model applied to China's Shibuya Reservoir, demonstrated significantly higher accuracy than the conventional method, with an average RMS error of 0.10 m, compared to 5.13 m for the conventional method. This model offers a reliable tool for real-time reservoir water level forecasts.

Chabi et al. (2019) carried out the water balance in the Ilauko reservoir to reduce short, medium and long-term water shortages due to climate change and meet the water needs of the population. The water balance is used to estimate water input to the watershed, based on the conservation principle of water volumes. Results show that inflows are greater than outflows, resulting in positive annual variations in volumes in 2012 and 2013. Additionally, 68% of water volumes are evaporated, 0.5% are infiltrated, and 32% are withdrawn to meet irrigation and drinking water needs in Savè town and its surroundings.

O'Reilly et al. (2020) developed a dynamic water balance/nonlinear reservoir model for a perched phreatic aquifer-River system, with four conceptualizations modeled. The model was applied at a location in the Lower Mississippi River Valley, USA, using hourly River gage measurements, calibrated to 382 days, and assessed for 3.5 years. The best performance was demonstrated by the model incorporating threshold effects, which elucidated four modes of GW-SW system behavior controlled by both Riverbank and aquifer properties. The dynamical system modeling approach incorporates the salient hydrologic processes of a GW-SW system with layered heterogeneity, making it broad applicability to many hydrogeologic settings.

Latif et al. (2021) developed accurate water losses and reservoir final storage forecasts to improve water quality monitoring and efficiency in reservoir operation. The study uses artificial neural networks (ANN) models with radial basis function (RBF) for high efficiency and accuracy. The proposed ANN Prediction Model uses inflow, dam release, initial and final storage of the reservoir, and water losses as inputs. Data collected over 11 years at Klang Gate reservoir was used to develop and test the model. Results showed that the model could provide monthly forecasting with a maximum root mean square error of $\pm 20.07\%$. The model offers information for water losses, final storage, and water level variation, enhancing reservoir operation.

Song et al. (2022) proposed an analytical framework to estimate reservoir inflow and outflow from water level observations using hydrological models and reasoning derived from expert knowledge and soft data. Partial reservoir inflow hydrographs were constructed using a continuity equation and knowledge-based constraints for periods of no spillway discharge. A bucket-type rainfall-runoff model was calibrated to the partial inflow hydrographs. A complete reservoir inflow hydrograph was constructed using calibrated models, which were then used to estimate detailed reservoir outflow components under a full water balance relationship. The proposed solution outperformed conventional approaches in accuracy and uncertainty in its application to agricultural reservoirs. The framework is expected to assist in reconstructing reservoir routing processes using water level observations for hydrological analysis and water resource management planning.

Gapparov and Mansurov (2023) investigated the impact of turbidity and sediments on the useable volume of a reservoir in the South Surkhan region. Field research was conducted, revealing that the reservoir's full volume decreased by 38.6% compared to the

design volume during operation, and the water surface area increased by 7.45 km². The study also used an electronic map of the reservoir bowl and evaluated morphometric indicators, considering the formation of muddy sediments. The full volume of the reservoir at the normal moisture level was 491.2 mln. These findings provide insights into the reservoir's useful volume change, morphometric indicators, and effective water reserve use.

2.2 Hydrological Modeling

The hydrologic behavior of a basin provides a significant contribution to the efficient management of the basin. The method that is the earliest, easiest, and most widely used to assess the effect of climate changes, land use, and other interventions on runoff and management of water resources is the construction of a link between rainfall and runoff through the use of hydrological modeling (Lin et al. (2010). The act of combining a variety of hydrological processes, such as precipitation, snowmelt, evaporation, transpiration, interception, infiltration, surface runoff, and subsurface runoff, over a watershed or catchment is referred to as hydrological modeling. In hydrological modeling, precipitation is considered an input that goes through a series of interconnected components, including soil, water, climate, and land uses. The interaction of these components with water under various conditions can be represented by a series of mathematical equations, which ultimately results in runoff at the outlet of the basin or sub-basin (Zhao et al., 2013). To predict surface runoff in the form of output, the majority of the models took into consideration all of the intermediate processes, which include evapotranspiration, evaporation, groundwater/surface-water exchange, and surface-water routing (Healy et al., 2007).

The hydrological model can be classified into three broad groups namely metric, physical-based, and conceptual models (Beck, 1990). The rainfall-runoff relationships in metric models are essentially based on observations and without characterizing different processes involved in the hydrologic system (Kokkonen & Jakeman, 2001). The linearity assumption-based unit hydrograph theory (Sherman, 1932), and catchment characteristics-based rational formula for peak runoff given by J. M. Thomas (1822-1892) and reproduced by Loague, 2010, Strange tables, etc. are some of the examples of metric modeling. The metric models are observation-based and developed using observed runoff and catchment characteristics without considering many hydrological processes.

The physically based models represent different hydrological processes through mass, momentum, and energy conservation equations. The finite difference or finite computation

schemes are generally used to solve partial difference equations used in these models. The physical models are capable of considering spatial variability of land use, slope, soil, and climate to deal with hydrological processes within the watershed. The physical models may be semi or fully distributed in nature. As physical models are distributed in nature require a large amount of topographical, soil, land use, and climatic data to provide a framework to explore the changes in the hydrological cycle due to human interferences and climate change for water resources management. At the same time, these models can depict complex hydrological processes and predict different components of the hydrological cycle with an acceptable limit of accuracy. The TOPMODEL, SHE, ISBA, SLURP MIKE SHE, SWAT, DPHM-RS, TOPNET, MISBA, HydroGeoSphere, CATFLOW, and CREST are some of the most commonly used fully or semi-distributed physical models.

The conceptual models are the hydrologic models that use simplified mathematical conceptualization of the system with the help of the number of interconnected storages used to represent different components of the hydrological process through recharge and depletion. The conceptual models are usually lumped in nature and use the same value of parameters for the whole watershed and ignore spatial variability of watershed characteristics. The conceptual models strongly rely on observed data and results depend on the quality of data used in the model. Large numbers of conceptual models have been proposed in the past including the Sacramento model (Brazil & Hudlow, 1981), the Clark model (Clark, 1945), Nash model (Nash, 1957), HBV model (Bergstrom 1992, 1995), HYMOD (Moore, 1985), Watershed Model (Crawford & Linsley, 1966), Tank model (Sugawara et al. 1974, 1983), AWBM model (Boughton, 1984), MODHYDROLOG model (Chiew and McMahon, 1994), HEC-1 model (Burnash et. al., 1973), Xinjiang model (Zhao & Liu, 1995), ARNO model (Todini, 1996), Variable Infiltration Capacity (VIC) model (Wood et al., 1992; Liang et al., 1994; Lohmann et al., 1998) etc.

In the present study, the MIKE 11 Nam model has been used for the computation of long-term hydrological series for all reservoirs in the MRP Complex. The model has been calibrated and validated for all reservoirs of the MRP complex. The calibrated parameter has been used for the assessment of future water availability.

2.2.1 Application of MIKE-NAM model

MIKE 11 NAM model is a conceptual, deterministic, and continuous time-scale rainfall-runoff model that is a part of the MIKE 11 RR module. Refsgaard and Knudsen (1996)

validated the MIKE 11 NAM and MIKE SHE for three catchments in Zimbabwe to help with water resource management where at least one year's data were available for calibration. Makungo et al. 2010 conducted a study and simulated The runoff hydrographs for the ungauged Nzhelele River by using the MIKE 11 NAM model and the AWBM. He finds out that the simulated runoff hydrographs can be used in water resources planning and management, and water resources systems operation. The rainfall-runoff 13 relationship in the Strymonas River catchment was studied by Doulgeris et al. (2012) using the MIKE 11 NAM model. MIKE 11 NAM was used for the simulation of rainfall-runoff process in the Strymonas River and Lake Kerkini by Doulgeris et al., (2008) for water resources management aspects.

Nannawo et al. (2022) applied a multi-regression-based regionalization technique to examine historical stream flow in the Bilate basin and to maximize water resource management sustainably. The estimated ungauged catchment's mean annual stream flow was 130.37 cumec. The MK statistic (Kendall's tau statistic) was used to assess a nonparametric trend in each of the stations on a seasonal and annual basis. The rainfall datasets revealed that on an annual basis, there are no positive trends across all of the stations of the basin. Seasonal rainfall has a downward trend, especially in the spring and summer while it has been noted that the temperature has an increasing trend. The deterministic, lumped, and conceptual hydrological model (MIKE11-NAM) was used to explore the effects of hydroclimatic factors on rainfall-runoff processes and River flow conditions. During calibration and validation, the coefficient of determination and water balance error were 0.83, 4.9, and 0.76 and 8.6, respectively. The streams originating from the northern, northwest, and southwest highlands feed the River with a maximum inflow of 188.86 m³ /s, comprising 44% of the basin's mean annual stream flow. The basin's central part has the lowest mean annual stream flow of 112.62 m³ /s (26% of total flow). The average stream flow in the non-observable catchment is 130.37 m³ /s over the years.

Shamsudin and Hashim (2022) used the MIKE11 NAM model for the estimation of rainfall runoff in Layang River. The reliability of MIKE11 NAM was evaluated based on the efficiency index (EI) and root mean square error (RMSE). The EI and RMSE obtained during this study were 0.75 and 0.08, respectively. **Kumar et al. (2022)** used the MIKE 11 NAM model to examine the performance, efficiency, and applicability at the Ram Munshi Bagh gauging station of Srinagar in the Jhelum River basin. The model was evaluated for the years 2006-2013 in terms of reproducing the basin's hydrological response to the rainfall and

accurately predicting daily runoff. The model was calibrated for the years 2006- 2009 and validated for the year 2010-2013. The Nash-Sutcliffe efficiency (NSE) was found as 0.907, the coefficient of determination (R^2) was 0.954 and the volume difference (Dv) was found as 17.8% for the calibration period, using the MIKE 11 statistical analysis tool. For the validation year of 2010- 2013, the NSE, R^2 and Dv were found as 0.963, 0.892, and 13% respectively. It was concluded that the developed model for the Jhelum River may be applied to basin-scale integrated water resource management and production.

Ghosh et al. (2022) used the MIKE 11 NAM model in the MIKE HYDRO RIVER environment as a long-term plan to integrate rainfall-runoff analysis with the hydrodynamic condition through the flood region of the Bhagirathi–Hooghly River. The model was calibrated (2005– 2014) and validated (2015–2018) based on the rainfall-runoff amount, including water level and runoff discharge. The calibrated result creates a fairly good relationship with the simulated data using 14 EI, R^2 , RMSE, and percentage bias (PBIAS) values. This model also gives a good idea of the region's water balance, and parameters such as coefficient of runoff (CQOF), time coefficient (CK 1,2), and soil moisture in lower zone (Lmax) were found very sensitive to high runoff discharge in this region.

Wickramaarachchi and Gunasekara (2023) applied MIKE 11 NAM to investigate the temporal transferability of a lumped conceptual hydrological model's calibrated model parameters for rainfall-runoff simulations in two different periods in Gin catchment, Sri Lanka. MIKE 11 NAM model was calibrated from 1995 to 1998 with Nash Sutcliffe efficiency (NSE) = 0.73, percent bias (PBIAS) = 3.9%, and the ratio of the root mean square error to the standard deviation of measured data (RSR) = 0.52. After successful calibration, the model was validated from 1999 to 2002 (NSE=0.66, PBIAS = 8.7%, RSR = 0.59). The temporal transferability of the calibrated/validated model parameters was tested using two scenarios formulated based on the temporal lag between the calibration period and the transfer period: i. Scenario A has a 4-year time lag, and ii. Scenario B has an 8-year time lag. Scenario A which evaluated the model performance using 2003-2006 stream flow data indicated only a marginal loss in the model performance in comparison to the calibration. It showed an overall 'good' performance (NSE=0.64, PBIAS = 8.6%, RSR = 0.59) including the promising capability to reproduce the peak flows.

Slieman & Kozlov (2023) applied the Mike 11 NAM model to surface runoff modeling in case of lack of data as a case study on the upper basin of the Orontes River in

Syria. The results showed the lack of reliability of this model according to the used data in the event of a lack of data in the study area. Therefore, this study recommended continuing research for the possibility of conducting hydrological analysis and modeling in light of the lack of data, as is the case resulting from crises of wars, and trying to use remote sensing and satellite data in this field, and to verify the possibility of applicability of other models. Singh et al. (1999) applied MIKE SHE, a physically-based distributed modeling system, to simulate the hydrological water balance of a small watershed in the western part of the Midnapore district of West Bengal, India, to develop the irrigation plan for paddy crops. The results of the study showed that it is possible to meet the irrigation demand of the crops with proper planning applicability of a MIKE SHE as a comprehensive hydrological modeling system for the management of water resources for agricultural purposes in a watershed.

2.3 Reservoir Sedimentation and Profiling

To stop the flow of excess water over a River, dams or weirs are built, creating artificial lakes or water bodies known as reservoirs. The reservoir's storage capacity is diminished by the silt deposits that enter it at various levels. A reservoir's ability to serve its intended goals is impeded when its storage capacity is reduced beyond a certain point. According to research by the World Council on Dams, sediment loss causes the world's storage capacity to drop by 1% annually on average (WCD, 2000). The rate of sedimentation in the reservoir is influenced by changes in flora and land use, and the absence of conservation efforts may have a major impact on the reservoir's lifespan and operation policies. (Kondolf et al., 2014 etc.). In addition to decreasing capacities, the sediment deposit has some extremely harmful consequences, such as declining water quality, raising the risk of flooding, decreasing the amount of hydropower produced and used for irrigation, degrading the Riverbed, having an impact on the ecosystem and coastal development, and raising maintenance costs, among other things.

Either traditional bathymetric survey and inflow-outflow methods or a recently developed method of digital image processing of remote sensing data can be used to assess the distribution and profile of sediment through the estimation of revised capacities at different levels of the reservoir. On the other hand, modern methods of digital image classification for remote sensing are quick, affordable, and feasible to perform every four to five years, with the drawback of not being able to obtain information below the dead storage level. Conventional methods are laborious, dangerous, and expensive. The assessment of sediment pattern and revised capacity at different reservoir levels can be achieved by applying the area incremental

approach proposed by Christiphano in 1953 or empirical area reduction (Borland & Miller, 1958 & 1960) after the sediment deposition is known.

White (1978) examined a variety of measuring techniques for the determination of reservoir surface areas extracted from near-IR imageries of Landsat MSS of different scales and compared their accuracy with field data. He concluded that none of the measuring techniques used was able to measure the reservoir water spread with consistent accuracy and no reason was attributed. The ability to map and estimate water spread from satellite data is well understood, and different techniques such as visual interpretation of satellite imagery, density slicing, and digital classification of water bodies have been employed for the delineation of water bodies (Work & Gilmer, 1976; Thiruvengadachari et al., 1980; Jain & Goel, 1993; Goel & Jain, 1996).

Jaiswal et al. (2012) used digital image analysis of remote sensing data for the estimation of revised water spread areas which in turn applied to the estimation of revised capacities and losses in reservoir storage of Shetrunji, Rajaval, and Kharo reservoirs of Southern Gujarat in India. In the analysis, multi-date LISS 3 data of Indian Remote Sensing (IRS) satellite IRS-1D and P-6 of the year 2006-07 were used and digitally manipulated in ILWIS GIS for determination of normalized deviation water index (NDWI) and water ratio (WR). The results of the analysis from the remote sensing technique were compared with the results of an earlier hydrographic survey conducted in these reservoirs in the year 2000. The analysis suggested that the average sedimentation rate in these reservoirs increased from 0.06 MCM/100 sq km/year before the year 2000 to 0.11 MCM/100 sq km/year during the period 2000-07.

Narasayya et al. (2012) carried out a sediment assessment of the Srisailem reservoir in India using remote sensing data and compared the results with the area reduction method and found the sediment deposit in this reservoir follows Type-I (lake) reservoir and a definite relationship can be established between shape and sediment pattern in this reservoir. In the study, the empirical-area-reduction method recommended by the Central Water Commission (CWC, 2015) and adopted by the U.S. Bureau of Reclamation (Morris & Fan, 1998) has been used considering uniform rate for future sediment patterns for three future periods.

Gopinath et al. (2014) presented a reservoir sediment assessment study on the Malampuzha reservoir, a multipurpose reservoir in Kerala (India) with the help of a bathymetric survey. The analysis suggested that the reservoir capacity was reduced from 226

MCM to 205.19 MCM in 55 years.

Fendreski et al. (2014) investigated and calibrated empirical area reduction and area incremental methods for the determination of sediment distribution in the Maroon reservoir of Iran and compared the results with the hydrographic survey conducted in the year 2004. The analysis of results confirmed the superiority of the empirical area reduction method which gave a standard error of 45 % as compared to 49% in the area incremental method. In the study, the parameters of the area reduction method were optimized which reduced standard error further to 22%. The results of optimized parameters from the empirical area reduction method were used to forecast sediment patterns for the years 2035 and 2055.

Shinde et al. (2016) compared empirical area reduction and area incremental methods for the assessment of the sediment pattern of the Ujjani reservoir in Maharashtra (India) and replicated the original elevation-capacity curve by both methods. From the analysis, it has been found that both the methods have proximity with the original curves although the empirical area reduction method showed better confirmation with the original curve. The percentage error was 4.26% in the area incremental method reduced to 0.6% in the empirical reduction method confirming its superiority in the field of assessment of sediment patterns.

Jaiswal et al. (2016) proposed the application of the Latin Hypercube-One at Time (LH-OAT) optimization technique to optimize the parameters (C, m, and n) of the empirical area reduction method and compared the results with a hydrographic survey for Ravi Shankar Sagar reservoir in Chhattisgarh (India) having gross capacity of 909.54 MCM. The results of the analysis suggested that the optimization technique conferred a root mean square error of 1.18% as compared to 1.3% from the conventional technique. The optimization technique was further used to determine sediment patterns for three future periods of 2020, 2040, and 2060 for future reservoir operation and planning irrigation releases.

Bilal et al. (2017) used a Sediment-dynamics modeling tool for estimating dam lifespan and cost-benefit analysis. However, collecting real data for this analysis is costly and time-consuming. Existing tools and data can be used for qualitative predictions of future bathymetric changes. This study demonstrates that proxy approaches can increase the spatiotemporal resolution of flow data and hypothesize River cross-sections and sediment data. The Tenryu River upstream of Sakuma Dam in Japan was analyzed using a 1D numerical model (HEC-RAS) to predict future bathymetric changes. The model yielded a good qualitative agreement, with an R^2 (coefficient of determination) of 0.8 for observed and

simulated bed profiles. A predictive simulation showed that the dam's useful life would end after 2035, in line with initial estimates. The study suggests that sediment-dynamic analysis can be performed with limited data, but it may only assess qualitative trends of sediment dynamics.

N.R. et al. (2018) applied Geospatial technology using high-resolution satellite data from sensors like Sentinel, Indian Remote Sensing Satellite, Landsat, and SPOT. However, cloudy optical data during monsoons makes it difficult to map water spread at the lowest reservoir level. Microwave synthetic aperture radar (SAR) data is now available in the public domain and can easily be retrieved from the cloud. This study estimated reservoir sedimentation for the Ghataprabha reservoir using SAR data for 2016-17. The original live storage capacity was estimated to be 1434.14 Mm³ at FRL 662.940 m, but the live capacity was reduced to around 171.732 Mm³ at 660.50 m. The rate of sedimentation is around 4 Mm³/yr. The revised capacity of the reservoir can be assessed using SAR microwave data.

Morris Gregory L. (2020) provides a comprehensive classification of proactive and adaptive strategies, providing functional descriptions and examples. This can be used to evaluate sediment management alternatives and communicate management activities. Widespread application of both active and adaptive strategies was needed to sustain water storage benefits for future generations.

Li et al. (2020) carried out a sediment assessment of the Three Gorges Reservoir (TGR) in China. The study found that sediments were deposited in the middle part of the reservoir, particularly during the summer flood season. Hydrodynamic gradients structured the sedimentation patterns, with averaged particulate C: N:P proportions estimated to be 68:7:1, 97:8:1, and 151:13:1, respectively. The middle part of the TGR, the "control point" of methane accumulation, exhibited a shift in stoichiometry and stable isotope signatures, suggesting a shift in sources of POM. P, specifically in smaller particles, was found to be a key dRiver regulating particulate C: N: P in the sediment, contributing to significant decreases in particulate C/P ratios and potentially regulating long-term CH₄ accumulation.

Shiferaw and Abebe (2020) used ArcGIS 10.5 and Golden Surfer 16 to conduct a bathymetric survey and a topo map to assess sediment volume on the Abrajit reservoir in Ethiopia's east Gojjam region, focusing on its siltation and remaining valuable life span. The results showed that the reservoir has accumulated 343,700.1 m³, reducing 20% of its total capacity. Annually, 28,641.675 m³ of sediment comes from catchments, contributing 1.66%

of the reduction. The Abrajit Dam's storage capacity is 1,388,870 m³, and it will not serve more than 12 years. The estimated specific sediment yield (SSy) is 4733.387 to km⁻² year⁻¹. To improve the reservoir's estimated life span, watershed management is crucial, and further studies are needed to identify areas for conservation. The reservoir volume is running down and cannot meet all its intended demand during the dry season. Operation curves should be mandatory to provide water service for critical water needs, and regular monitoring of sediment accumulation is recommended.

Ayele et al. (2021) investigated the spatial variability of sediment yield, amount of sediment delivery into the reservoir, and reservoir sedimentation in the Koga Reservoir using the Soil and Water Assessment Tool (SWAT). The tool was calibrated from 1991 to 2000 and validated from 2002 to 2007 using monthly observations. The results showed acceptable values for model performance indicators and good agreement between measured and simulated sediment yields. The measured rating curve and SWAT predictions showed comparable mean annual sediment values of 62,610.08 tons/yr and 58,012.87 tons/yr, respectively. The findings can help policymakers make better land and water management decisions and serve as a prototype for other catchments. Validating SWAT for the Koga Reservoir is a first step in supporting policymakers in implementing land and water management decisions.

Iradukunda and Bwambale (2021) Carried out a sedimentation assessment and the impact of anthropogenic activities on the Murera reservoir dam in Kenya's Murera watershed. The research used the Bathymetric Survey System (BSS) and a multi-frequency acoustic system to assess the reservoir's sediment impacts on storage loss. The results showed that the reservoir depth increased from the north to the south, with a maximum depth of 7.78 meters and water storage of 707,862.03 m³. Sediment deposition was concentrated in the southern part of the reservoir, with a maximum sediment layer thickness of 0.8 meters. The total sediment storage capacity was 117,683.39 m³, indicating that the reservoir lost 14% of its actual storage capacity. The findings provide valuable information for policymakers in Kenya regarding the development, prioritization, and assessment of mitigation and remediation strategies to address sedimentation problems in Kenya's water resources.

Mekonnen et al. (2022) evaluated the rate of sedimentation and remaining capacity of the Adebra night storage reservoir (NSR) using a bathymetric survey and ArcGIS 10.8. The study found that the Adebra NSR reservoir capacity decreased by 24.8% over 8 years of

operation, with an average deposition rate of 1147.5 m³/year. The expected life of the night storage reservoir is currently reduced due to inadequate soil conservation practices in the catchment areas. The study suggests that to improve NSR capacity, different techniques of sediment control and removal should be planned and implemented, depending on the estimation of sediment production from watersheds of inlets and outlets of reservoirs.

Yao et al. (2023) applied a new approach to estimate reservoir sedimentation rates and storage capacity losses is proposed using Sentinel-2 satellites and daily in situ water levels. Validated on eight reservoirs in the central and western US, the method has a mean error of 4.08% and 0.05% yr⁻¹, respectively. The estimated storage capacity losses to sediment vary among reservoirs, aligning with survey data. The approach also has potential applications in ungauged reservoirs, as it can be combined with sub-monthly water levels from recent satellite altimeters.

Haveen Muhammed Rashid (2023) analysed sediment in the Dukan Reservoir using geospatial methods and satellite data from 2010 to 2022. The results showed a significant decrease in the reservoir's live storage capacity at elevation 511.78 m, resulting in a capacity loss of 14.59% and 15.83%, respectively. The annual sedimentation rate was 13.78 MCM and 14.95 MCM, respectively. The sedimentation rate in the reservoir exceeds the critical rate, indicating that the sedimentation rate is exceeding the critical rate. The findings will help develop sediment management strategies to preserve the reservoir's capacity.

Singh et al. (2023) examined the loss in live storage capacity of Samrat Ashok Sagar Reservoir in Vidisha, Madhya Pradesh, India, due to sedimentation caused by eroded sediment particles. Satellite imageries were used to analyse the water spread at various elevations, using the Normalized Difference Water Index (NDWI) derived from green and NIR band's images. The study found that sedimentation in the reservoir was approximately 46.48 Mm³ over 20 years (1997-2017), with a sedimentation rate of 2.324 Mm³/year or 0.9% per year. The reservoir silting rate was also compared with the empirical formulas of Khosla's and Joglekar's. The study highlights the importance of monitoring and managing water storage structures in Rivers.

2.3.1 Efficient segmentation algorithm

Soil erosion from the catchment and subsequent loss of reservoir capacity from incoming sediment can be considered a universal phenomenon causing the most serious

ecological hazard of recent times affecting large economic development (Jain and Kothiyari 2000; Andredaki et al., 2015). The deposited sediment may reduce reservoir capacity, power generation, and irrigation potential, increase flood risks, degrade water quality, complications in reservoir operation along with wear and tear of turbine blades (Kothiyari et al. 2002; Syvitski 2003; Vorosmarty et al. 2003; Smith and Pavelsky 2009; Jaiswal et al. 2016, etc.). Rakhmatullaev et al. (2003) mentioned that worldwide, 0.5 to 1% of the total capacities of reservoirs are being lost every year, and if this trend continues, about 25% of the total world's reservoir capacity will be lost in the next 25 years. The International Committee on Large Dams (ICOLD) figured out that 0.98% of the storage capacity of reservoirs in the world is being lost annually (ICOLD, 2009), while WCD (2000) reevaluated this rate to 1%, while the same is about 1.41% in India (CWC, 2015). As per an estimate in India, about 70% of reservoirs have an actual sediment rate that is more than twice the designed rate (Mathur et al. 2001).

The estimate of the revised capacity of a reservoir, which in turn gives the rate of sedimentation, can be determined by the conventional techniques, viz., bathymetric survey and inflow-outflow technique or recent technique of digital image processing of multi-date satellite data in optical bands (Singh et al 2021). The ability to map and estimate water spread area from satellite data is well understood and the digital classification of water bodies has been used by many investigators (Work and Gilmer 1976; Thiruvengadachari et al. 1980; Goel and Jain 1996; Goel et al. 2002; Jain and Kothiyari 2000; Jaiswal et al. 2009; Merina 2016; Fallah et al. 2016, etc.).

Most of the work till now for the assessment of revised capacities of the reservoir was done using optical bands where the unsupervised technique of classification including normalized difference water index (Gao 1996) is commonly used to identify water pixels from the rest of the image (Dadoria et al, 2017; Pandey et al, 2016; Avinash & Chandrmouli, 2018). Condeca et al. (2022) used the Google Earth engine to select images and automatically calculate water spreads and stored water volumes with the help of NDWI from images of Landsat 4 and 5 ETM and Landsat 8 Operational Land Imager. The identification of water pixels from optical sensors has major disadvantages of cloud interference, chlorophyll concentration, total suspended solids, colored dissolved organic matter load, etc. (Pekel et al 2016). On the other hand, microwave data have no interference from clouds and chlorophyll and can be used for the identification of water pixels using the segmentation technique.

Goumehei et al (2019) applied the Wishart Markov Random Field (WMRF) which is a combination of Markov random fields with Wishart distribution for the identification of surface water bodies from Synthetic Aperture Radar (SAR) data. The microwave data are commonly used to identify water spread and soil moisture due to their capability to penetrate clouds (Sathiyamoorthy et al 2003) and be least affected by atmospheric effects (Chen et al 2021). With the advent of technology and efficient computing techniques, these data are commonly used for different purposes. In the microwave dataset for identification of water areas, thresholding techniques are commonly used to distinguish water under the assumption of low backscattering from water in contrast with other features (Li and Wang 2015).

The image classification for the identification of water pixels using segmentation divides an image into conceivably discrete, homogenous sections and is widely employed in a variety of applications, including text detection and text recognition (Sari et al 2014; Esphtein et al 2010; Shekhar et al 2015; Francis et al 2020, etc.), medical image processing (Lin et al 2017; Bindu 2009; Feng et al 2017; Nyo et al 2022), document binarization (Nina et al 2011; Mustafa et al 2017; Karthika & James 2015) and remote sensing (Pare et al 2021; Srinivas et al 2019; Biswas et al 2015; Campos et al 2012; Tulbure and Broich 2013). Object detection is a popular use of image segmentation where it is a normal procedure to locate things of interest in the image rather than processing the complete image (Marr et al 1980; Pal & Pal 1993; Suresh & Srinivasa Rao 2021). Sometimes, when the whole image is not of interest but needs knowing about some parts having the same character, image segmentation may provide the solution. With the development of technology in image processing, segmentation techniques are commonly used in image processing to differentiate an object from the background (Jena et al. 2018). Many segmentation techniques have been proposed in the past mainly edge, region, or threshold-based detection, and few of them use complex computational operations (Rogowska 2009). The segmentation techniques can be categorized in the following ways based on different criteria:

- Manual, semiautomatic, and automatic,
- Pixel-based (local methods) and region-based (global methods).
- Manual delineation, low-level segmentation (thresholding, region growing, etc), and model-based segmentation (multispectral or feature map techniques, dynamic programming, contour following, etc.),

- Classical (thresholding, edge-based, and region-based techniques), statistical, fuzzy, and neuralnetwork techniques.

The simplest approach for segmenting images is called threshold segmentation, which is also one of the most popular parallel segmentation techniques (Khan & Ravi 2013). Threshold segmentation is a prominent segmentation technique in region-based segmentation algorithms. Its objective is to automatically choose the appropriate threshold based on a given criterion and then use these pixels to perform clustering based on the grey level (Haralick & Shapiro 1985). It is a typical segmentation algorithm that splits the processing of picture grey scale information depending on the multiple targets' varying grey values. There are two types of threshold segmentation: local threshold method and global threshold method (Senthilkumaran & Vaithegi 2016). The target and background are separated into two parts of the image by a single threshold using the global threshold method (Davis et al 1975), while the local threshold chooses multiple values and separates the image into multiple regions and backgrounds. The main advantage of threshold segmentation lies in its simplicity, faster convergence, and usefulness when the target and background have high contrast. On the other hand, where there is no significant difference in grayscale difference or large-scale overlap, segmentation becomes difficult due to the non-identification of threshold values. The highest interclass variance method suggested by Otsu (Otsu 1979) is the most widely used threshold segmentation algorithm, where a globally optimal threshold is chosen by maximizing the variance between classes (Liu 2011; Zhu & Jing 2010). The Otsu approach is a global adaptive binarization threshold image segmentation algorithm that computes the largest variance between the foreground and the background by analyzing the image's grey values and determining the suitable threshold to distinguish the target from the background (Huang et al 2021).

The downloading and processing of RS data require specialized software which is costly and needs high computer hardware support (Ranade et al 2015). Nowadays, the Google Earth Engine (GEE) is commonly used to process remote sensing due to its capability of having very large geospatial datasets of petabyte-scale and high-performance computing facilities on the cloud (Gorelick et al 2017; Jain et al 2021). GEE can handle a big dataset due to quantiles of autonomous parallel processing, fast computing platform (Coleman et al., 2020), and powerful graphics processing unit capable of analyzing raster data more quickly than the local computer (Martin et al., 2019; Gorelick et al., 2017). The GEE makes it easy to disseminate the

results to policymakers, researchers, field managers, and others and can be used as decision support to solve complex problems (Kumar & Mutanga 2018). The GEE has wide applicability in the field of land cover mapping (Wahap et al 2020; Goldblatt et al 2018; Bui et al 2020; Rayner et al 2021) floods (Kumar et al 2022; Agnihotri et al 2019; Clemente et al 2020; Amitrano et al 2018; etc.), disaster management (Ghaffarian et al 2020), vegetation (Yang & Wang 2020; Liu et al 2021; Juntakut et al 2021), etc. Matunga & Kumar (2019) expressed that GEE has huge potential due to its easy-to-use frontend, simple environment for interactive data and management of own datasets and collection on the cloud. Nghia et al (2022) used Sentinel 1 SAR data and observed data from two hydrologic stations to assess floods downstream of the Mekong River delta and found decreasing floods in the area.

This study suggested and applied the Otsu algorithm in GEE for the identification of revised water areas for a series of Sentinel 1 SAR data which in turn were used to compute revised capacities of reservoirs in the Mahanadi Reservoir Project (MRP) of India and compared it with bathymetric surveys to assess the performance of the proposed segmentation technique.

2.4 Land use/Land cover Change Detection and Forecasting

The Mahanadi Reservoir Project complex (MRP complex) is a significant water resource development project in India. As with any water resource development project, land use and land cover (LULC) change analysis are crucial to understanding the project's impact on the surrounding environment. LULC change analysis provides valuable insights into the temporal and spatial dynamics of land use and land cover changes over time, which is essential for assessing the ecological and socio-economic impacts of the project (Abraham A. & Kundapura C. 2022).

The use of machine learning classifiers that provide the highest accuracy is necessary to obtain precise land use land cover classification of hyperspectral remote sensing data. Recently, the use of web-based, powerful, user-friendly, and open-source cloud computing tools such as Google Earth Engine (GEE) has become widespread for reliable land cover classification of LANDSAT data (Nouri, J. et al 2014). GEE and machine learning algorithms have gained appeal in a variety of satellite data applications, including LU/LC categorization, deforestation, drought, agricultural monitoring, hydrology and land cover mapping and monitoring, and environmental protection (Tamiminia, H. et al 2020). Users of GEE can assess all publicly accessible, large volumes of LANDSAT and SENTINEL data without

needing to download it to their personal computers (Gorelick, N. et al 2017).

Random forest is the most popular algorithm for remote sensing land cover classification (Jin, Y. et al 2018). Random forest is a non-parametric machine learning classifier that can be used to classify heterogeneous areas (Pokhariya, H.S. et al 2023). The number of trees (m-tree) and the number of split variables (n-tree) are the only two input parameters that the user must choose, making RF a straightforward classifier to use (Maxwell, A.E et al 2018). Several studies have discovered that the accuracy of conventional land cover classification systems suffers from several limitations (Manandhar, R. et al 2009, Yang, C. et al 2017). Numerous investigations have revealed that among the six different machine learning classifiers, RF and SVM have the highest overall accuracy (Maxwell, A.E. et al 2018). Geographic information systems (GIS) and remote sensing (RS) are crucial tools for providing precise and up-to-date LU/LC data, as well as analysing patterns in a study area ((Manandhar, R. et al 2009). The Cellular Automata-Markov model is frequently used to produce the transition probability matrix from two different periods derived from land cover maps. In GIS investigations of changes in land use and land cover, transition probability matrices are frequently employed to objectively quantify the pace of change.

2.5 Crop Water Requirement Assessment

The accurate estimation of irrigation water demand of the Mahanadi Reservoir Project complex (MRP complex) command is also essential for developing a rational policy for sustainable water resources. Rainfall is a basic input for fulfilling the crop water requirement in any region. For the planning of irrigation and efficient operation of water resources projects, the water requirement of crops under different rainfall scenarios and probability analysis of rainfall are essential in semi-arid and drought-affected regions. Irrigation water requirements are usually defined to avoid crop stress implicitly assuming that maximum yield is desired. Improvements in irrigation management are urgently needed in regions where water resources for irrigation are being depleted.

Kuo et al.(2001) studied on Crop Wat Model to Evaluate Crop Water Requirements in Taiwan and an irrigation management model, CROPWAT, was used to estimate crop evapotranspiration, irrigation schedules, and agricultural water requirements for different cropping patterns. Field experimental data from Taiwan were analyzed and input into the model. Results showed that in the Hsueh Chia area, annual potential evapotranspiration was 1,444 mm, effective rainfall was 897 mm, and crop water requirements for paddy fields

varied depending on the rice crop. The model demonstrated the ability to estimate crop water requirements effectively, but further research is needed to adapt it to complex cropping patterns and enhance irrigation management capabilities in Taiwan.

Doll & Siebert (2002) studied the Global modeling of irrigation water requirements to evaluate future water and food scenarios. It is crucial to model irrigation water needs due to their significant global consumption. This study introduced a global model that utilizes a high-resolution map of irrigated areas. It accurately simulated cropping patterns, growing seasons, and irrigation requirements for rice and non-rice crops. By analyzing long-term climatic data, the model computes present-day irrigation requirements and assesses the influence of climate variability. The model's performance aligns well with independent estimates, making it suitable for global and continental research on water and food dynamics.

Liu et al. (2009) studied on Spatial distribution characteristics of irrigation water requirement for main crops in China and this study assessed the temporal and spatial distribution of crop water requirement and irrigation requirement in China. Utilizing meteorological data from over 200 stations and crop growth stage data, crop water requirement (ET_c) and net irrigation requirement (IR) were estimated for 30 crops. The results were validated against observed data from irrigation stations. Isoline maps of average ET_c and IR were created using GIS and interpolation methods. Analysis of wheat, maize, cotton, and rice revealed their spatial distribution characteristics. The irrigation requirement index (IR/ ET_c) indicated that certain regions relied heavily on irrigation, while others had lower irrigation needs.

Chakraborty et al.(2013) studied Long-term Changes in Irrigation Water Requirement in the Context of Climatic Variability and this study examines the impact of climatological variables on reference evapotranspiration and agricultural water use in the Seonath basin, Chhattisgarh State. The analysis reveals a significant rise in annual temperature over 51 years, with more pronounced increasing trends. The main drivers of the increasing ET_o trend are identified as temperature and relative humidity. The study emphasizes the importance of considering changing irrigation demand in future irrigation management systems for the Seonath River basin due to projected changes in meteorological variables.

Lalic et al. (2013) studied an assessment of climate change's impact on crop water requirements in Serbia in 2030 using CROPWAT mode and efficient and sustainable mitigation and adaptation options for crops and the environment are needed to address the impact of climate change on agriculture. A study used the CROPWAT 8.0 software package to calculate the impact of climate change on effective rain, crop water demand, and irrigation requirements in Serbia. Future climate projections were taken from ECHAM5 models with the SRES-A2 scenario for greenhouse gas emissions. Follow-up research is expected to focus on identifying crop varieties and soil management techniques to mitigate the negative effects of climate change.

Saravanan & Saravanan (2014) studied on determination of water requirements of main crops in the tank irrigation command area using CropWat 8.0 and a study in the Perumal Tank irrigation area, Cuddalore district, determined water requirements for main crops (rice, groundnut, sugarcane) using climatic data and CROPWAT 8.0 software. Crop evapotranspiration ranged from 0.74 to 6.57 mm/day, with water requirements varying from 0.0 to 244 mm/dec. The peak water requirement was 9.6 mm/day (1.11 l/s/ha, 70% application efficiency).

Bouraima et al. (2015) studied on Irrigation water requirements of rice using the CROPWAT model in Northern Benin and finds This study focused on estimating crop water requirements (CWR) for rice in the semi-arid Benin's sub-basin of the Niger River using the CROPWAT model. The research computed crop reference and actual evapotranspiration for the rice crop based on long-term climatic, crop, and soil data. The results indicated an annual reference evapotranspiration of 1,967 mm, with the lowest monthly value in August (123 mm) and the highest in March (210 mm). Crop evapotranspiration and irrigation requirements were determined for both rainy and dry seasons, providing insights for efficient water use scheduling in irrigation projects.

Putthividhya & Sukgerd (2015) studied on Water Requirements & Irrigation Scheduling of the Ban Khai Irrigation Project using GIS And CROP WAT Model in Rayong Province Thailand & found that water resource estimation plays a crucial role in planning and managing water resources, especially in the face of climate change and increasing water crises. This study focused on the Ban Khai area in Thailand, which faced severe water problems. By gathering data on crop water requirements, irrigation withdrawals, soil types,

and climate conditions, a GIS-based method was employed to estimate evapotranspiration, climatic water deficit, and yield reduction under different rainfed and irrigated conditions. The analysis highlighted the potential of supplemental irrigation schedules, developed using the CropWat model, to mitigate water stress and reduce yield losses in the future management of water resources.

Surendran et al.(2015) analyses of the water resources and modeling of agricultural water needs using FAO-CROPWAT are used to manage water resources sustainably in the Kerala district of India's humid tropical climate. The CROPWAT 8.0 model of the FAO has been used to calculate the crop water requirements of the main crops in the various Agroecological zones of Palakkad, and the results have been compared with the district's water resources. Rice, coconut, banana, areca nut, vegetables, legumes, rubber, tea, coffee, cotton, etc. are the main crops grown nowadays. It has been calculated how much water these crops will need overall in each Agroecological zone. **Shah et al. (2015)** studied wheat, rice, and sorghum crop water requirements and irrigation planning in the Waghodia region of Vadodara, Middle Gujarat, India. According to the study, sorghum requires a crop water demand of 187.5 mm. Net irrigation needs for sorghum are 173.3 mm per stage at a set interval, with four irrigations taking place on September 3, September 28, November 17, and December 17 at variable depths of 9.6 mm, 3.9 mm, 11.4 mm, and 48.4 mm, respectively.

Nithya and Shivapur (2016) studied on Study on Water Requirement of Selected Crops under Tarikere Command Area using CROPWAT & finds in Tarikere taluk, Karnataka, India, determined the crop water requirements for various crops using 30-year climatic data and CROPWAT and AV (2016) studied on Study on Water Requirement of Selected Crops under Tarikere Command Area using CROPWAT & finds in Tarikere taluk, Karnataka, India, determined the crop water requirements for various crops using 30-year climatic data and CROPWAT. The reference evapotranspiration ranged from 2.5 to 3.36 mm/day. The gross water requirement for the entire crop area of 4466 ha was calculated as 342.42 mm/year, with a 70% application efficiency. Consequently, the dam's water supply of 16 MCM is sufficient to meet the irrigation needs of the area.

Khilesh et al.(2017) studied crop water need estimation and irrigation planning in the Bina River basin using CROPWAT. The Bina River basin's average daily reference evapotranspiration, which ranges from 3.05 to 7.63 mm/day, has been calculated to be 4.73 mm/day. In the Bina River basin, 682.5 mm of effective rainfall on average has been

recorded. The Bina River Basin's effective rainfall was found to be 56.03% of the total rainfall. Using the CROP WAT 8.0 model, it was determined that the crop water requirements for wheat, gram, maize, black gram, mustard, soybean, groundnut, and rice in the Bina River basin were 372.6 mm, 312.6 mm, 432.2 mm, 273.1 mm, 330.3 mm, 486.5 mm, 314.8 mm, and 654.2 mm, respectively.

Hossain et al.(2017) studied on Irrigation Scheduling of Rice (*Oryza sativa* L.) Using the CROPWAT Model in the Western Region of Bangladesh and a study in the western region of Bangladesh utilized the CROPWAT model to estimate irrigation requirements and develop irrigation scheduling for T. Aman (wet season) and Boro (dry season irrigated) rice. By employing historical climate data, soil information, and crop data, the model estimated annual reference evapotranspiration of 1408 mm, with the highest amount in April and the lowest in December. The effective rainfall for plant growth was calculated as 986 mm out of an average annual rainfall of 1592 mm. The model provided specific irrigation recommendations based on transplanting dates, with varying irrigation requirements for different rice varieties. The CROPWAT model demonstrated its potential for irrigation scheduling of various crops.

Doriya et al. (2020) studied using CROPWAT, to project future crop water needs for 2020 and 2050. This study's goal was to use CROPWAT in combination with climatic scenarios obtained from SDSM to assess the effects of projected climate change on the daily and overall crop water requirements (CWR) of peaches in Southern Ontario. Baseline climate is based on two time periods in the future, concentrating on the decades of the 2020s (2010-2039) and 2050s, and 30 years, 1971-2000 of the mean monthly normal (2040-2069). The SDSM (version 3.1) approach was used to downscale the climatic parameters of temperature, precipitation, relative humidity, sunlight length, and wind speed. The CROPWAT model (FAO, 1992) was used to simulate the daily and seasonal total crop water needs (CWR) to forecast future crop water requirements (CWR).

Roja et al. (2020) Using the FAO CROPWAT 8.0 Model, estimate the crop water requirements for the maize crop. Using the FAO's CROPWAT 8.0 model, an effort has been undertaken to determine the crop water needs of maize in the northern coastal districts of Andhra Pradesh. Water usage was made effective by using CROPWAT 8.0 to schedule irrigation properly and optimally. The Penman-Monteith technique was included in the model to calculate evapotranspiration. Irrigation was thought to be a viable option for 80% of critical

soil moisture loss. The crop water requirements for the maize crop at various growth stages were estimated by the model on a daily, decadal, and monthly scale. The crop water and irrigation needed for the maize crop are 238.6 mm and 212.6 mm, respectively. The findings show that effective water management becomes essential and significant in typical situations.

Sharma & Tare (2021) studied on Assessment of irrigation requirements and scheduling under the canal command area of the Upper Ganga Canal using the CROPWAT model & determine the timing and irrigation needs for the Upper Ganga Canal command region. In the Upper Ganga Canal command, this research identified the ideal irrigation area and its other irrigation needs. CropWat 8.0 simulation software was also suggested for irrigation planning. Due to inadequate planning and irrigation techniques, it is anticipated that the total agricultural water needed in the command area is 1763 MCM, which is more than the actual water availability.

Agrawal et al. (2020) studied the Impact of Climate Change on rice crop water requirement in the Varanasi district, India. This study used the NEX-GDDP and CROPWAT 8.0 models to assess the impact of climate change on rice Crop Water Requirement (CWR) and Net Irrigation Requirement (NIR). Results showed an increasing trend in maximum and minimum temperatures, with an expected increase of 1.7°C by 2040. NIR could increase by 4% and 9% in 2030 and 2040, respectively, due to variations in effective rainfall. Linear scaling performed better than the modified difference approach. The study's findings can inform the development of adaptation measures to address the impact of climate change on rice production.

Jaiswal et al. (2021) studied on Assessment of Climate Change on Crop Water Requirement in Tandula Command of Chhattisgarh (India) and this study focuses on the impact of climate change on crop water requirements in the command area of the Tandula reservoir in Chhattisgarh, India. Statistical downscaling of climatic parameters using CMIP5 scenarios was employed to project future climatic conditions. The analysis revealed a rising trend in maximum temperature throughout the year, with a significant increase in minimum temperature during winter and the rainy season. The study estimated that the crop water requirement for kharif paddy will increase during the near and mid-century periods but decrease during the far century period. The mid-century period is considered the most critical, requiring the development of adaptation measures to address climate change.

Jangre et al. (2022) studied on assessment of rice water requirements under

Inceptisol in the Raipur district using CROPWAT 8.0 and the study estimated crop water requirements for rice grown in Inceptisol soil in Raipur using the CROPWAT 8.0 model and climate data from the past 21 years. The Penman-Monteith method was used to calculate reference evapotranspiration, and the crop coefficient was adjusted for different stages of rice growth. Effective rainfall was set at 80% of total rainfall, and field-specific water requirements for rice ranged from 1192.3 to 1317.9 mm, accounting for application losses and special requirements. Average irrigation needed for rice crops between June 23 and November 14 was 362.53 mm.

Jaiswal et al. (2023) studied Rainfall and Agro Related Climate Extremes for Water Requirement in Paddy Grown Mahanadi Basin of India and this study examined the impact of extreme climate events and seasonal rainfall on irrigation water requirements (IWR) for Kharif paddy crop in the Mahanadi basin of India. Analysis of rainfall and extreme indices revealed that higher demand, low seasonal rain, and intense extreme events in the upper part of the basin result in greater water requirements for paddy cultivation. A multi-linear regression model was developed with high accuracy to assess the influence of climate extremes on IWR, providing valuable insights for water resource planners and enabling optimal resource utilization. Similar regression models can be developed for other crops and regions based on relevant extreme indicators.

2.6 Reservoir Operation in Development of Rule Curve

A reservoir is an important component of a water resources development project. The principal function of a reservoir is to regulate the natural stream flow thereby, changing the temporal and spatial availability of water for beneficial purposes such as municipal and industrial water supply, irrigation, hydropower generation, and navigation.

Reservoirs are commonly built in India for conservation and flood control purposes. Because of the high time and space variability of rainfall, reservoirs play a very important role in the planning and management of water resources. More than 3000 major and medium dams have already been completed. Thus, NIH has developed NIH_resyp software to regulate reservoirs. This software is very useful for various analyses related to the design and management of reservoirs. The main objective of this software is to operate a reservoir for different purposes computing reservoir capacity using the Sequent Peak algorithm, interpolating the Elevation-Area-Capacity table for any elevation interval, determining the firm power from a reservoir, or simulating the operation of a hydropower project, simulating

the operation of a multi-purpose multi-reservoir system for conservation purposes, carry out flow routing through a reservoir using the hydrologic routing methods, determine the reservoir operation policy using Stretched Thread method, determine the rule curve levels using mass balance approach, determine the required reservoir storage for a given yield or vice versa.

Geol et.al. (2004) developed a spatially distributed water balance model to simulate various components of the hydrologic cycle at the scale of a River basin. This model incorporates the spatial variation of land use, soil type, rainfall, evapotranspiration, physiographic characteristics, groundwater conditions, River network, and hydraulic structures in a River basin. GIS is employed to fill the spatial data with the simulation mode and project the model results in map form for easy visualization. The basin is divided into grid cells of uniform size (1 km), and the model computes various components of hydrology, such as actual crop evapotranspiration, overland flow, groundwater reservoir, and regenerative soil water flow separately for each grid cell. Using this model, various scenarios of water availability in a River basin can be generated. Another model, 'NIH_ReSyP', was developed for simulating a multi-purpose multi-reservoir system, spread across water basins for conservation and wood control. By taking repeated runs of the ReSyP model for different scenarios droughts, retables, and sustainability resources management plans can be enumerated.

Jothiprakash & Mohandoss (2010) developed a weekly operational planning model using a simulation technique for the Tambiraparani River system in Tamil Nadu, India. The model incorporates the existing operational policy, which focuses on paddy cultivation in three seasons. The water resources manager's main task is to identify the area under paddy during the Advance Kar season. The study simulated the temporal distribution of available water in the Tambiraparani River system for various initial storage conditions. Results showed that the entire system was managed without deficit by reducing water release by 10-25% during non-stress crop periods and lagging the starting period by one or two weeks. This management can maintain the same final storage as the initial storage during the start of the season. The study's policies were useful for system managers, enabling them to authorize the area under paddy during the Advance Kar season and maintain required storage for the next season.

Thankachan & Anitha (2015) used a system approach to develop an optimal

operation plan for three reservoirs in the Kuttiadi River basin in Kerala. The reservoirs, Banasurasagar in Wayanad district, Kakayam, and Peruvannamuzhi in Kozhikode district, serve various purposes such as irrigation, domestic water supply, and hydropower generation. The Standard Linear Operation Policy (SLOP) was developed to fulfill these purposes. A multi-reservoir multi-purpose simulation technique was used to optimize the conservation storage of the three reservoirs. The simulation studies revealed that Banasurasagar and Peruvannamuzhi reservoirs consistently serve water supply purposes. Banasurasagar's irrigation and water supply reliability is 86%, while Peruvannamuzhi's reliability is 77%. Power generation demand can be met with 90% dependability. The system can be linked to the water supply from Banasurasagar reservoir to Wayanad district and from Peruvannamuzhi reservoir to Kozhikode district.

Arunkumar & Jothiprakash (2018) developed a weekly operational planning model using a simulation technique for the Tambiraparani River system in Tamil Nadu, India. The model incorporates the existing operational policy, which focuses on paddy cultivation in three seasons. Banana cultivation is not recognized in the policy. The water resources manager's main task was to manage the area under paddy during the Advance Kar season. The study simulated the temporal distribution of available water in the Tambiraparani River system for various initial storage conditions. Results show that the entire system can be managed without deficit by reducing water release by 10-25% during non-stress crop periods and lagging the season's start by one or two weeks. This management can maintain the same final storage as the initial storage during the start of the season. The study's policies would be useful for system managers, enabling them to authorize the area under paddy during the Advance Kar season and maintain required storage for the next season.

Geol et.al. (2020) developed operation procedures for individual projects, honoring tribunal awards, using the Krishna River basin as an example. The proposed procedure tracks total inflows, water usage, and balance utilization in real-time at each project, state, and River basin. The percentage utilization achieved by different sharing states, especially in deficit years, was close to the values specified by the tribunal. The methodology can be applied to any River basin with suitable modifications.

Thomas et al. (2021) assessed the potential impacts of climate change using the Soil and Water Assessment Tool (SWAT) of the Narmada basin in central India. The dam was incorporated into the model for simulation. The model was calibrated and validated. The Co-

ordinated Regional Climate Downscaling Experiment datasets for South Asia (CORDEX-SA) were used to investigate future climate changes and simulate future stream flow. The proposed dams were also incorporated for modeling future developmental scenarios. The analysis suggested that changes in precipitation patterns and warming trends contributed to higher variability in water availability. A future scenario with lower water availability and higher water demands calls for optimal utilization of available water resources. Various adaptation strategies were explored using engineering/technical solutions, including simulation-only and genetic algorithm-based simulation-optimization approaches. The simulation-optimization framework-based integrated reservoir operation led to better reservoir performance, reduced irrigation failures, and reduced hydropower failures under the RCP8.5 scenario. No failures were found in meeting domestic water supply and environmental flow demands, which may be an important adaptation measure to address climate change impacts on water resources in the Narmada basin.

Jain et al. (2023) reviewed the operation of multipurpose reservoirs during flood season, highlighting the importance of balancing conflicting purposes. Despite numerous studies, a comprehensive review paper on this topic was lacking. Te studied classified conventional and advanced techniques used in flood control operations of single and multiple reservoirs. The best results were obtained through judicious use of current data and forecasts. Operators must balance conflicting demands with uncertain inflows, requiring risk assessment and management. The paper also provides suggestions for future research and development on this topic.

3.1 General

The Mahanadi Reservoir Project Complex (MRP Complex) comprises four reservoirs namely Ravishankar Sagar Reservoir, Muramsili (Madamsilli) Reservoir, Dudhawa Reservoir in the Mahanadi basin, and Sondhur Reservoir in the Pairi basin. The Mahanadi is the 8th largest basin having a total catchment area of 139681.51* Sq.km which is nearly 4.28% of the total geographical area of the country. The geographical extent of the basin lies between 80°28' and 86°43' east longitudes and 19°8' and 23°32' north latitudes.

3.2 Chhattisgarh State

The 21st-century state of Chhattisgarh was established on November 1, 2000. The state of Chhattisgarh, located in eastern India, spans between 17°46' to 24° and from 80°15' to 84°24' E longitude. It is bigger geographically than Kerala and Tamil Nadu, with an approximate total area of 13.5 million hectares. The state is divided into three agroclimatic zones: the northern hills area, the Bastar plateau, and the plains of Chhattisgarh. It has a mostly dry, subhumid climate. The monsoon begins in the middle of June in the southern regions and ends fully in the state on September 25. It begins to recede in the northern regions in mid-September. The location of Chhattisgarh is shown in **Figure 3.1**

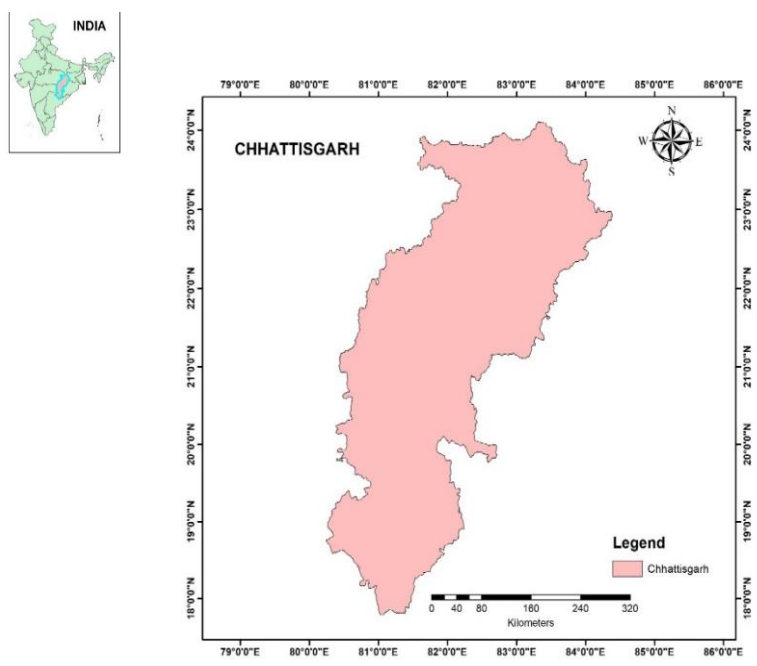


Figure 3. 1 Location map of Chhattisgarh.

3.2.1 Agro-climatic zones of Chhattisgarh

The state of Chhattisgarh is divided into three major agro-climatic zones namely Chhattisgarh Plains (CP), Northern Hills Zone (NHZ), and Bastar Plateau (BP). Covering 51.0%, 28.0% and 21.0% of the geographical area, respectively. The location of the state is such that it is close to the Bay of Bengal, which is instrumental in bringing monsoon to the Southern side of the country. The cropping intensity of the state is about 135%. The agro-climatic zones of Chhattisgarh are shown in **Figure 3.2**. The details of agro-climatic zones are shown in **Table 3.1**.

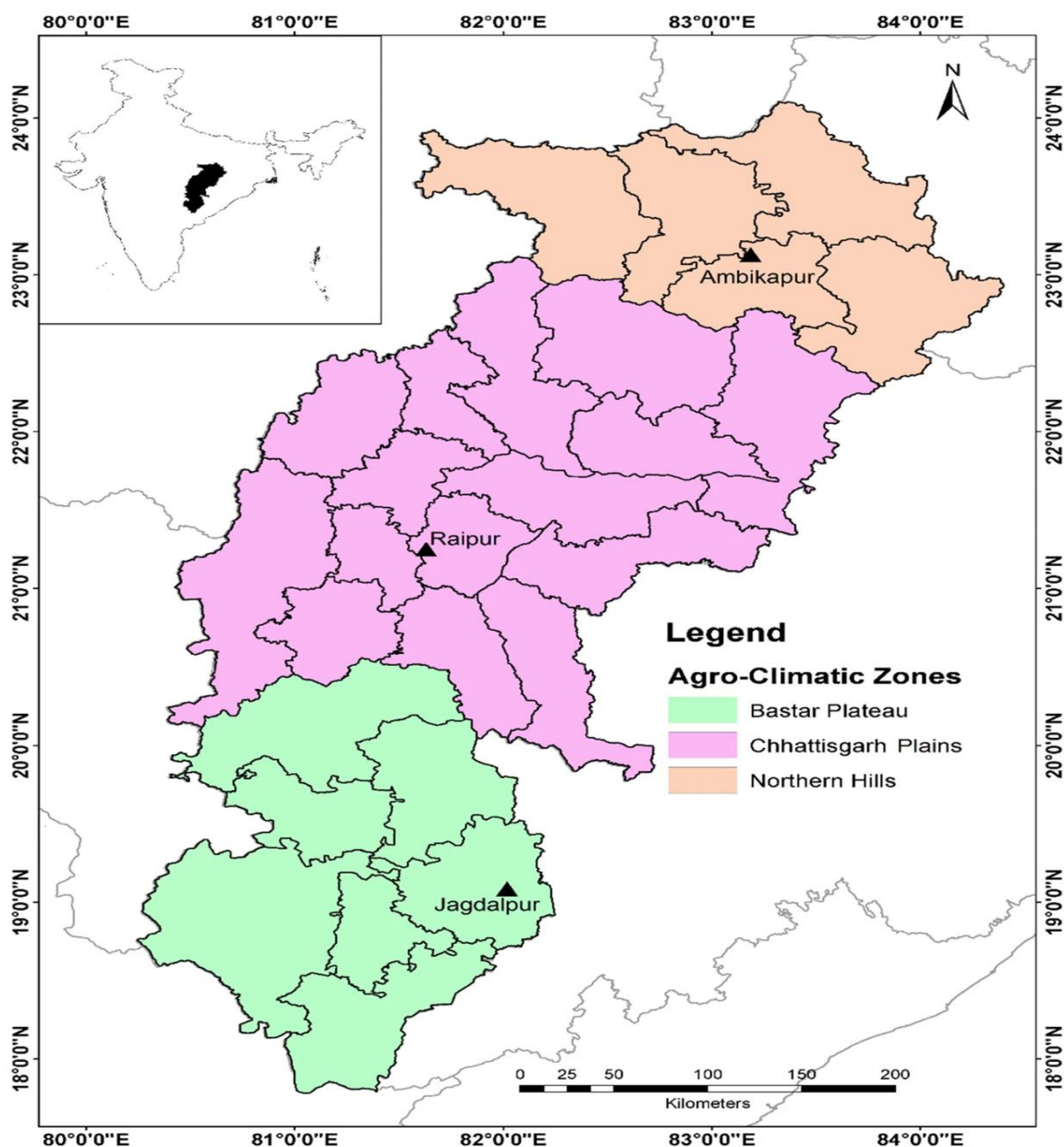


Figure 3.2 The agro-climatic zones of Chhattisgarh.

- I. **Northern region:** The districts that are part of this region (Korea, Surguja, Jashpur, Raigarh, and Korba) have similar geographical, climatic, and cultural contexts and harbor dense forests, hills, and water reservoirs. It is home to several indigenous tribal communities such as Paharikorba and Pando, etc. Governed largely by tribal customs, culture, and traditions, in the rural areas of the region, people are dependent largely on agriculture and non-timber forest produce (NTFP). The level of migration from this region is comparatively limited. The urban centers are limited to Korba and Ambikapur. Korba is the largest town, and the limited industry is concentrated here. There are coal mines in Surguja and Korea districts.
- II. **Central Plains region:** Raipur, Bilaspur, Janjgir-Champa, Kabirdham, Rajnandgaon, Durg, Dhamtari, and Mahasamund are the districts that fall in the central plains. Mahanadi is the primary source of water for irrigation and domestic use. Owing to the presence of a large number of indigenous varieties of rice, the central plains of Chhattisgarh are known as the ‘rice bowl’ of Central India. Bhilai and Durg are well-known urban areas, both with large steel plants. Rural craft is well-developed in the region and well-known (e.g. the silk weavers of Janjgir-Champa). The region is densely populated with Raipur and Durg accounting for almost half the total urban population of Chhattisgarh.
- III. **Southern region:** The districts in this region (Kanker, Bastar, and Dantewada) are known for their varied and rich forests, diverse tribal populations, and unique culture. These districts are bordered by the States of Maharashtra, Andhra Pradesh, and Orissa. The people of the region are dependent on traditional agriculture and forests for their livelihood. The Bailadila mines in Dantewada district represent the limited industry in the region.

Table 3.1 Agro-climatic zones and details.

Agro Climatic Zone	Districts Included	Total Geo. Area	Net sown area	Soil Type	Irrigation %	Cropping Intensity
C.G. Plains (15 Districts)	Raipur, Gariaband, Balodabazar, Mahasamund, Dhamtari, Durg, Balod, Bemetara, Rajnandgaon, Kabirdham, Bilaspur, Mungeli, Korba, Janjgir, Raigarh & a part of Kanker	68.49 lakh ha. (50%)	32.95 Lakh ha.	Entisol (Bhatha) -- 36 %; Alfisol (Matasi) -- 21 %; Inceptisol	43 %	139

	Districts (Narharpur & Kanker Block)			(Dorsa) -- 22 %; Vertisol (Kanhra) -- 8 %; Alluvial (Kachhar) -- 3 %		
Bastar Plateau (7 Districts)	Jagdalpur, Narayanpur, Bijapur, Kondagaon, Dantewada, Sukma, and the remaining part of Kanker Districts	39.06 lakh ha. (29%)	6.40 Lakh ha.	Entisol -- 26 %, Alfisol -- 25 %, Inceptisol -- 34 %, Vertisol -- 10 %, Alluvial -- 5 %	5 %	122
Northern Hills (5 Districts)	Sarguja, Surajpur, Balrampur, Korja, Jashpur & Dharam Jaigarh Tehsil of Raigarh Districts	28.47 lakh ha. (21%)	8.35 Lakh ha.	Entisol -- 3 %, Alfisol -- 29 %, Inceptisol -- 28 %, Vertisol -- 28 %, Alluvial -- 2 %	11 %	135

3.2.2 River system in Chhattisgarh

Chhattisgarh state is rich in water resources and traversed by several important Rivers such as Mahanadi, Godavari, Narmada, and Indravati. These Rivers play an important role in the state's economy and ecology, providing water for irrigation, drinking, and hydropower generation. Rivers in Chhattisgarh are also home to a variety of aquatic life and support the livelihoods of millions of people.

3.2.2.1 Mahanadi River system

The Mahanadi is the longest River in Chhattisgarh, flowing through the state for over 850 kilometers. It is also the state's most important River, providing water for irrigation, drinking, and hydropower generation. The Mahanadi is also a popular tourist destination, known for its scenic beauty and abundant wildlife.

The Average annual runoff of Mahanadi is 66.9 BCM. The basin receives uneven rainfall thus drought is prevalent in some districts. A total of fourteen districts in the basin are covered under the Drought-prone area program. Districts Jagatsinghpur, Puri, and Kendraparha which are situated near coastal parts of Mahanadi face waterlogging problems.

3.3 Mahanadi Reservoir Project Complex

The Mahanadi Reservoir Project Complex (MRP Complex) comprises four reservoirs

namely Ravishankar Sagar Reservoir, Murrumsili (Madamsilli) Reservoir, Dudhawa Reservoir in the Mahanadi basin, and Sondhur Reservoir in the Pairi basin. **Figure 3.3** shows the location of all the dams in the MRP complex. The Mahanadi Canal System, one of the oldest canal systems of Chhattisgarh, has been in operation since 1915. During the first year of its operation in 1915-16, irrigation was developed in 3,089 ha. Subsequently, to meet the increased irrigation demand, the Muramsili dam was constructed in the year 1923, later on, the construction of the Dudhawa dam was taken up in 1954 and the dam was completed in 1963.

The largest dam in the MRP complex, the Ravishankar Sagar Project (RSP) dam was constructed in 1978. It is a multipurposereservoir that serves municipal and industrial demands, irrigation demand, and hydel-power generation. Ravishankar Sagar located in Dhamtari District is the longest dam in Chhattisgarh. This dam supplies year-round irrigation, allowing farmers to harvest two crops per year and key water supplier of Bhilai Steel Plant and generate 10 MW of hydroelectric power.

The Muramsili dam is an earthen embankment dam on the Sillari River, a tributary of the Mahanadi River in central-eastern India. It is Asia's first dam with Siphon Spillways, having been built between 1914 and 1923. Dudhawa Dam was built over the Mahanadi River in Dhamatri District. The dam was conceived in 1951, and after two years, construction began. After eleven years of concerted effort, the dam was completed in all respects in 1964. The dam's construction took place in the village of Dudhawa.

The Sondhur Dam Project across River Sondhur, a right-bank tributary of Mahanadi, was contemplated by the erstwhile Madhya Pradesh Government in 1972. The catchment area of the Sondhur River up to the dam is 518 km². **Figure 3.4** shows the catchment area maps of all the dams and **Table 3.2** shows the salient features of all these dams. **Figure 3.5** shows the command area maps of the Dhudhawa Dam and Ravishankar Dam commands. The details of commands, their area, and district benefits are presented in **Table 3.3**.



Figure 3.3 Location map of reservoirs in Mahanadi Reservoir Complex in Chhattisgarh.

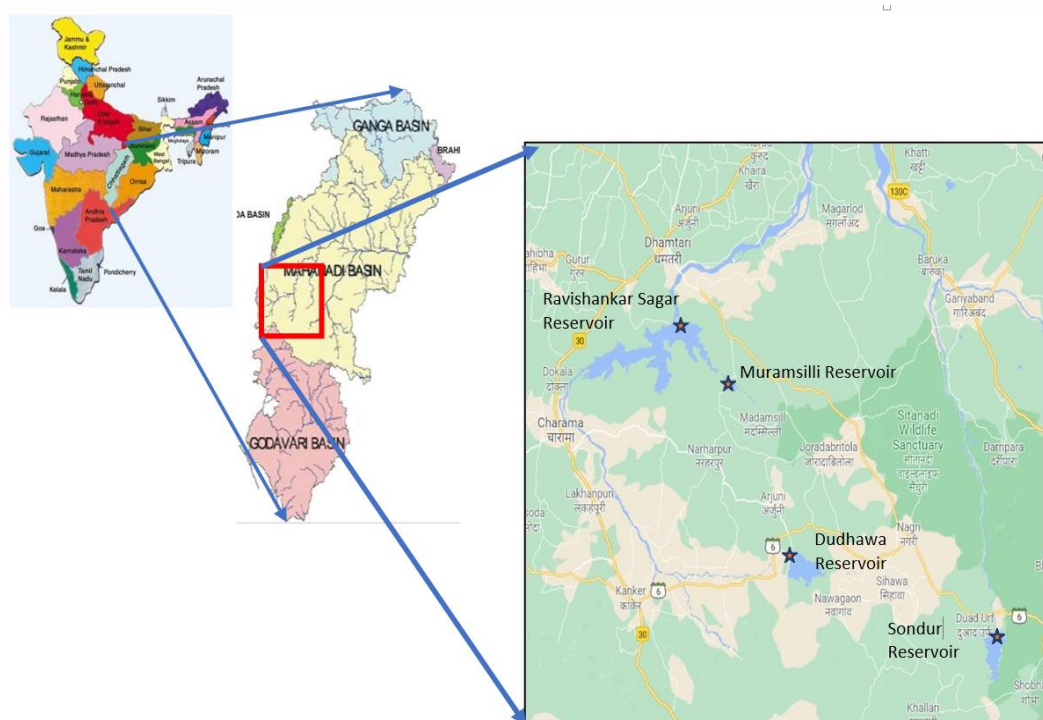


Figure 3.4 Catchment Area Map of Project.

Table 3. 2 Salient features of MRP complex.

Dam	Ravishankar Sagar dam	Murumsilli Dam	Dhudhawa Dam	Sondhur Dam
River Basin	Mahanadi	Mahanadi	Mahanadi	Pairi
Year of construction	1979	1923	1972	1964
Latitude & longitude	20°37' N & 81°34'10" E	20°37' N & 81°34'10" E	20°37' & 81°34'10"	20°37' & 81°34'10"
Catchment Area (sq. km)	3760	484.33	625.27	512
Design Flood (Cumec)	23500	5930	8904	-
Reservoir				
Gross Storage Capacity at FRL (Mcum)	910.5	165.343	203.7	
Live Storage Capacity at FRL (Mcum)	767	161.916	199.16	179.6112
MWL (m)	350.7	378.25	427.54	471.965
FRL (m)	348.7	376.28	423.12	471.065
LSL (m)	322.47	361.19	409.93	459.265
TBL (m)	353	378.87	430	474.265
Water Spread Area at FRL (sq. km)	95.4	35.35	44.8685	24.2
Cumulative Command Area (acres)	–	80192.6	688906	1270.3

3.3.1 Rudri barrage

In 1915, a barrage was constructed on the Mahanadi River near Rudri village for irrigation purposes, due to which 33,000 hectares of additional irrigable land area were added to the region. However, it was not possible to supply 116 cusecs of water to the Mahanadi main canal from the existing Rudri barrage. As a result, around 264,310 hectares of land in the Mahanadi irrigation area remained underserved. Hence, the construction of a new Rudri

Barrage was deemed necessary to facilitate the flow of 391 cumecs of water for irrigation purposes. Thus, the new Rudri Barrage was built 136.80 units upstream from the old Rudri Barrage.

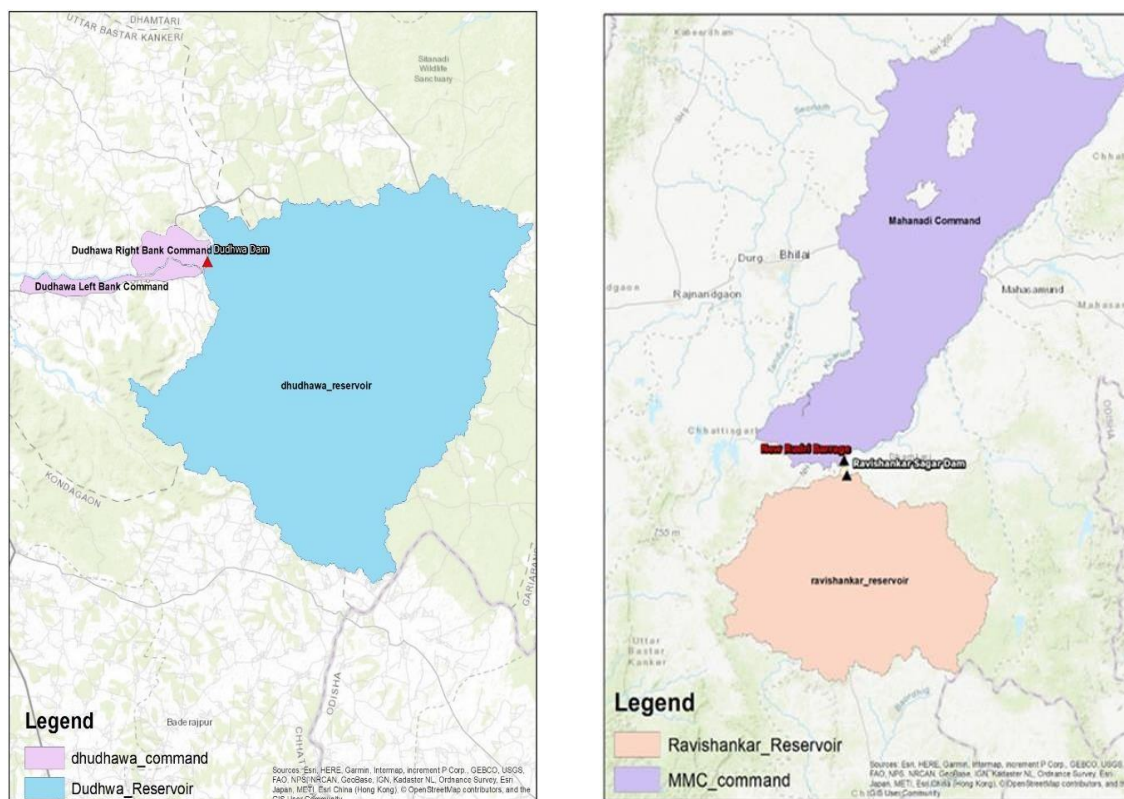


Figure 3.5 Command Area Map of Dhudhawa and Ravishankar.

Table 3. 3 Command Area and district benefitted.

Command name	Type	Area(ha)	District benefitted
Dudhawa Right Bank Command	Major	1699.08 6	Dhamtari, Raipur, Durg, Uttar Bastar, Kanker
Dudhawa Left Bank Command	Major	1654.43 5	Dhamtari, Raipur, Durg, Uttar Bastar, Kanker
Mahanadi Command	Major	2643111	Dhamtari, Raipur, Durg, Uttar Bastar, Kanker

The primary purpose of the New Rudri Barrage is to regulate the flow of water. It

manages the water that is transferred from the RS Sagar Dam after power generation and redirects it to the Mahanadi main canal for both irrigation and domestic use. The Location map is shown in **Figure 3.6**. The elevation area capacity of the barrage has been presented in **Table 3.4**. The silent Feature has been presented in **Table 3.5**.

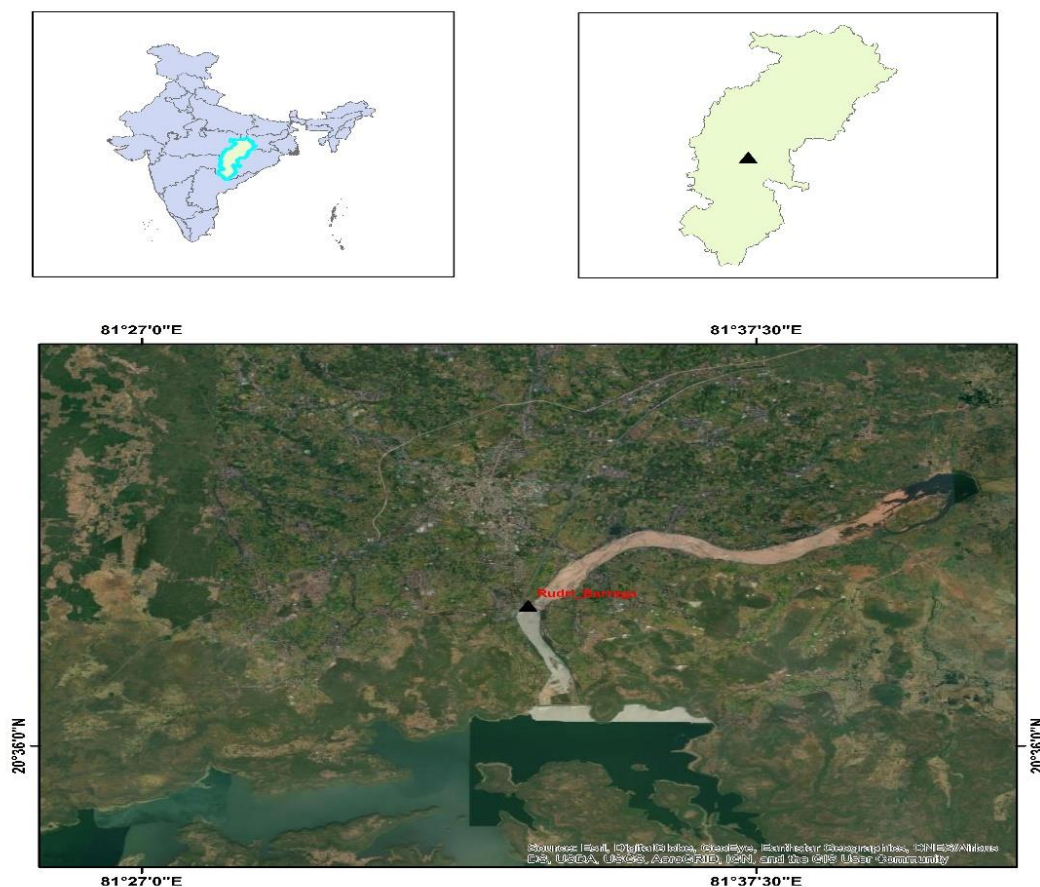


Figure 3. 6 Location Map of Rudri Barrage.

Table 3. 4 The elevation area capacity of New Rudri Barrage.

S.NO	Level	Area in Sqm	Capacity in MCM	S.NO	Level	Area in Sqm	Capacity in MCM
1	320.20	270000.00	0.000	17	321.80	917500.00	1.468
2	320.30	290000.00	0.029	18	321.90	959411.76	1.631
3	320.40	330000.00	0.066	19	322.00	1001111.11	1.802
4	320.50	383333.33	0.115	20	322.10	1042631.58	1.981

5	320.60	432500.00	0.173	21	322.20	1084000.00	2.168
6	320.70	466000.00	0.233	22	322.30	1125380.10	2.363
7	320.80	515000.00	0.309	23	322.40	1166818.18	2.567
8	320.90	561428.57	0.393	24	322.50	1208260.87	2.779
9	321.00	606250.00	0.485	25	322.60	1249583.33	2.999
10	321.10	641111.11	0.577	26	322.70	1291200.00	3.228
11	321.20	678000.00	0.600	27	322.80	1332692.31	3.465
12	321.30	715454.55	0.787	28	322.90	1374074.07	3.710
13	321.40	755000.00	0.906	29	323.00	1415714.29	3.964
14	321.50	794615.38	1.033	30	323.10	1457241.38	4.226
15	321.60	792142.86	1.109	31	323.20	1498666.67	4.496
16	321.70	876000.00	1.314				

Table 3. 5 Salient feature of New Rudri Barrage.

1.0 Location		
1.1	State	Chhattisgarh
1.2	District	Dhamtari
1.3	Tahsil	Dhamtari
1.4	Village	Rudri
1.5	Distance from District HQ	5 Km.
1.6	Lattitude	20°-39'40"
1.7	Longitude	81°-33'56"
2.0 Details of transition-canal		
2.1	Bed-Width	32.00 m.
2.2	Bed-Level	317.810 m.
2.3	Side-Slopes	2:1
2.4	Full Supply depth	A-At Discharge 293.30 Cumecs- 4.05

		m.
		B-At Discharge 391.06 Cumecs- 4.95 m.
2.5	Designed discharge of a canal	391.06 Cumecs
2.6	Freeboard	0.91 m
2.7	Bed-Grade	1:4500
2.8	Crest-Level of Head Regulator	320.250
2.9	Perimeter at F.S.D	4.05 m. -50.11 m.
		4.95 m. – 54.14 m.
3.0 Details of barrage and principle levels		
3.1	Maximum pond level	323.200
3.2	Capacity of NRB at full pond level	4.4475 m.cum
3.3	Max. discharge passed through one HR gate	3384 cusecs
3.4	Max. discharge passed through one spillway gate at level	323.20=5874 cusecs
3.5	Average Riverbed level	319.000
3.6	Max. flood discharge released in the River (on date 09.07.01)	219659 cusecs
3.7	Crest level of under sluice	318.000
3.8	Crest level of Spillway gate	320.200
3.9	Crest level of H.R. gate	320.25 m
3.10	Total length of Barrage	464 m
3.11	Total Nos. of HR gate & size 5 Nos.	10x2.95 m.
3.12	Total Nos. under sluice gate & size 3 Nos.	18x5.35 m.
3.13	Total Nos. Spillway gate & size 20 Nos.	18x3.15 m.
3.14	Max. water level during flood	327.800

3.4 Rainfall and Climate

The Mahanadi Reservoir Project Complex (MRP Complex) is in the central part of India and experiences a tropical monsoon climate with distinct wet and dry seasons. The region receives most of its rainfall during the monsoon season, which lasts from June to September. During this period, the MRP Complex receives an average rainfall of around 1,200-1,500 mm. The rainfall is crucial for the reservoirs in the complex as it helps to replenish their water levels and support the irrigation needs of the region.

The dry season in the MRP Complex lasts from October to May, during which time the region receives very little rainfall. The average temperature during this period is around 25-30°C, with daytime temperatures often reaching over 35°C. The dry season can be challenging for agriculture in the region, and farmers often rely on irrigation to grow crops. The climate in the MRP Complex is influenced by its location in the Deccan Plateau, which is a semi-arid region. The complex is also located in the rain shadow region of the Eastern Ghats, which affects the amount of rainfall it receives. The region's topography, which includes hills and valleys, also influences the local climate and rainfall patterns.

3.5 Geology

The geology of the Mahanadi Reservoir Project Complex is influenced by the diverse topography and lithology of the region, which includes a combination of hard rocks, sedimentary rocks, and alluvial deposits. The region where the Ravishankar Sagar Reservoir is situated is characterized by hard rocks such as granite, gneiss, and schist. These rocks provide a stable foundation for the dam and reservoir.

The Muramsili Reservoir is located in an area that is dominated by sedimentary rocks such as sandstones, shales, and conglomerates. These rocks provide a suitable foundation for the reservoir and help to prevent leakage of water from the reservoir.

The Dudhawa Reservoir is situated in an area that is characterized by alluvial deposits, which include sand, silt, and clay. These deposits have been transported and deposited by the Mahanadi River over time and provide a suitable foundation for the reservoir.

The Sondhur Reservoir is located on the Pairi River, which is a tributary of the Mahanadi. The geology of this area is similar to that of the Dudhawa Reservoir, with alluvial deposits providing a suitable foundation for the reservoir.

3.6 Soils

The soils in the Mahanadi Reservoir Project Complex (MRP Complex) are diverse and influenced by the geology and topography of the region. The soil types can be broadly classified into alluvial soils, black cotton soils, and red soils.

The alluvial soils in the MRP Complex are found in areas where the Mahanadi and Pairi Rivers have deposited sediments over time. These soils are rich in nutrients and are highly

suitable for agriculture, making them an important resource for the region. The black cotton soils are characterized by their high clay content and ability to hold moisture. They are typically found in the upland areas of the MRP Complex, where the elevation is higher and the soil has been formed from weathered basalt rocks. The red soils are formed from weathered granite and are found in the upland areas of the MRP Complex, where the elevation is higher. These soils are generally less fertile than the alluvial soils but are still used for agriculture.

3.7 Data Collected/Used

The estimation of revised reservoir capacity involved the use of various data sources such as the original elevation-capacity table, reservoir levels recorded on different dates from 2019 to 2022, and reservoir characteristics including Riverbed, dead storage level, and highest flood level. To extract revised water spreads, Synthetic Aperture Radar (SAR) data from Sentinel-1, which was available in Google Earth Engine (GEE) from 2019-2022, was utilized. Furthermore, the results of the bathymetric survey conducted in 2021 for three reservoirs were compared with the proposed methodology.

For the LU/LC study, the data used included USGS Landsat 5 Surface Reflectance Tier 1 imagery of 1985 and 1995, and Landsat 7 Surface Reflectance Tier 1 imagery of 2005, which were obtained from the Google Earth Engine platform. Other data sources such as SRTM DEM, Road Layer, Waterbodies Layer, and Population Grid were downloaded from OSM and DIVA-GIS, respectively, to create an Elevation Map, Slope Map, Distance from Roads Map, Distance from Water Bodies Map, and Distance from Population Map. These maps were used as driving factors in TerrSet 2020 for predicting future LU/LC. The list of collected data has been presented in **Table 3.6**.

Table 3. 6 List of collected and created GIS Data.

Data collection	
Data collected	Period
1. Daily reservoir level-release data	
a. Ravishankar Dam	June 2003 – May 2021
b. Murumsilli Dam	June 2003 – May 2021

c. Dudhawa Dam	June 2003 – May 2021
d. Sondhur Dam	June 2003 – May 2021
2. EAC of Dams	Original elevation-area-capacity table of Ravishankar, Sindhur, Dudhawa and Murumsilli dams
3. Command area of dams	Command area maps of dams
4. Salient features of dams	Reservoir characteristics levels, FSL, MDDL, RBL, MWL, etc.
GIS data creation	
GIS data	Description
1. DEM of catchment and command for slope, elevation map	SRTM
2. Road Layer for Distance from road map	OSM
3. Population Grid for Distance from populationmap	Diva GIS
4. Waterbodies and drainage layer Distance from Waterbodies map	OSM and hydro shed
5. Surface reflectance Landsat 5/7/8 and Sentinel-2 satellite image for LULC preparation	1985–06, 2005-06, 2015-06 & Jan 2021

Complex reservoir operation involves the strategic management of water resources stored in reservoirs to meet various demands such as irrigation, domestic supply, power generation, and industrial use like steel production. This process requires sophisticated planning and coordination to ensure optimal utilization of water while considering multiple objectives and constraints. For irrigation planning, reservoir operation involves regulating water releases to meet the seasonal water requirements of crops, balancing the needs of various agricultural areas, and accounting for factors like soil moisture levels and crop growth stages. This often requires the use of predictive models and real-time monitoring to adjust water allocations based on changing conditions. In the case of domestic water supply, reservoir operation ensures a reliable and sustainable supply of clean water to meet the needs of urban and rural populations. This involves maintaining sufficient water levels in reservoirs, implementing water treatment processes, and distributing water through networks efficiently. For power generation, reservoirs are often used in hydropower systems where water is released through turbines to generate electricity. Complex reservoir operation aims to optimize power generation while considering factors such as electricity demand, environmental regulations, and the availability of water resources. In industries like steel production, water is essential for various processes such as cooling, cleaning, and material handling. Reservoir operation in this context involves ensuring a continuous and reliable supply of water to support industrial operations while minimizing water use and waste.

Overall, complex reservoir operation for irrigation planning, domestic supply, power generation, and industrial use requires a multidisciplinary approach that integrates hydrology, engineering, economics, and environmental considerations to achieve sustainable water management and meet diverse societal needs.

This reported work consists of the development of a GIS database, collection of canal data, discharge, reservoir level of all dams and soil, analysis of meteorological and hydrological data, water balancing of the reservoir, modeling, NAM model for rainfall-runoff modeling, MIKE 11 NAM model for assessment of the impact of climate change on water availability, the impact of climate change in agriculture, Application of NIH_Resy for developing rule cure, development of the the MIKE HYDRO basin for irrigation management and irrigation planning, domestic water supply, hydropower generation and reservoir operation and planning.

The study was carried out through the following six interrelated modules.

- Module-I: Water balance of reservoirs
- Module-II: Rainfall-runoff model for the catchment of reservoirs
- Module-III: Assessment of future profile of capacity of reservoirs
- Module-IV: Application of NIH_ResyP for developing rule curve
- Module-V: Water management model for scenario generation
- Future-VI: Projection of climatic variables and rainfall

The framework designed for the study used results of Module-I (Water balance of reservoirs) and Module-II (rainfall-runoff modeling) for rainfall-runoff modeling to compute multiple runoff series from the catchments of Sondhur, Dudhawa, Murumsilli, and Ravi Shankar Sagar reservoirs for the base and in Module-III (Future projection of climate variable and rainfall) as inputs in Module-II to assessments of runoff for future periods. The soil erosion and subsequent deposition from catchments of reservoirs reduce useful storage; therefore, Module IV was designed to compute the present and future revised capacities of the Sondhur, Dudhawa, and Ravi Shankar Sagar reservoirs. The results of Module-II, III, and IV were used in the water management model proposed in Module V for the development of a rule curve for the MRP complex. In Module VI select future adaptive strategies according to future demand. The sequential alignment of different modules has been given in **Figure. 4.1** Different modules suggested under the framework for the present study are given below and described in the next section.

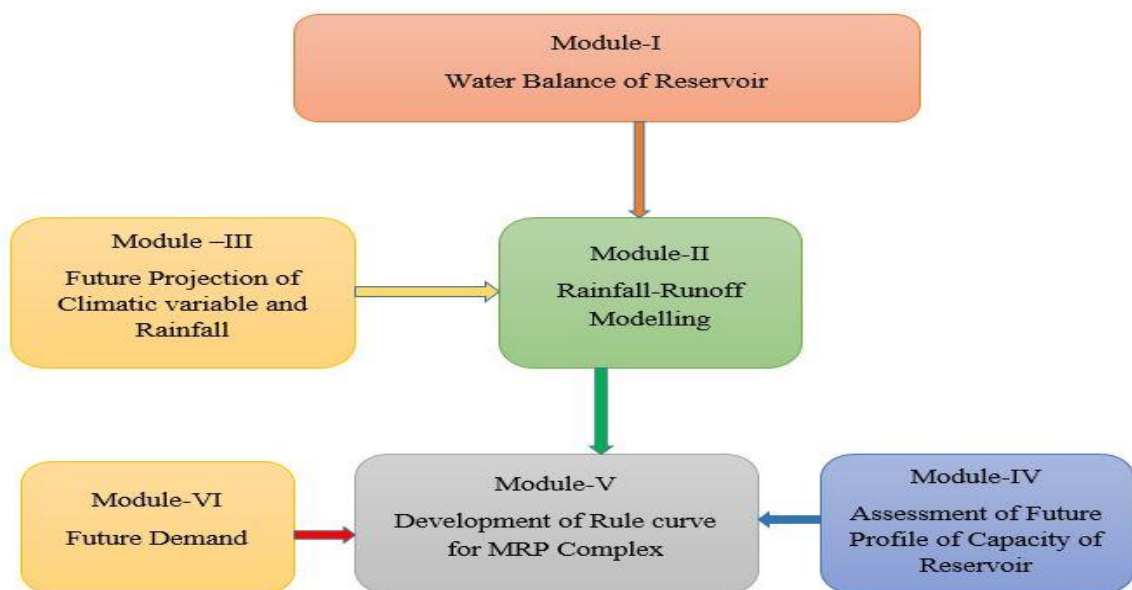


Figure 4.1 Modules for generation & evaluation of scenarios under different framework.

4.1 Water Balance of Reservoirs

The water budgeting along with the quantitative assessment of different components in hydrological processes paves the way for effective water management and ecological and environmental planning. It is useful to understand the effects of climatic variability and human intervention if any significant spatial and temporal variation is observed. The water balance of different areas is useful to assess the effect of geology, soil, land use/land cover, vegetation, etc. (Healy et al., 2007). The water balance study of catchments, reservoirs, lakes, and groundwater basins can be used for allocation, control redeployment, and rational use of water resources in space and time (Sokolov & Chapman, 1974). The water balance can be carried out for any sub-system of any shape and size to compute one unknown of the hydrological cycle. The water balance equation works on the principle of conservation of mass and can be used to compute inflows and the long-term availability of water in the reservoir. It is a useful tool for the assessment of source sustainability, current status, and long-term trend of water availability in the reservoir over a specific period. The water balance is a form of “bookkeeping” of a basin or reservoir where all significant components are considered for a specific period. The basic continuity equation for the water balance of a system can be written as:

$$\left[\begin{array}{c} \text{Input} \\ \text{to the} \\ \text{System} \end{array} \right] - \left[\begin{array}{c} \text{Outflow} \\ \text{from the} \\ \text{System} \end{array} \right] = \left[\begin{array}{c} \text{Change} \\ \text{in} \\ \text{Storage} \end{array} \right] \quad (4.1)$$

The hydrologic balance in the case of water bodies provides stored water in a controlled section and inflows from the basin and uses simple mass balance where the sum of all outflows deducted from the sum of inflows provides a change in stored volume over a specific period (Sokolov & Chapman, 1974; D’Urquiza-Díaz et al., 2009, etc). The water balance equation of a reservoir can be summarized and written as:

$$V_t = V_{t-1} + (Q_{in})_t - (Q_{out})_t - U_t - (P_t - E_t - S_t)A_t \quad (4.2)$$

where, V_t and V_{t-1} are the volumes of water at any time t and $t-1$ respectively. $(Q_{in})_t$ and $(Q_{out})_t$ are the inflow and outflow volume from the reservoir, P_t , E_t , and S_t are the depth of precipitation, evaporation, and seepage from the reservoir and A_t is the area of the reservoir at time t and U_t is the volume of water that passes through the waste weir. The daily reservoir data including reservoir levels, elevation-area-capacity table, pan evaporation, spillway capacity table, outflows including irrigation release, seepage loss, transfer to other reservoirs if any, and evaporation data were used to determine daily runoff from the watersheds of Sondhur, Dudhawa, Murumsilli, and Ravi Shankar reservoirs. The water balance module for the water

balance of reservoirs has been presented in **Figure 4.2**.

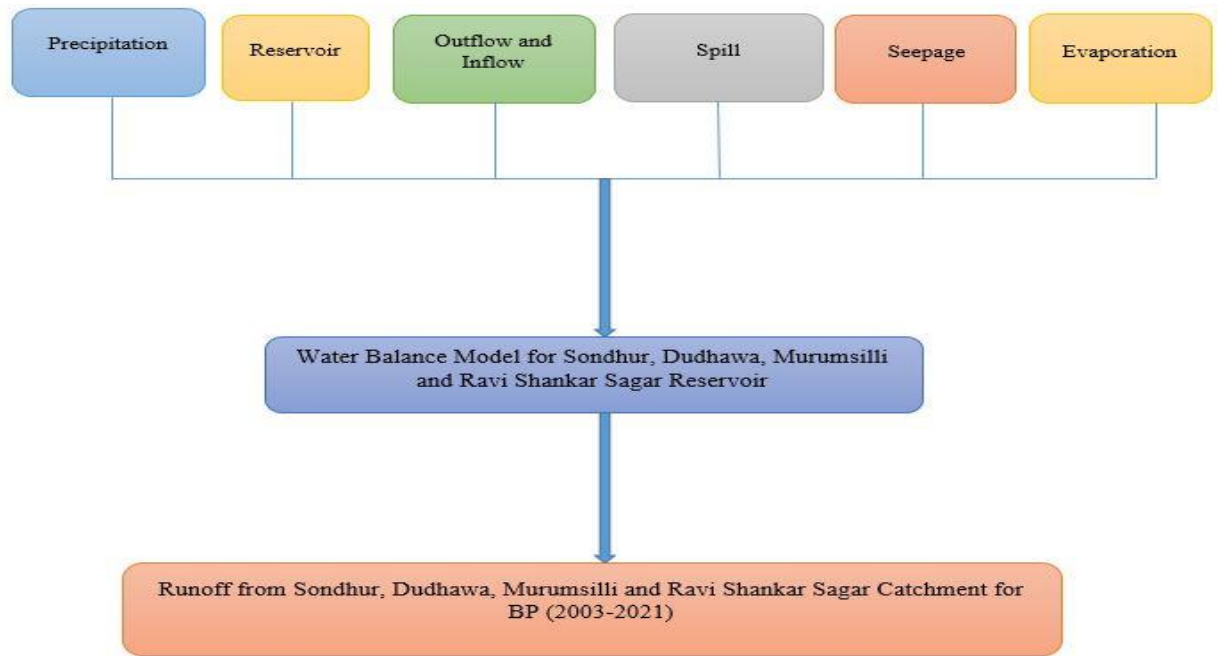


Figure 4.2 Workflow for Module-I.

For water balance, an Excel program has been developed where all interconnected expressions were written for all incoming and outgoing components of water balance as positive and negative components for all four reservoirs of the Ravi Shankar Sagar complex. The different components of a typical reservoir are presented in **Figure 4.3**. To determine runoff from a reservoir catchment, all positive and negative components from a runoff point of view were computed. The positive components are those outflows/losses from the reservoir that, if not withdrawn may contribute towards runoff from the catchment. The positive components consist of evaporation, seepage, irrigation, and non-irrigation supplies from the reservoir on a daily timescale. The irrigation and non-irrigation uses were IR_t and NI_t respectively, determined based on the release data on i^{th} day of the reservoir. The non-irrigation uses consist of evaporation (E_t), seepage loss (S_t), flow from waste weir (WW_t) and diversion for other uses and/or reservoirs (DR_t) can be expressed by the following equation:

$$NI_t = E_t + S_t + WW_t + DR_t \quad (4.3)$$

The evaporation (E_t) is the major loss from the reservoir and can be computed using pan evaporation data using the following equation:

$$Et=K*PEt*At \quad (4.4)$$

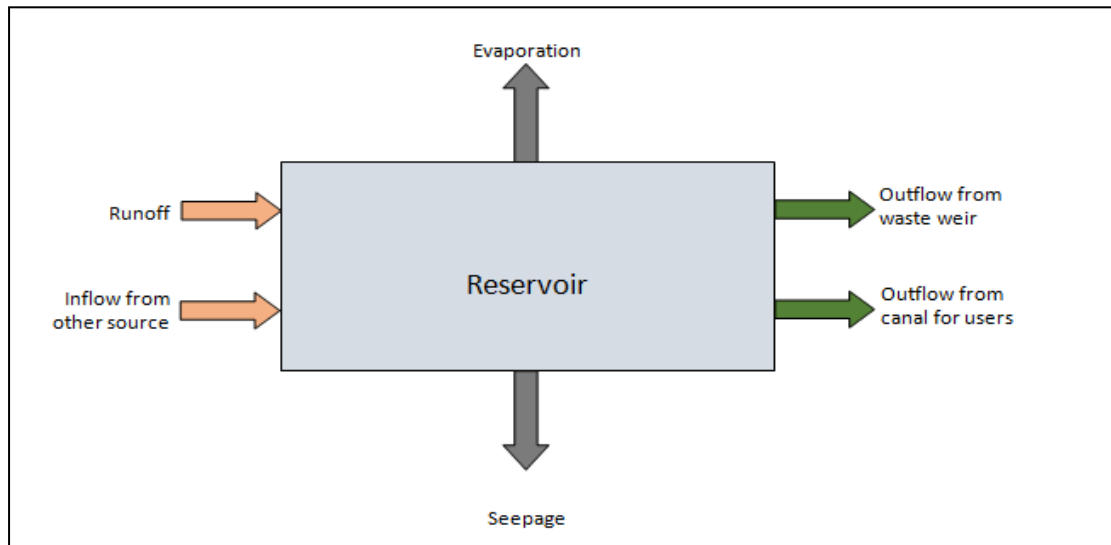


Figure 4.3 Different water balance components in a reservoir system.

Where K is the pan coefficient, PE_t is the pan evaporation and A_t is the reservoir area on t^{th} day. For the computation of seepage loss, a simple method suggested by the Food and Agriculture Organization (FAO) (http://www.fao.org/fishery/static/FAO_Training/FAO_Training/General/x6705e/6705e02.htm) has been used. The loss of water through seepage depends on soil texture and structure of soil in the bottom of the pond as sandy soil has more losses than clayey soil. The seepage loss suggested by FAO has been used for the computation of seepage loss given in **Table 4.1**. The volume of water passed through the waste weir (WW_t) has been computed using the height of water over the weir and the elevation-outflow table of the spillway. The volume of water diverted to other users and/or reservoirs for i^{th} day is DR_t was determined using the flow from the diversion canal.

Table 4.1 Seepage loss from different soils

S.N.	Nature of soil	Seepage loss (mm/hr)
1.	Sand	25-250
2.	Sandy Loam	13-76
3.	Clay Loam	8-20
4.	Loamy Clay	2.5-15
5.	Clay	1.25-10

The negative component for water balance can be the inflow from the other sources (IoT) to the reservoir and can be determined using the measurement of transferred water. The

change in storage may be either positive or negative as per the levels of the reservoir. The change in storage (Δt) for a reservoir computed with the help of elevation-capacity table reservoir levels at $t-1$ and t days may either be positive or negative. The interpolation function of excel was used to compute volumes at measured reservoir levels which were further used to compute the change in storage using the following equation:

$$\Delta_t = V_{t-1} - V_t \quad (4.5)$$

Where V_{t-1} and V_t are the storage of the reservoir on $t-1$ th and t^{th} days respectively. The runoff from reservoir catchment Q_t can be computed using the following equation subjected to the condition that the equation gives a positive value else flow is zero.

$$Q_t = NI_t + IR_t - IO_t + \Delta_t \quad (4.6)$$

The validation of water balance was carried out every year (from June 01 to May 31), where all inflows and outflows from the system were summed up to determine the change in storage and compared with the change in storage based on reservoir levels. If the yearly percentage error comes within the range (Generally 10%), it appears that water balance has considered all major components, and runoff can be used for modeling purposes.

4.2 Rainfall-Runoff Modeling for Catchment of Reservoir

The concept of Rainfall-runoff modeling refers to the interaction of an input with a system i.e., rainfall and catchment to produce the outflow hydrograph. Researchers and soil conservationists find RR modeling as a promising area for the design and development of hydraulic structures, impact assessment analysis, and conservation works. In the mathematical model of rainfall-runoff processes (R-R processes), the input and output variables of a particular hydrological system are connected in a simplified manner. According to Clarke (1973) and Fleming (1979), the relationship is composed of mainly physical processes that alter input values and transform them into output values. Mathematically speaking, this is a solution algorithm of an equation system that describes the structure and behavior of the system. Nash (1958) conceptualized a watershed as a series of identical reservoirs and calculated their instantaneous hydrographs by routing a unit inflow through the reservoirs:

$$u(0,t) = \frac{1}{k} \sqrt[n]{(t/k)^{n-1} e^{-t/k}} \quad (4.7)$$

Where,

$u(o,t)$ is the instantaneous ordinate of unit hydrograph at time t .

k is the storage parameter. (hr)

t is the time after the beginning of surface runoff. (hr)

n is a dimensional parameter.

As stated by Kumbhare and Rastogi (1984), Nash's conceptual model resulted in good agreement with the actual runoff hydrograph when tested with the two-parameter model. Legesse et al. (2003) used a physically-based distributed model to find that a catchment's hydrological response to climate and land use changes in south-central Ethiopia aligns with the peaks of the rising, cresting, and falling limbs. A wide variety of empirical, conceptual, and physically based models with distributed or lumped parameters are available. The model's selection depends mainly on the purpose of the study, data availability, availability of time and resources, and modeler capability. In the present study, the MIKE 11 NAM model was used for rainfall-runoff modeling of the Sondhur, Dudhawa, Murumsilli, and Ravi Shankar Sagar catchment considering its further use in climate change, future water availability, and MIKE HYDRO Basin water management model.

4.2.1 MIKE11 NAM

The MIKE11 NAM is a professional hydrological tool that was developed for water resource planning and management applications. The MIKE11 NAM was developed by the Danish Hydraulic Institute, Denmark. Mike 11 modeling system includes a module that simulates rainfall-runoff processes at the catchment scale called NAM. The inputs of one or more contributing catchments can be used to simulate the dynamics of a River network either independently or as part of a larger simulation of the whole system. This approach enables it to predict the extent and flow of Rivers and waterways in a single catchment as well as a large drainage basin of Rivers and streams containing a mix of catchments within a complex network of Rivers and channels.

NAM is an abbreviation of “Nedbor-Afstromnings-Model” and is a lumped, conceptual, and deterministic model to understand hydrological processes in the catchment. The catchment is considered a single unit since it is a lumped model. However, even though the model parameters and variables are averaged across the entire catchment, the module can estimate parameter values by calibrating them against hydrological observations over time. During runoff estimation, this module addresses four different types of interrelated storage that represent different physical characteristics of a catchment. NAM replicates the land phase of the hydrological cycle including manmade interventions such as irrigation and groundwater pumping, in addition to the four basic storage namely Surface storage, Lower or root zone storage, Groundwater storage, and Snow storage. NAM continuously accounts for water content in mutually interrelated storage representing the overland flow, interflow, and base flow. In the

present study, snowmelt storage is not considered because the temperature in the study area has never fallen below freezing point. **Figure 4.4** represents the different types of storage in the NAM model.

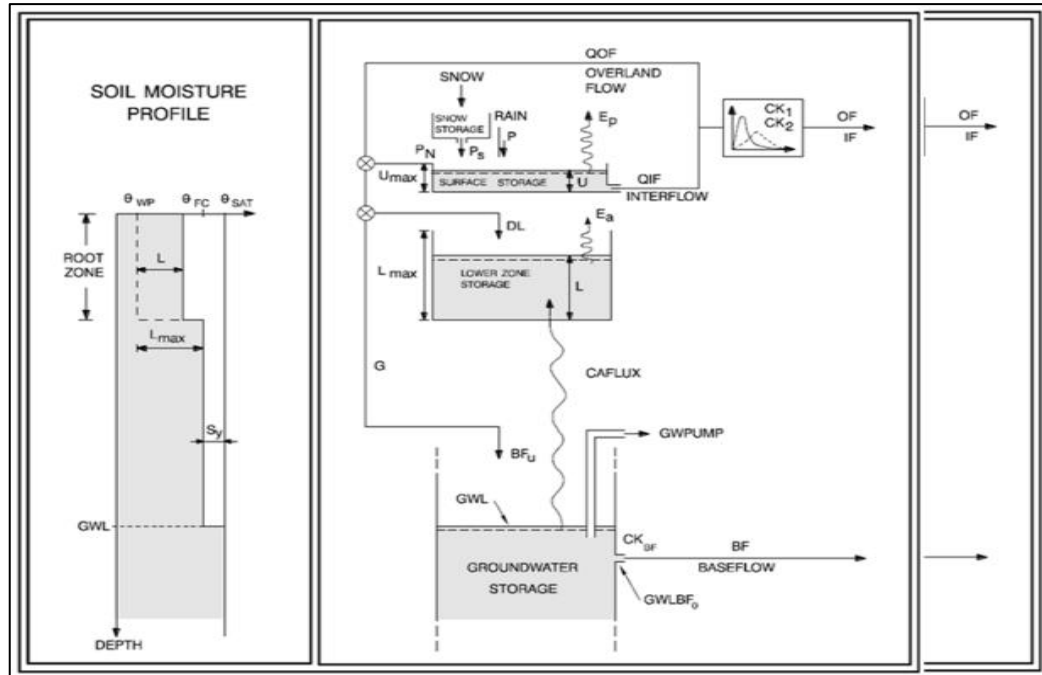


Figure 4.4 Different types of storage in the NAM model.

4.2.1.1 Data Requirement

The following input data are required for the MIKE11 NAM model

1. Meteorological and hydrological data
2. Model parameter
3. Initial conditions

Based on the above-inserted data model generates the time series of catchment runoff, subsurface flow contribution, and information related to other components of the hydrological cycle such as groundwater recharge, soil moisture content, etc. The results depend on the quality and consistency of the input data, and proper modeling procedures. Thus, it is required to input well-arranged and processed data for more accurate results.

4.2.1.2 Model Parameters

The hydrological processes in the basin are defined in MIKE 11 NAM model through nine different parameters i.e. maximum water content in surface storage (U_{max}), the maximum

water content in the lower zone/root storage (L_{max}), overland flow coefficient ($CQOF$), interflow drainage constant ($CKIF$), time constant for overland flow and interflow (CK_{12}), Threshold for overland flow (TOF), Threshold for interflow (TIF), threshold for groundwater recharge (TG), and Time constant for base flow ($CKBF$) which are divided into four groups: Surface storage, rootzone storage, Groundwater, and snow storage. However in this study snow storage was not considered because in the study area, the temperature has not fallen below the freezing temperature. The description of model parameters and their effects are represented in **Table 4.2**.

Table 4.2 Model parameters and their effects.

Parameter	Unit	Description	Effects	Common Range
U_{max}	mm	maximum water content in the lower zone/root storage	overland flow, infiltration, evapotranspiration, interflow	5-35
L_{max}	-	Overland flow coefficient	Overland flow, infiltration, evapotranspiration, base flow	50-400
$CQOF$	mm	Interflow drainage constant	Volume of overland flow and infiltration	0.0-0.1
$CKIF$	-	Threshold for overland flow	Drainage of surface storage interflow	200-2000
TOF	-	Threshold for Interflow	Soil moisture demand must be satisfied for overland flow to occur	0-0.9
TIF	-	Threshold for groundwater recharge	Soil moisture demand must be satisfied for interflow to occur	0-0.9
TG	hrs	The time constant for overland flow and interflow	Soil moisture demand must be satisfied for groundwater recharge to occur	0-0.9
CK_{12}	hrs	The time constant for base flow	Routing overland flow along catchment slopes and channels	3-72
$CKBF$	mm	maximum water content in the lower zone/root storage	Routing recharge through linear groundwater recharge	500-5000

i. Surface storage:

Surface storage includes the total quantity of water stored in intercepting storage (i.e., on plants and depressions) and in the top soil layers. The U_{max} is the upper limit of water that may

be held in surface storage. Evaporative losses and interflow are continuously causing depletion in the quantity of surface water storage (U). When the surface storage reaches its maximum capacity, part of the surplus water (P_N), flows as overland flow into streams, and the remaining water enters into the rootzone and groundwater storage.

ii. Root or lower zone storage:

Root zone storage is the moisture available below the land surface. The L_{max} represents the upper limit of moisture in this storage. Plants can extract this water through roots to fulfill transpiration losses. The groundwater recharge and interflow will depend on the availability of water in rootzone storage.

iii. Evapotranspiration:

In the NAM model, the evapotranspiration demands of the basin are first met by surface storage, and when the requirement exceeds a water content in surface storage ($U < E_p$), the remaining fraction of the requirement is assumed to be accomplished from the rootzone storage. The actual evapotranspiration (E_a) is proportional to the potential evapotranspiration and varies linearly with the relative soil moisture content (L/L_{max}) of the lower zone storage.

$$E_a = (E_p - U) \frac{L}{L_{max}} \quad (4.8)$$

iv. Overland flow:

This parameter specifies how surplus rainfall is distributed between overland-flow by infiltration. When the upper soil surface gets saturated i.e. $U > U_{max}$, the excess water P_N leads to overland flow and infiltration. The QOF denotes the fraction of P_N that contributes to overland flow. The P_N is assumed to vary linearly with the relative soil moisture content, L/L_{max} , of the root zone storage.

$$QOF = \begin{cases} CQOF \frac{L/L_{max} - T_{OF}}{1 - T_{OF}} P_N & \text{for } L/L_{max} > T_{OF} \\ 0 & \text{for } L/L_{max} \leq T_{OF} \end{cases} \quad (4.9)$$

Where; $CQOF$ is the overland flow runoff coefficient and T_{OF} is the threshold value for overland flow.

v. Interflow:

The interflow contribution, QIF , is assumed to be directly proportional to U and to vary linearly with the relative moisture content of the root zone storage.

$$QIF = \begin{cases} (CKIF)^{-1} \frac{L/L_{max} - TIF}{1 - TIF} U & \text{for } L/L_{max} > TIF \\ 0 & \text{for } L/L_{max} \leq TIF \end{cases} \quad (4.10)$$

Where; $CKIF$ is the time constant for interflow and TIF is the root zone threshold value for interflow and ranges from 0 to 1.

vi. Interflow and overland flow:

A linear reservoir concept is used to route the interflow through two linear reservoirs in series with the constant CK_{12} . The overland flow is structurally similar but with a variable time constant.

$$CK = \begin{cases} CK_{12} & \text{for } OF < OF_{min} \\ CK_{12} \left(\frac{OF}{OF_{min}} \right)^{-b} & \text{for } OF \geq OF_{min} \end{cases} \quad (4.11)$$

where; OF is the overland flow (mm/hour), and OF_{min} is the upper limit for linear routing. In practice, OF_{min} is taken as 0.4 mm/hour. For overland flow, $b=0.4$ corresponds to using the manning formula to model the flow. The above equation ensures that the surface flow will be routed kinematically. Subsurface flow is treated as overland flow and routed as a linear reservoir.

vii. Groundwater recharge:

Groundwater recharge of any area depends on the relative value of the root zone's moisture content.

$$G = \begin{cases} (P_N - Q_{OF}) \frac{L/L_{max} - TG}{1 - TG} & \text{for } L/L_{max} > TG \\ 0 & \text{for } L/L_{max} \leq TG \end{cases} \quad (4.12)$$

where TG is the root zone threshold value for groundwater recharge.

viii. Soil moisture content:

The lower zone storage is the water present in the root zone. After dividing the net rainfall between groundwater infiltration and overland flow, the remaining part of the rainfall increases the moisture content L in the lower zone storage by the amount ΔL can be represented by the following equation:

$$\Delta L = P_N - Q_{OF} - G \quad (4.13)$$

ix. Base flow:

The base flow (BF) from the groundwater storage is calculated as the outflow from a linear reservoir with a time constant ($CKBF$).

4.2.1.3 Initial Condition

Initial conditions refer to the state of the basin at the start of a storm event. The MIKE11-NAM model requires an initial set of conditions including surface, root zone, and interflow data, as well as base flow and overland flow initial conditions. At the end of a dry period, it is often sufficient to set all initial values to zero, except the moisture content in the root zone and the base flow. Ideally, the root zone should contain moisture between 10% and 30% of the capacity, with a base flow value close to the observed discharge.

4.2.1.4 Meteorological and hydrological data

i. Rainfall:

There are so many rain gauge stations situated in the catchment of all dams (Sondhur, Dudhawa, Murumsilli, and Ravishankar Sagar) that were used in the development of rainfall-runoff modeling. The daily rainfall data at these stations is collected for the period of nineteen years i.e. from 2003 to 2021 from the Water Resource Department, Chhattisgarh. The Thiessen polygon method was used to calculate a weighted average of precipitation in the catchment with the help of Arc Map 10.2 software.

ii. Potential Evapotranspiration:

Potential evapotranspiration (ET_0) is one of the most essential inputs to setup the MIKE 11 NAM model because of its large impact on runoff in the form of losses from the surface. Daily potential evapotranspiration data for the period of 2003-2021 was used to setup the model. Numerous scientists around the world have developed a large number of more empirical methods for estimating evapotranspiration from various climatic variables. The Penman Montieth equation was used to compute evapotranspiration because of its suitability and recommended by the FAO. The ET_0 calculator developed by the FAO was used to calculate the daily evapotranspiration using daily maximum temperature and minimum temperature as inputs.

$$ET_0 = \frac{0.408(R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (4.14)$$

Where ET_0 is the reference evapotranspiration (mm/day), R_n is the net radiation at the crop surface (MJ/ m²-day), G is the soil heat flux density (MJ/ m²-day), T is the air temperature at 2 m height (°C), U_2 is the wind speed at 2 m height (m/sec), e_s and e_a are the saturation and actual vapor pressures (kPa) respectively, Δ is the slope of vapor pressure curve (kPa/°C), and γ is the Psychrometric constant (kPa/°C).

iii. Discharge:

For model calibration and validation, observed discharge data at the catchment outlet is to be compared with simulated runoff. In the present study, daily discharge data in cumec for a period ranging from 2003 to 2021 (computed through the water balance of the reservoir) was used as input. The NAM Model used different input data in specific formats and **Table 4.3** described the required input data and their required formats.

Table 4.3 Input data requirement by the model.

Variable	Type	Unit	TS Type
Daily Rainfall	Rainfall	mm	Step accumulated
Daily potential evapotranspiration	Evaporation	mm	Step accumulated
Daily discharge	Discharge	m ³ /s	Instantaneous

4.2.1.5 Calibration, validation, and sensitivity analysis of the NAM model

The NAM model of all basins was developed using a digital elevation model through an automatic delineation technique. The rainfall, evapotranspiration, and observed runoff were assigned to the model as inputs. The NAM model was calibrated from 2004 to 2015 and validated from 2016 to 2020 for each catchment. Initially, an auto-calibration technique available in the model was chosen to fit the parameters automatically considering the rainfall and evapotranspiration as inputs and observed runoff as output. The comparison of daily and accumulated observed and computed runoffs, coefficient of determination, etc. were checked. The sensitivity of the parameters was assessed through the Latin Hypercube-One Parameter at a Time (LH-OAT) method, where systematically, the value of a parameter was changed in its reasonable range and the change in the coefficient of determination was determined. After getting a few sensitive parameters, fine-tuning through trial and error methods of these sensitive parameters was made to attain a higher degree of accuracy. After getting satisfactory results, the calibrated model was validated with an independent data set from 2016 to 2020 and analyzed for best-fit criteria. As the results were found satisfactory in calibration as well as in validation, the model can be used to understand the hydrological processes within the basin and the impact of land use/climate change on runoff. The developed model was used in the future water availability and MIKE HYDRO Basin model for the planning of irrigation releases in the command and operation of the Ravi Shankar Sagar dam.

4.3 Assessment of Future Profile of Capacity of Reservoir

The capacity of reservoirs is reduced with passes of time and needs to be evaluated for long-term planning. The revised capacity can be computed using conventional techniques of hydrographic survey/inflow-outflow techniques or advanced techniques of digital image processing (DIP) of remote sensing data. The conventional techniques are time-consuming, costly, and risky, while DIP is easy, less time-consuming, and economical. This section was designed to perform the task of determining present and future revised capacities of all reservoirs in the Ravi Shankar Sagar Reservoir complex.

4.3.1 Methodology adopted for estimation of revised reservoir capacities

The estimation of revised capacity with the help of digital image analysis is an indirect method that works on the principle that the sediment deposited in the reservoir reduces the water spread from its original spread at the same level (**Figure 4.5**). The revised water spread areas at different levels are used to compute revised estimates of capacities and differences between original and revised capacities can be considered as loss in volume due to sediment. The important steps for computation of loss of storage or sedimentation include identification of remote sensing data, processing of data for determination of revised area, and computation of revised capacities and losses. The flow chart for the computation of revised capacities is presented in **Figure 4.6**. The present study uses Otsu based segmentation technique in GEE for SAR data from Sentinel-1 satellite to obtain a chart and select different dates and their corresponding revised water spreads.

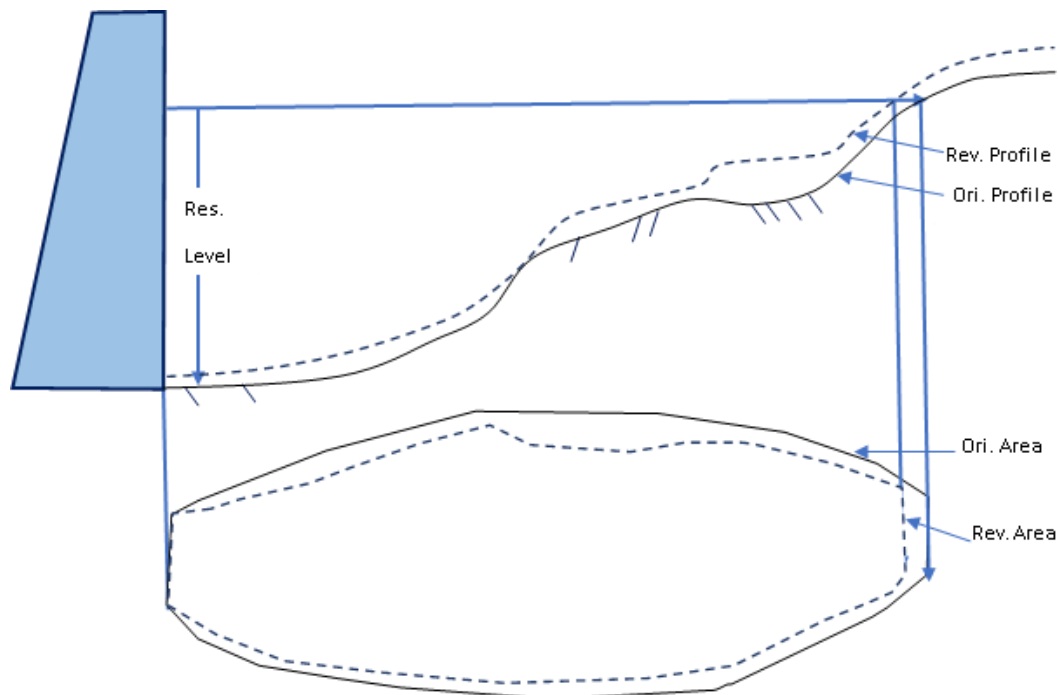


Figure 4.5 Principle of computation of sedimentation in a reservoir using RSdata.

4.3.1.1 SAR microwave data

The microwave data used in the study were obtained from the constellation of Sentinel satellites 1A and 1B launched on April 10, 2014, and April 22, 2016, respectively by the European Space Agency (ESA). These satellites are stationed at a sun-synchronous, near-polar, circular orbit of 693 km having a combined revisit period of six days (12 days for each satellite). The Sentinel satellite has C-band synthetic aperture radar (5.4 GHz) with incidence angles ranging from 29 to 46 degrees. Sentinel-1 satellites feature dual-polarization capabilities. i.e.,

HH& VV (same transmitted and received polarization), HV (horizontally transmitted and vertically received) VH (vertically transmitted and horizontally received), allowing for the acquisition of images regardless of weather and at any time of day and night for a wide range of applications, including surface water monitoring (Pham Duc et al 2017). The same transmitted and received (HH & VV) polarization is found most useful in the case of water delineation (Bourgeau-Chavez et al 2021). The sentinel has four different acquisition modes including the extra wide swath of 400 km swath for oceans and coastal monitoring, the strip mode of 80 km on special order, the wave mode of 20 km for the ocean, and an interferometry wide (IW) swath of 250 km for land features. The GEE collection of SAR data from Sentinel 1 are ground range detected (GRD), multi-looking, and projected to ground range using earth ellipsoid. The terrain height supplied in the product general annotation is used to correct the ellipsoid projection of the GRD products. This processing is called pre-processing and is done with the help of the Sentinel 1 toolbox before loading SAR data on GEE. A median filter was applied as a speckle filter to reduce granular noise that occurred due to interference at the transmitter and receiver antenna.

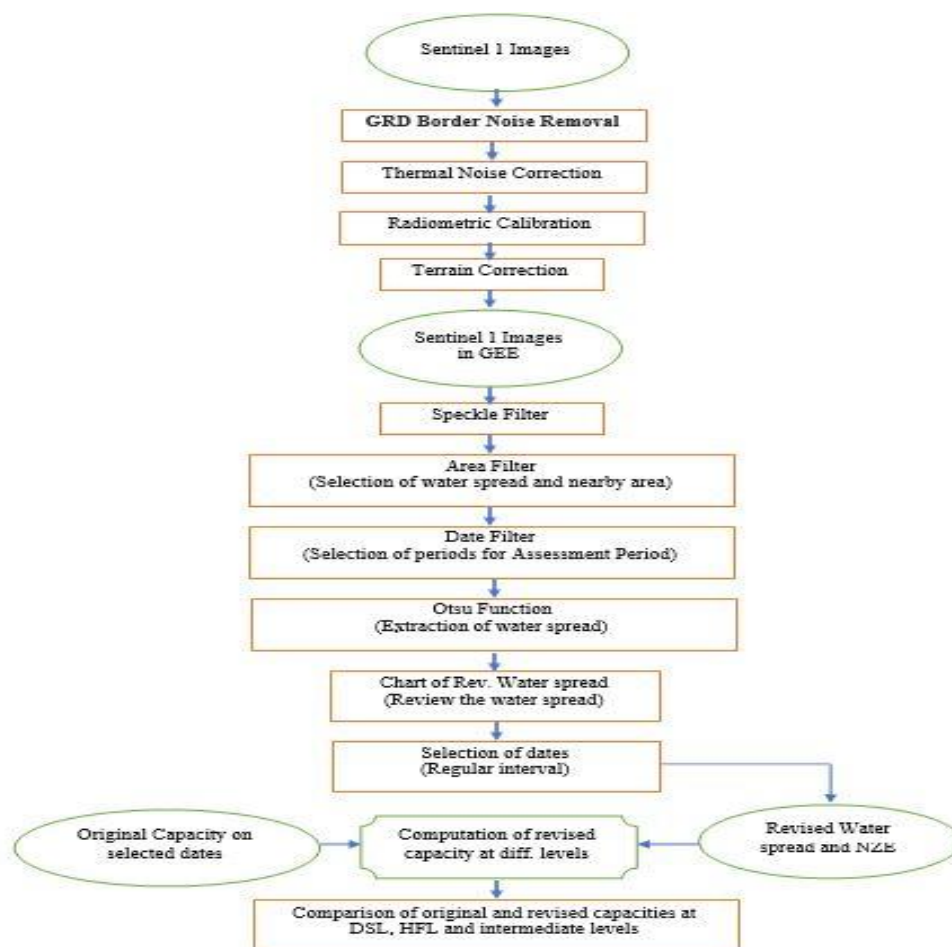


Figure 4. 6 Flow chart for computation of revised capacity of the reservoir using the Otsu technique.

4.3.1.2 Application of Otsu algorithm in GEE

The date and area filters were applied to select all the scenes within the selected period to get the data set for the period of interest in GEE through Java scripting. In this study, the “VV” mode of polarization and instrument mode, “IW” were used to select SAR data of the area of interest. The image processing of remote sensing data for the identification of water pixels from the rest of the image is essentially a binarization where thresholding is an efficient technique.

The Otsu method is one of the most popular and successful methods due to its simplicity and effectiveness for image thresholding and uses a search algorithm for the global optimal cutoffpoint (Liu & Yu 2009; Cao et al 2021). The Otsu method was proposed by Nobuyuki Otsu (Otsu 1979) and used for automatic image thresholding for image processing and computer vision (Sezgin & Sankur 2004). The Otsu image segmentation method greatly helps in depicting the foreground and background pixels when the object(s) of interest in an image can be distinguished from the background in terms of brightness. Otsu method is based on the principle of computation of interclass variance among different classes. The difference in inter-class variation among different clusters is the key to the perfect segmentation of the image. The gray-scale characterization is used to divide an image into background and foreground and this division depends on how accurately the threshold is determined. The Otsu method converts an image into a binary image (0 or 255: black or white) to reveal the important part of the image. To obtain the binary image, a threshold value is selected between 0 to 255 on a gray-level image (Figure 4.7).

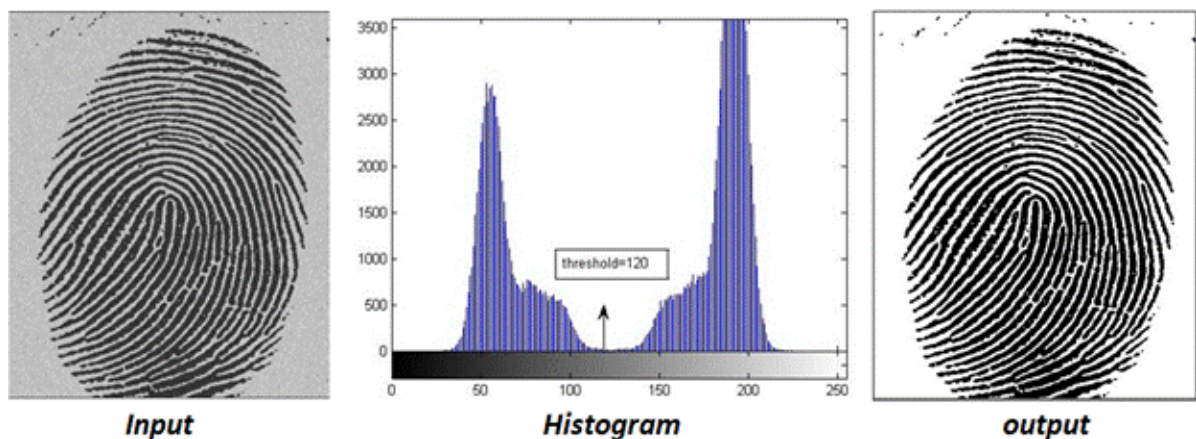


Figure 4.7 The input, histogram with threshold and output from the Otsu segmentation technique (Reproduced from <https://cse19-iiith.vlabs.ac.in/exp/image-segmentation/theory.html>).

The Otsu method finds this threshold by minimizing the variance of within-class density or maximizing variance between classes. The histogram of the image is determined as

input for the Otsu binarization process. An initial threshold (t) is selected which divides the whole histogram into two clusters. The within-class variance can be computed using the following equation:

$$\sigma^2(t) = w_1(t)\sigma_1^2(t) + w_2(t)\sigma_2^2(t) \quad (4.15)$$

Where, $w_1(t)$ and $w_2(t)$ are the probabilities of two clusters divided by the threshold value (t), $\sigma_1^2(t)$ and $\sigma_2^2(t)$ are the variance of these two clusters. The variance of these clusters was determined using the following equation:

$$\sigma^2(t) = \frac{\sum_{i=1}^n (X_i - \mu)^2}{n-1} \quad (4.16)$$

Where X_i is the pixel value of the i^{th} pixel, μ is the mean value of pixels and n is the total number of pixels. Using the above equation, variance is computed for both clusters and interclass variance for different threshold values and the threshold value gives the minimum within-class variance and is considered the Otsu threshold for the division of the image into two classes (black and white). On the other hand, Otsu suggested the other option of maximizing the between-class variance ($\sigma^2(t)$) using the following equation:

$$\sigma^2(t) = w_1(t)w_2(t)[\mu_1(t) - \mu_2(t)]^2 \quad (4.17)$$

Where $\mu_1(t)$ and $\mu_2(t)$ are the means of the first and second clusters. In the present study, the within-class variance was applied in GEE with modification in a function already available on the internet. The developed GEE program resulted from a threshold value having a maximum within-class variance, and a chart showing water pixels, and water spread on different dates of pass of Sentinel 1 over the area of interest.

4.3.1.3 Computation of revised capacity and sediment

For the estimation of revised capacities for the reservoir, water spread areas at nearly equal intervals obtained from the Otsu segmentation technique were used to determine the revised bed level by fitting an appropriate curve. It is evident that the storage up to the revised bed level is filled with sediment and above it, the cone formula (Ninija Merina et al. 2016; Dadoria et al. 2017; Rai et al. 2019; etc.) was used to determine revised water volumes between two consecutive levels. The cone formula can be written as follows:

$$\Delta V_R = \frac{h}{3} (A_{1R} + A_{2R} + \sqrt{A_{1R}A_{2R}}) \quad (4.18)$$

Where, ΔV_R is the revised volume between two consecutive levels h_1 and h_2 , $h=h_2-h_1$ is the difference between these two levels, and A_{1R} and A_{2R} are the revised water spread on these levels. The cumulative revised capacities were computed by adding revised volume

between these levels and compared with the original cumulative capacities to ascertain the loss of capacities at different levels of the reservoir. The revised capacities obtained from Otsu-based image classification were compared with bathymetric survey results conducted in the year 2021 for three reservoirs in MRP.

4.4 Methodology Adopted For LU/LC Change Prediction and Forecasting

USGS Landsat 5 Surface Reflectance Tier 1 of 1985 and 1995 and Landsat 7 Surface Reflectance Tier 1 image of 2005 were imported in GEE using **ee.ImageCollection()** function. The imagery was filtered by date and cloud cover and clipped to the study area boundary. Using a machine learning Random Forest classifier in Google Earth Engine (GEE) as shown in **Figure 4.8**, these images were classified into 5 LULC classes: water bodies, built-up areas, barren land, Cropland, and forest.

The kappa statistics and overall accuracy were calculated for the accuracy evaluation. Simulated classified LU/LC maps of 1985, 1995, and 2005 using GEE are imported to the TerrSet model, 1985 & 1995 were used to predict the 2005 & 2021 LULC maps in TerrSet 2020 software using the Markov chain algorithm.

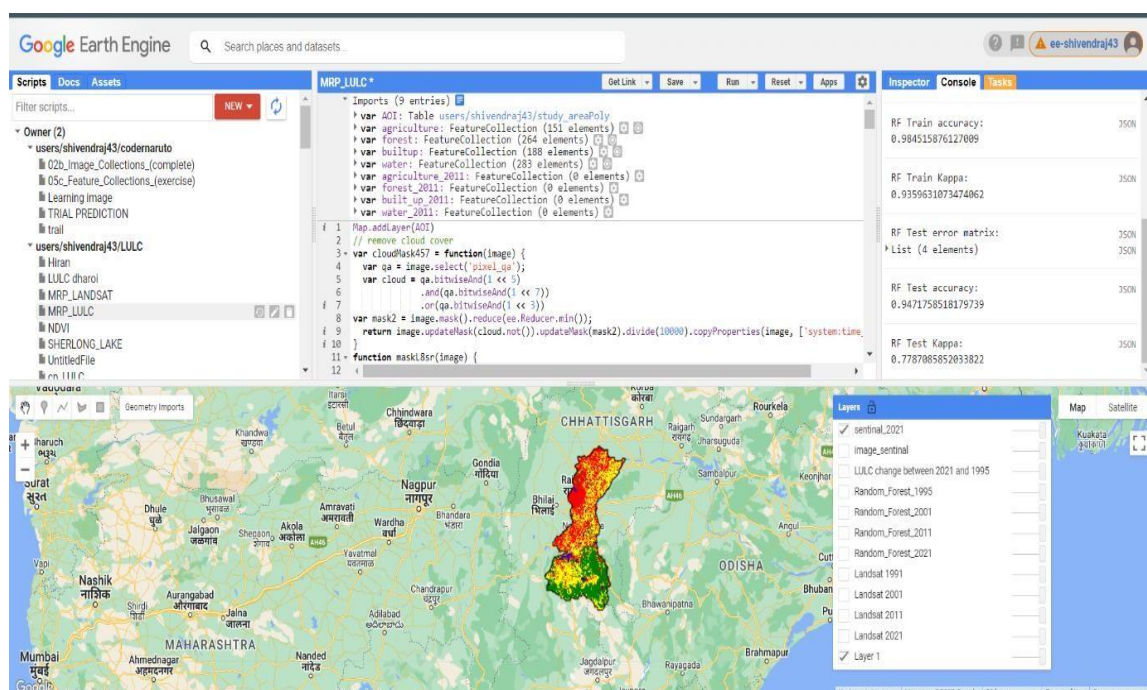


Figure 4.8 GEE platform and LULC classification.

Markov chain modeling is a statistical method used to analyze and predict the patterns of land use and land cover (LULC) changes over time. In this method, the transition probabilities of a pixel's LULC state from one time period to another are calculated based on

the historical LULC data.

The Markov chain model assumes that the probability of a pixel transitioning to a particular LULC class in the next period depends only on its current LULC class and not on its history or any other external factors. This makes it a memory-less model that is useful for predicting the future states of a LULC system based solely on its current state. To use the Markov chain model for LULC change analysis, a transition probability matrix is constructed for each period, which specifies the probability of a pixel transitioning from one LULC class to another over time. This matrix is based on the analysis of the historical LULC data and can be used to predict the LULC patterns for future periods. The Markov chain model can be used in combination with other modeling techniques, such as Cellular Automata (CA), to simulate and predict future LULC changes. The CA-Markov model is a widely used method for LULC change analysis that combines the Markov chain model with a spatially explicit CA model to simulate the spatial patterns of LULC changes over time. The methodology adopted for the study is shown in **Figure 4.9**.

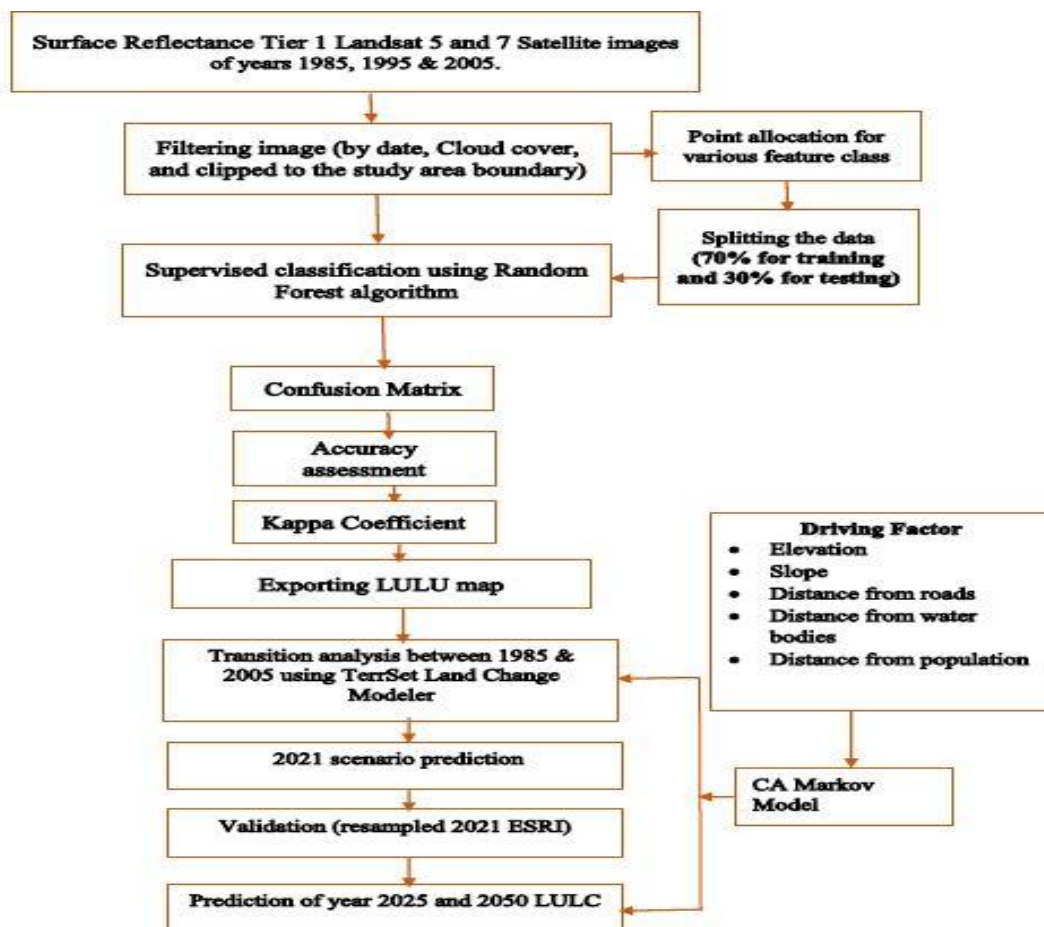


Figure 4. 9 Flow chart of the LU/LC change prediction methodology.

4.5 Reservoir Operation

Reservoir operation involves making decisions about when to store water, how much water to release, and at what rate. A reservoir is operated according to a set of rules or guidelines for storing and releasing water depending upon the purposes it is required to serve. For reservoirs that are designed for multi-annual storage, the operation policy is based on long-term targets. The estimates of water availability are made using long-term data. The demand for conservation uses like irrigation, water supply, navigation, and hydroelectric power are worked out by projecting the demand figures. If hydroelectric power generation is not one of the purposes of the reservoir, water is allocated among various consumptive uses. The extent of water releases for a variety of uses which can be served from storage in the reservoir on a long-term basis are determined and the reservoir is operated accordingly.

4.5.1 Reservoir operation policies

Reservoir operation policies dictate how water stored in the reservoir will be allocated and released to meet various objectives, such as flood control, water supply, irrigation, hydropower generation, environmental conservation, and recreation. The operating policy of reservoirs designed and operated for seasonal storage is based on yearly operation. A reservoir operation study is carried out for long-term records taking into account the demand estimates for various conservation uses. Policy decisions are arrived at introducing the concepts of reliability.

4.5.1.1 *Standard linear operation policy*

The simplest of the reservoir operation policies is the standard linear operation policy (SLOP). According to this policy, if in a particular period, the amount of water available in storage is less than the target demand, whatever quantity is available is released. If the water available is more than the target but less than the target demand plus available storage capacity, then a release equal to the target demand is made and the excess water is stored in the reservoir. In case, even after making releases equal to the target demands, there is no space to store the excess water, all the water over maximum storage is released. The SLOP is graphically represented in **Figure 4.10**.

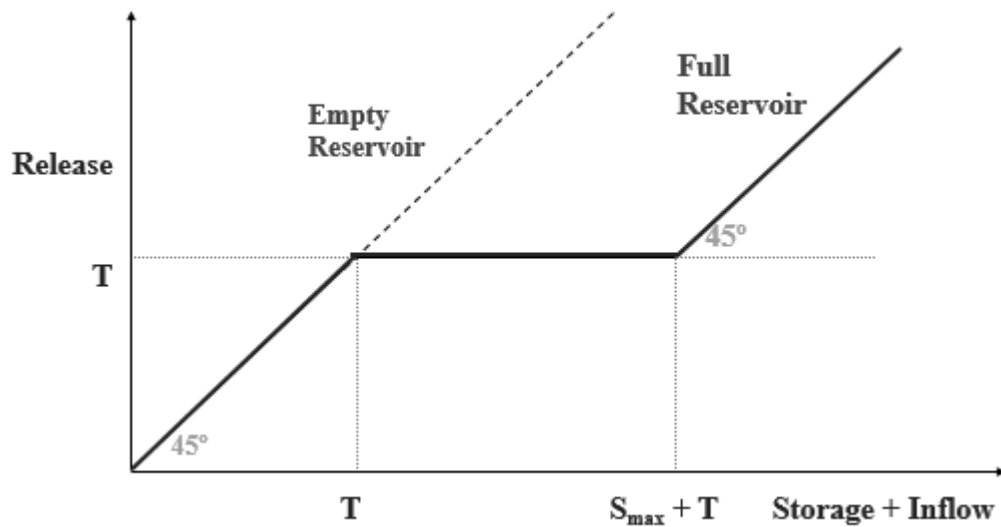


Figure 4.10 Graphical representation of SLOP.

4.5.1.2 Rule curve

Rule curves are predefined water level targets that direct how reservoir storage should be managed throughout the year. These targets are often based on historical hydrological data and are designed to balance competing water uses while ensuring flood control and reservoir safety. A rule curve or rule level specifies the storage or space to be maintained in a reservoir during different times of the year. Here the implicit assumption is that a reservoir can best satisfy its purposes if the storage levels specified by the rule curve are maintained in the reservoir at different times. The rule curve as such does not give the amount of water to be released from the reservoir. This amount will depend upon the inflows to the reservoir, or sometimes it is specified in addition to rule curves. Different rule curves are prepared for different types of conservation demands from a reservoir, say domestic supply, irrigation, hydropower, and minimum flow requirement in the downstream channel. Rule curves represent the warning levels at different times of the year which depend on the amount and priority of demands and the likely inflow in the reservoir. A graphical representation of a typical rule curve is shown in **Figure 4.11**. The upper rule curve guides for spilling, the upper-middle rule curve for irrigation supply, and the lower rule curve for highest priority demand, i.e., domestic supply demand.

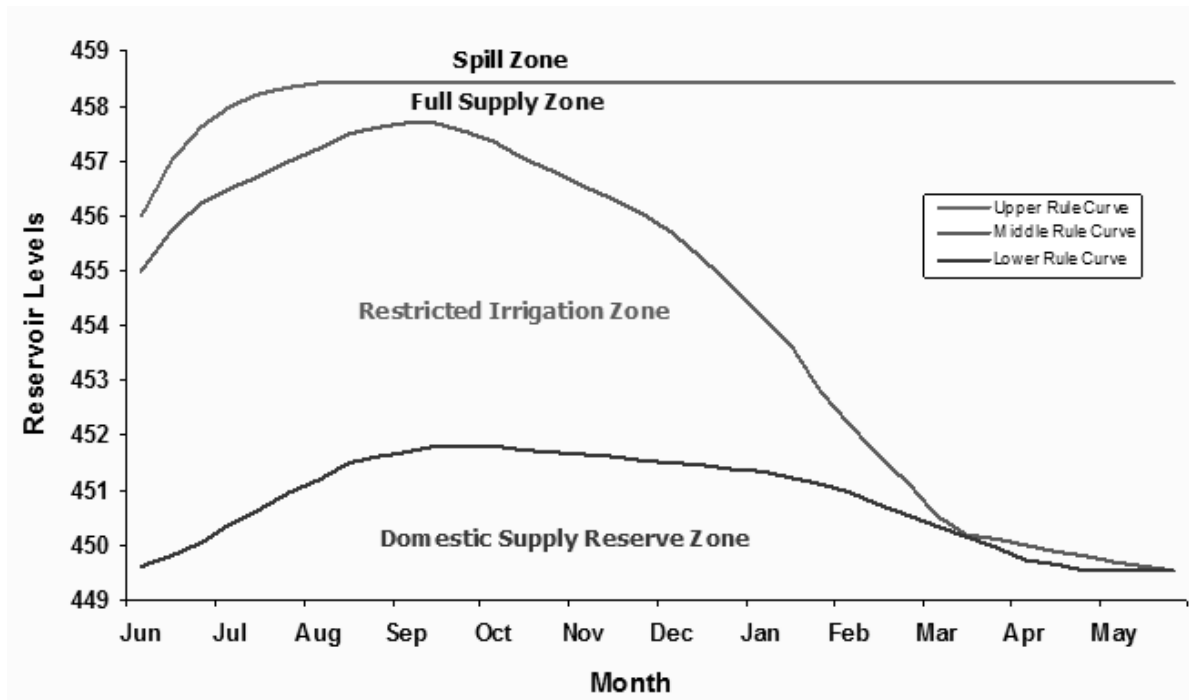


Figure 4.11 Rule curves for different demands from a reservoir.

4.5.2 Integrated operation analysis of MRP

Integrated operation analysis is carried out for a multi-purpose multi-reservoir system in which projects are interconnected either in series or in parallel and they affect or are affected by the operation of other reservoirs in the system. For integrated operation analysis, a comprehensive data file is prepared for each node in the system, and the simulation analysis is carried out with due consideration to the linkages and d/s demands to be met from u/s projects. Integrated operation analysis helps in visualizing the outcome of operating a large system as per the given operation policy. This can also be used to formulate or fine-tune the operation protocol of projects in conflicting situations to maximize the system output following some specified criteria.

The objectives of the study are:

- To carry out integrated operation analysis considering all projects at 10 daily time steps under different scenarios of water availability using SLOP.
- To develop rule curve-based integrated operation of the MRP system for different scenarios of water availability.

As per the objectives of the present study, the operation of the MRP system was simulated at a 10-daily time step. A network diagram of the system is shown in **Figure 4.12**. The input data for simulation consists of the details of each of the projects such as Full Reservoir Level

(FRL), Minimum Draw Down Level (MDDL), initial storage at the beginning of the simulation, and Elevation – Area – Capacity (EAC) table.

Monthly demands for different purposes for each project were available from WRD Chhattisgarh, in addition to this working tables of each project were also.

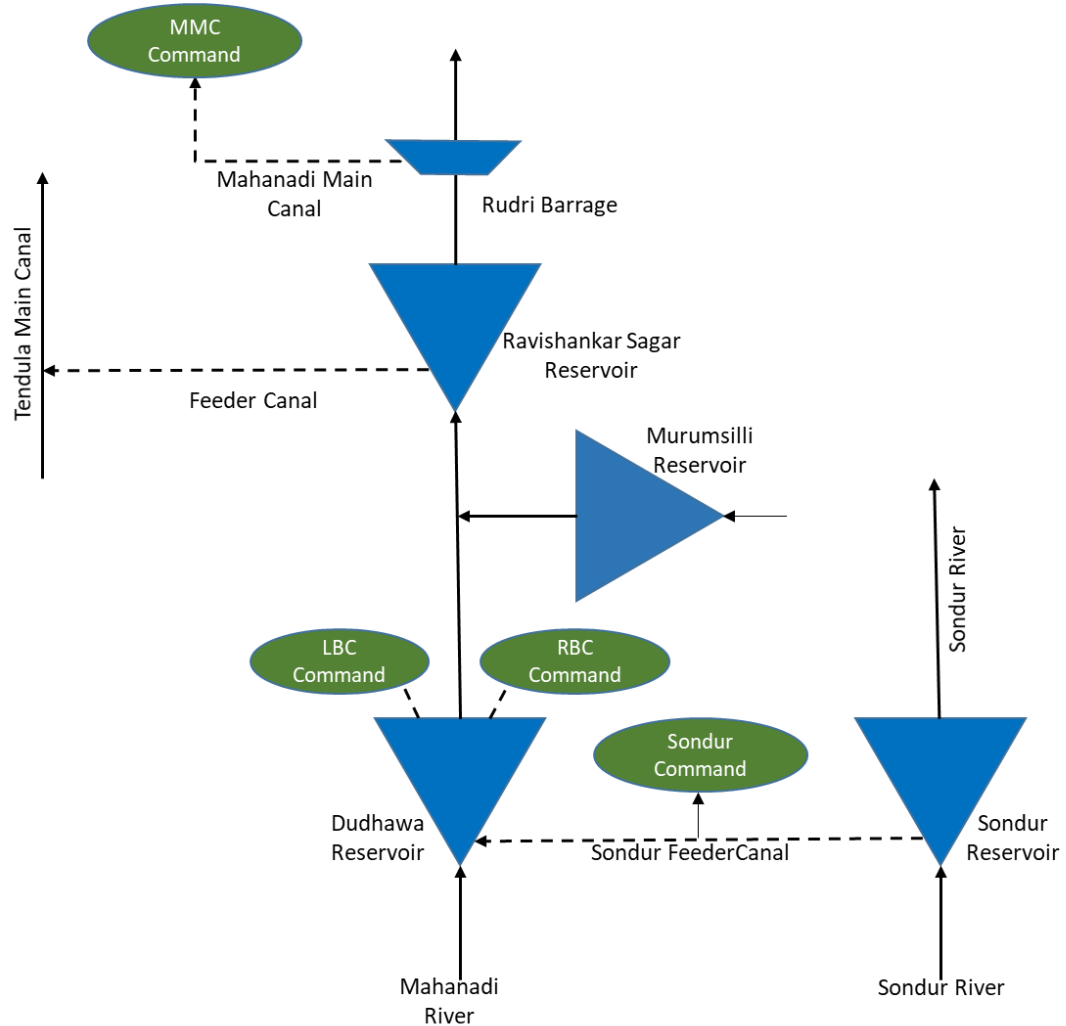


Figure 4.12 Network diagram of MRP system.

Available at a daily time step. Hence monthly demands were converted to 10-daily from the available average monthly demand data. Link demand was computed by using the maximum of the release made for the past 10 years in the working table of the Soudhur reservoir at the 10-daily time step. For each of the projects, the number of demands, the value of demand for each ten-daily period, and the corresponding off-take level (if given) were used in the model.

To simulate the operation, first total water availability at the project for a given time step is estimated. It consists of inflow through the River and return flow from releases for various demands by the immediate upstream projects. The total water availability is compared

with the demand and water is allocated, beginning with the highest priority demand, as available. Storage projects have a reservoir to store surplus water. Here, the total water availability is obtained by adding the amount of water in active storage at the beginning of the period, plus inflow through the River and return flow from releases for various demands by the immediate upstream projects. Now beginning with the demand having the highest priority, water is allocated to meet the demand if the storage level is above the offtake level for that demand. All the demands are sequentially considered in this manner.

Evaporation loss from a reservoir is computed by multiplying the average reservoir water surface area with the normal depth of evaporation for the period. To compute the average water surface area, a trial value of the reservoir surface area at the end of the period is assumed and used with the known water surface area at the beginning of the period. After allocating water to all the demands, the final reservoir storage and the final surface area are computed. If the final area is different from the assumed value, the final area is taken as the value for the next iteration, and computations are repeated till the difference between the two is less than a threshold value. Checks are also made to ensure that the final reservoir storage does not exceed the maximum storage or is not below the minimum storage. For flow computations at a project site, the inflow series is computed at a project using a water balance approach with the help of available working tables.

4.5.3 Application of NIH_ResyP for developing rule curve

India is bestowed with rich water resources but more than 80% of the annual rainfall over this country falls in the four monsoon months from June to September. Because of the high time and space variability of rainfall and the uncertain nature of monsoon, it is imperative to utilize the available water resources optimally and efficiently. The reservoirs are one of the most important components of a water resources development project. The principal function of a reservoir is the regulation of natural stream flow by storing surplus water in the rainy season and releasing the stored water in the dry season to supplement the natural River flow. Reservoirs are the most effective means of changing the temporal and spatial availability of water. More than 4000 major and medium dams have already been constructed all over the country to tap the available water resources so that the water can be utilized following the requirements of mankind.

Once structured facilities like dams, barrages, hydropower plants, etc. come into being, the benefits that could be reaped depend, to a large extent, upon how well these facilities are

managed. The efficient use of water resources requires not only judicious design but also proper management of the hydraulic structures. Further, given the increasing demands, water resources systems management aims to search for operation policies so that various demands can be satisfied to the maximum extent possible. Reservoir operation forms a very important part of the planning and management of the water resources system. Reservoir management involves allocating available water among multiple uses and users, minimizing the risks of water shortages and flooding, and optimizing the beneficial use of water. A reservoir operation policy specifies the amount of water to be released from the storage at any time depending upon the state of the reservoir, the level of demands, and any information about the likely inflows in the reservoir. Detailed guidelines are formulated to enable the operator at the dam site to make appropriate management decisions.

The management of reservoirs is a very challenging problem because it deals with a natural system with all the associated uncertainties. A tailor-made solution methodology for this problem is not available. For developing operation policies for a system of reservoirs, it is imperative to understand their integrated operation. Mathematical models are constructed to analyze and understand the systems. Several techniques are available for reservoir operation, viz., standard linear operating policy, rule curves, the concept of storage zoning, etc. Systems analysis has proved to be a very powerful tool in the formulation and screening of policies for reservoir operation. There are several cases where system analysis techniques have been used to arrive at the operation policies for multipurpose reservoirs and the derived policies have shown to result in an improvement over the historic performance. The integrated operation of a complex system is necessary for efficient management of the limited resources to meet various target demands.

The system engineering techniques like simulation and optimization are extensively used in the reservoir operation problem. Among the optimization techniques, two techniques that are most frequently used nowadays are linear programming and dynamic programming. The water resources literature contains many references as to which systems approach is better for reservoir operation analysis optimization or simulation. There is a consensus now that optimization models are more suited for screening studies while simulation models provide higher flexibility in detailed and realistic representation of a complex configuration. Repeated runs of a simulation model are made to analyze the system performance under different conditions. A large number of models, generalized as well as system-specific, have been developed during the last two decades. Some popular models include HEC-3 and HEC-5 of the

Hydrologic Engineering Centre, SIMYLD-II of the Texas Water Development Board, the ACRES (Sigvaldason 1976), the RESER (Simonovic 1992) and the IRIS (Iris 1990).

4.5.3.1 Description of NIH_ReSyP

Given the importance of the reservoir operation problems in the Indian context and the non-availability of a generalized software for reservoir analysis, the National Institute developed a generalized software named “SRA – Software for Reservoir Analysis” for reservoir analysis Jain et. al (1996). This software linked several individual computer programs for carrying out various kinds of reservoir analysis such as capacity computation, storage yield analysis, hydropower simulation, reservoir routing, EAC interpolation, inflow estimation using the rate of rise method, initial rule curve derivation, and operation of a system of multiple reservoirs for conservation purposes. However, the preparation of data files for various modules and the graphical representation of results was a difficult task.

To address these limitations, a WINDOWS-based software named “**NIH_ReSyP – Reservoir Systems Package**” has been developed. The software has been developed in the Visual Basic platform and provides a user-friendly environment for carrying out various hydrological analyses related to reservoirs. The software is capable of presenting the results in tabular as well as graphical form.

4.5.3.2 Function of NIH_ReSyP

NIH_ReSyP is a WINDOWS-based comprehensive and easy-to-use software with a menu screen for various analytical modules and online help to guide the user for each module. The package includes many tabular and graphical options facilitating efficient analysis and reporting.

The software is a menu-driven interactive package. The opening banner (given in **Figure 4.13**) shows the drops representing various kinds of hydrological analysis that can be performed for a reservoir with the software. Some of the modules have been added in the first version (Version 1) while some modules (for example spillway rating table and reservoir sedimentation) are planned to be added in the subsequent versions of the software. At the opening banner, there are options to enter inside the NIH_ReSyP by clicking on the Start_ReSyP button or to exit the system by clicking on the Quit_ReSyP button. On entering the software, the Main menu screen appears as shown in **Figure 4.14**.



Figure 4.13 Opening Banner of NIH_ReSyP.



Figure 4.14 Main-menu Screen.

The main menu bar at the top of the screen displays the names of various analytical options that can be used with the software. By clicking on a particular module, various sub-modules related to the selected analytical option appear on the screen. For example, on clicking the Cap-Comp (Capacity computation) module, two sub-modules related to this analysis, i.e. sequent peak analysis and storage-yield analysis appear on the screen. For any module/sub-module, a window appears showing various sections for filling data form, analyzing using the filled data form, and viewing the results in either Tabular or Graphical form. The analysis ladder for a particular module/ sub-module is presented in **Figure 4.15**.

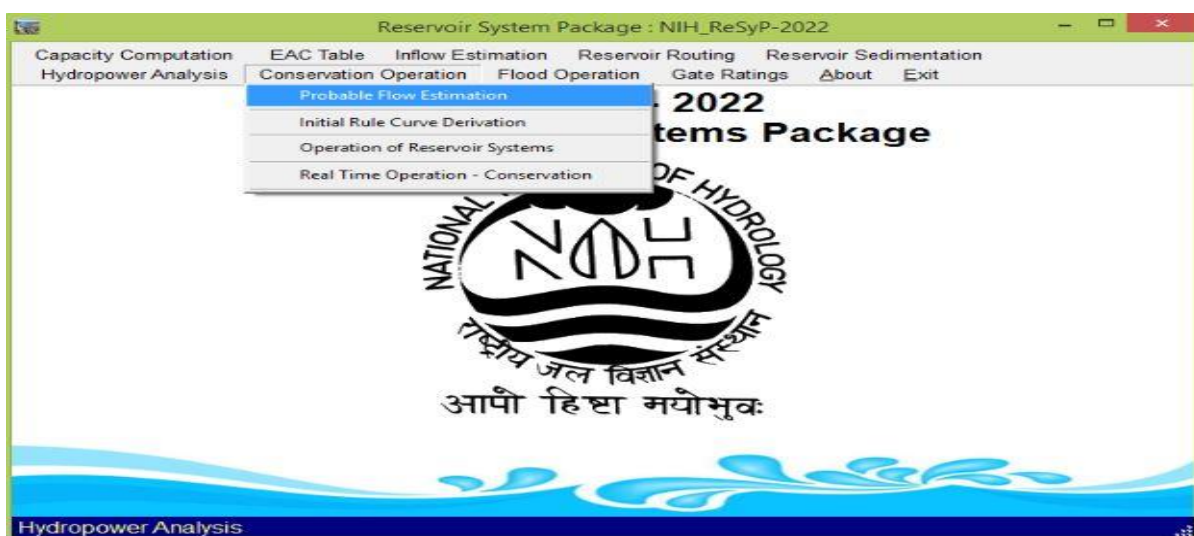


Figure 4.15 Analysis ladder for a module.

By clicking on the “Fill Data Form”, the data form designed for the chosen analysis option appears. In the data form, various options; such as retrieving an old data file, generating a new data file (by clearing various cells), making changes in the retrieved data file and saving it with a new name, etc. are provided. The software invokes an interactive window so that the analyst can save/retrieve the data file to/from the desired location. A sample data form is shown in **Figure 4.16**. Each analytical module is given specific and related input and output file extensions. So, while working on any module, only the files with related extensions are displayed for selection. This option avoids the confusion in selecting files from a large group of files (related to different modules).

After the data file is generated for the selected module and the program is to be run with the generated data file, the “Analysis” section is invoked. Clicking on this section invokes a window (shown in **Figure 4.17**) that asks for the input and output data file names along with their path. By using the “Browse” button, the file can be selected from any location After the

data file is generated for the selected module and the program is to be run with the generated data file, the “Analysis” section is invoked. Clicking on this section invokes a window (shown in **Figure 4.17**) that asks for the input and output data file names along with their path. By using the “Browse” button, the file can be selected from any location on the computer. After the input and output file path is provided, the “Run” button activates which when clicked, executes the program on the data file and generates the result file with the specified name.

The screenshot shows the 'Probable Flow Estimation' window. It has a menu bar with 'Perform Analysis', 'View Tabular Result', and 'Help'. The form contains the following fields:

- Title of the analysis: sondhur
- Starting month of flow series: Jun
- Number of years of flow series: 18
- First reliability level (%): 50
- Second reliability level (%): 60
- Third reliability level (%): 70
- Fourth reliability level (%): 75
- Fifth reliability level (%): 80
- Sixth reliability level (%): 90

Below the form is a table titled 'Monthly Flow (MCM) Series (Press F1 for Paste)'. The table has columns for S. No., Year, and months 6 through 12. The data is as follows:

S. No.	Year	6	7	8	9	10	11	12	1	2	3	4	5
1	1961	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	1961	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	1961	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	1961	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	1961	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6	1961	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7	1961	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

At the bottom of the window are buttons for 'Retrieve Data', 'Save Data', 'Clear', and 'Close'.

Figure 4.16 A sample Data Form.

The screenshot shows the 'Probable Flow Estimation' window with an 'Analyze' dialog box open. The dialog box has the following fields and buttons:

- Input File Name (*.pfi): F:\CHHATTISGARH_MRP\cc.pl
- Output File Name (*.pfo): CHHATTISGARH_MRP\cc.pl.pfi
- Buttons: Browse, Run, Close

The background window shows the same form as Figure 4.16, but the 'Monthly Flow (MCM) Series' table is partially obscured by the dialog box.

Figure 4.17 A window for Analysis using Input & output files.

The software is linked to Notepad for presenting the input data and result files in tabular form. A sample of the tabular presentation of results is shown in **Figure 4.18**. For the graphical presentation of results, two options are provided – either by generating the graphs using MS-EXCEL or by generating the graphs through a built-in subroutine within the software (this is provided for the cases when MS-EXCEL is not available on the computer). Different graphical options are provided for different kinds of reservoir analysis.

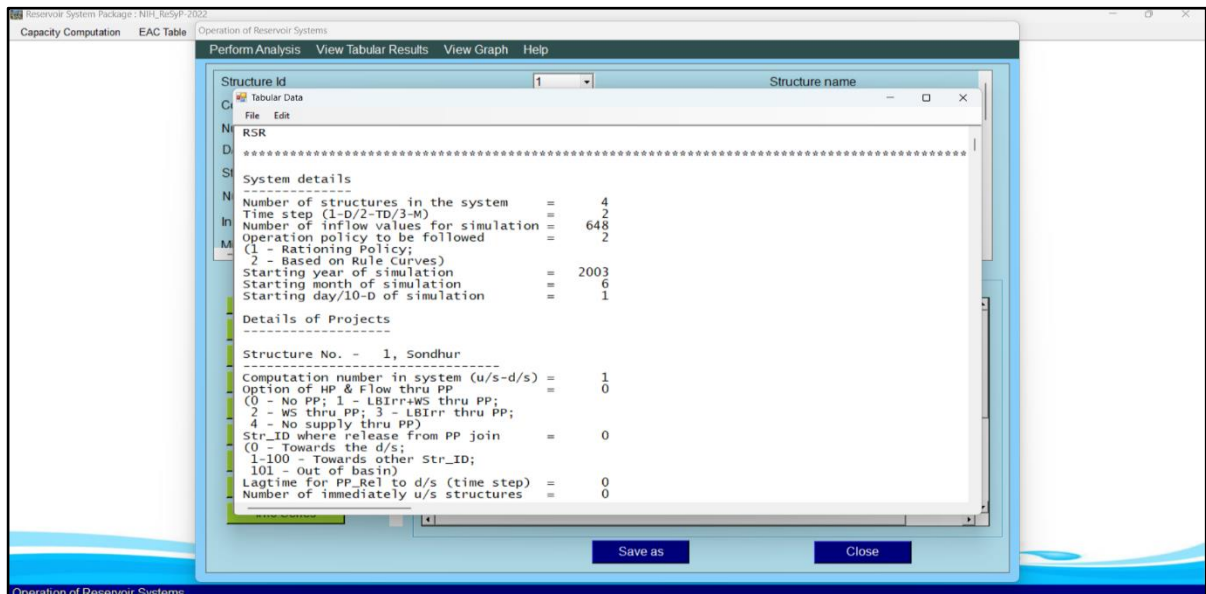


Figure 4.18 A sample of tabular presentation of results.

In addition, one section related to “Help” for each module is provided. Clicking on the “Help” section provides details about the brief methodology of the analytical module, a description of various data items, and the generated results. It needs to be mentioned that under any module, a help file on the related topic is opened.

The user can select a particular module and its subsequent operations by clicking the left mouse button. Switching from the menu to its submenu is performed by moving the cursor to the desired option and clicking the left mouse button. At any step of the analysis ladder, if the analysis wishes to go back, he/she can do so by pressing the <Esc> key.

4.5.4 Modules available for analysis

The current version of the software is capable of performing the following types of analyses:

- Reservoir capacity computation using sequent-peak analysis
- Interpolation of elevation-area-capacity (EAC) table
- Hydropower analysis

- Firm power determination
- Hydropower simulation
- Reservoir inflow estimation using the rate of rise method
- Multi-purpose multi-reservoir operation analysis for conservation purposes
 - Probable flow estimation
 - Initial rule curve derivation
- Multi-reservoir operation analysis for flood control
- Reservoir Routing
 - Mass Curve Method
 - Puls (Modified) Method
 - Goodrich Method
 - Coefficient Method
- Storage-Yield Analysis
 - Storage known, Yield unknown
 - Yield known, Storage unknown

The software is developed in FORTRAN for some of these modules has been taken from NIH reports. The program for sequent-peak analysis has been taken from Jain (1985). For storage yield analysis, the computer program developed by Jain (1986) has been utilized. A program for power transformation technique for probable flow analysis has been developed by Seth and Perumal (1982). Software for the simulation of a multi-reservoir system for conservation has been developed by Jain and Goel (1994) while such a program for flood control has been developed by Jain and Goel (1999). Reservoir routing analysis software has been adopted by Jain and Gupta (1989).

4.6 Climate Change Scenarios

The future is always uncertain and it is highly difficult and challenging to exactly state the future conditions and happenings. To study the earth's climate change and impact on various sectors, different scenarios are developed. These scenarios are alternate images of the future, with certain assumptions, answering how the future might be. In short, these are essential scientific tools or methods for exploring possible future in the context of climate change and its impact. The development of scenarios started in the 1990s with the IS92 scenarios (the first developed set of long-term scenarios) (Leggett, et al., 1992) and was most widely used by the IPCC Special Report on Emission Scenarios (SRES) in 2000 (Nakicenovic & Alcamo, 2000). The Four storylines A1, A2, B1, and B2 were developed and for each storyline separate

scenarios were developed leading to a total of 40 scenarios, of which six were selected as demonstrative scenarios that can be widely used (one for each of the storylines in addition with high and low emissions variants of A1 storyline) (Ebi et al., 2014; IPCC, 2007). **Figure 4.19** shows all six SRES scenarios with GHG emissions along with global surface warming from 2000-2100 to better understand SRES scenarios.

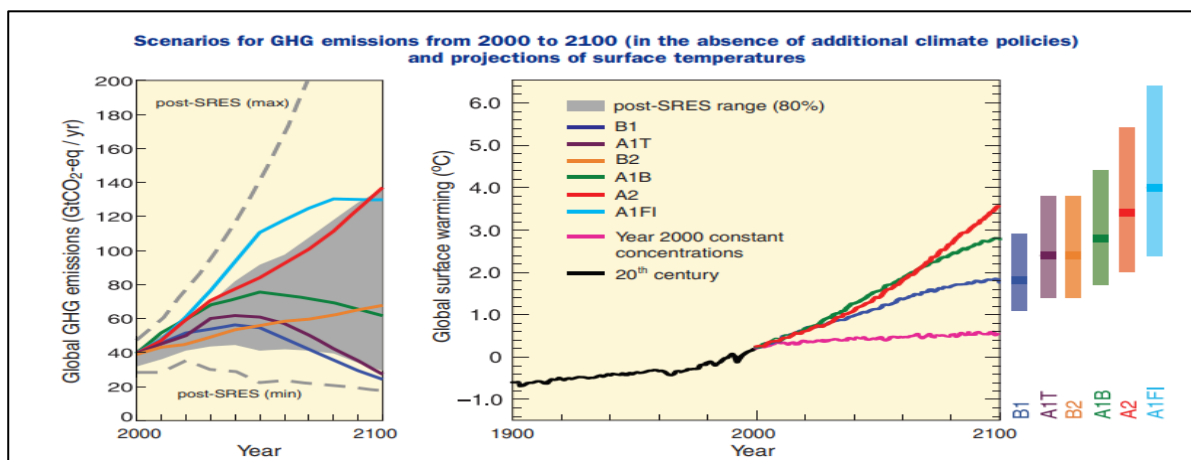


Figure 4.19 Global GHG emission and surface warming with SRES scenario Source.

The four Representative Concentration Pathways (RCP2.6, 4.5, 6.0, and 8.5), as its name explains, have been suggested in the AR5 report where trajectories of GHG concentrations with radiative forcing (in W/m^2) along with mitigation actions in their formulation to stabilize the radiative forcing at the end of 21st century. RCP2.6 is considered as the best-case scenario whereas RCP8.5 is considered as the worst-case scenario. The RCPs and their development are further elaborated by (Van Vuuren, et al., 2011). **Figure 4.20** shows the graphical picture of GHG emission with RCP scenario from 2000-2100 to better understand RCP scenarios.

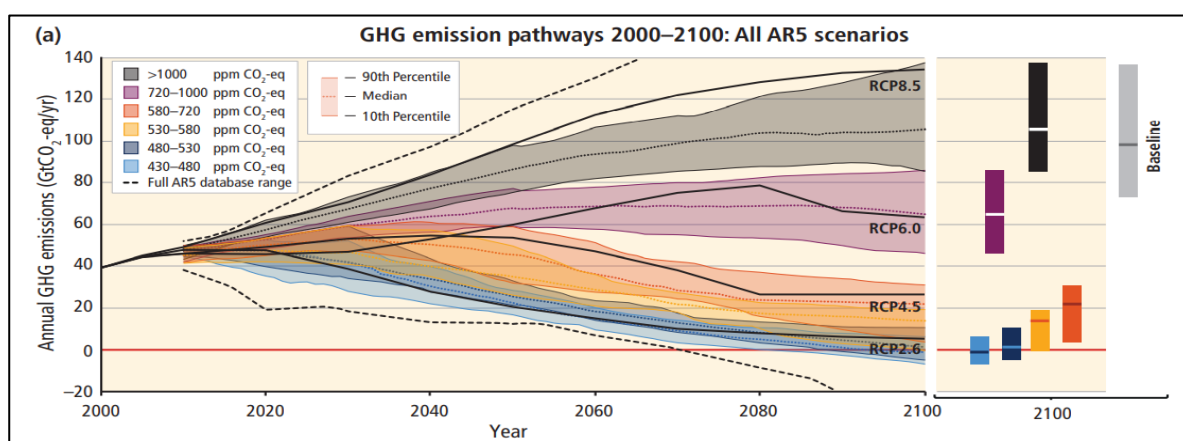


Figure 4.20 GHG emission with RCP scenarios Source: (IPCC, 2014).

In the AR6 report of IPCC, five Shared Socioeconomic Pathways (SSP1, SSP2, SSP3, SSP4, SSP5) are development scenarios, each with different qualitative and quantitative characteristics that describe how the societal future might appear in terms of population growth, administrative effectiveness, inequality, socio-economic developments, institutional elements, technological evolution, and environmental conditions (Arnell & Lloyd-Hughes, 2014). The characteristics of SSPs explained by (O'Neill, et al., 2014) and extracted in short table format by (Arnell & Lloyd-Hughes, 2014) are shown in **Table 4.4**. The graphical representation of the SSP pathway from 2014 to 2100 is presented in **Figure 4.21**. In the present study, to develop a reservoir operation plan under climate change, climate data from downscaled GCMs of CMIP 6 were analyzed to arrive at the best-fit climate models.

Table 4.4 Shared Socioeconomic Pathways (in context to mitigation and adaptation challenges level (O'Neill, et al., 2014; Arnell & Lloyd-Hughes, 2014).

SSP1	Sustainability	Low challenges to mitigation or adaptation
SSP2	Middle of the road	Intermediate challenges
SSP3	Fragmentation	High challenges to both mitigation and adaptation
SSP4	Inequality	Low challenges to mitigation, but high adaptation challenges
SSP5	Conventional development	Low challenges to adaptation, but high challenges to mitigation

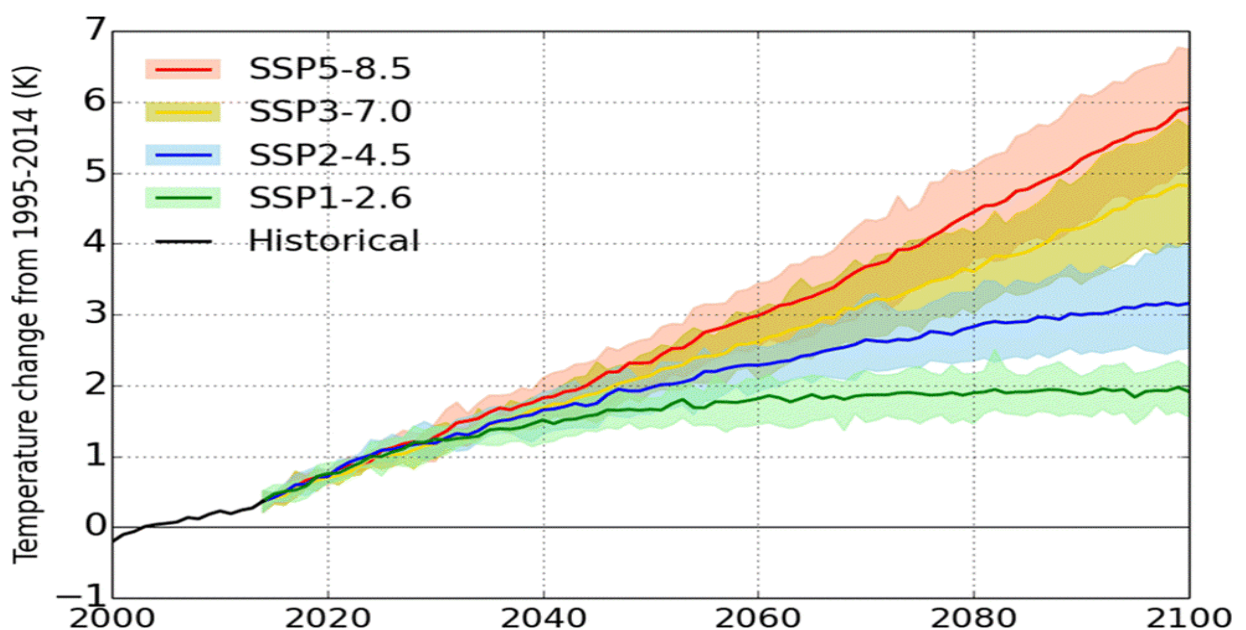


Figure 4.21 SSP Path (Source: Sung et al. (2021)).

4.6.1 Climatic model used in the study

The models listed are all general circulation models (GCMs) used in climate modeling. Here is some information on each of these model's coverage. The future rainfall, maximum, and minimum temperature projections during 2015-2099 under SSP1-2.6, SSP2-4.5, and SSP5-8.5 are obtained from Mishra et al. (2020) (<https://zenodo.org/record/3873998#.XthJB-TuGEd>), providing bias-corrected and downscaled GCM dataset for different River basins across South Asia from 13 models taking part in the CMIP6. A list of climate models used in this study along with country of origin, horizontal resolution, and key references are given in **Table 4.5**.

Table 4.5 List of climate models used in this study along with horizontal resolution, country of origin, and key references.

S. No.	CMIP6 Model Name	Country	Horizontal resolution	Key reference
1.	ACCESS-CM2	Australia	1.9°×1.3°	Bi et al. (2020)
2.	ACCESS-ESM1-5	Australia	1.9°×1.2°	Ziehn et al. (2020)
3.	BCC-CSM2-MR	China	1.1°×1.1°	Wu et al. (2019)
4.	CanESM6	Canada	2.8°×2.8°	Swart et al. (2019)
5.	EC-Earth3	Europe	0.7°×0.7°	Massonnet et al. (2020)
6.	EC-Earth3-Veg	Europe	0.7°×0.7°	Massonnet et al. (2020)
7.	INM-CM4-8	Russia	2°×1.5°	Volodin et al. (2018)
8.	INM-CM5-0	Russia	2°×1.5°	Volodin et al. (2018)
9.	MPI-ESM1-2-HR	Germany	0.9°×0.9°	Gutjahr et al. (2019)
10.	MPI-ESM1-2-LR	Germany	1.9°×1.9°	Mauritsen et al. (2019)
11.	MRI-ESM2-0	Japan	1.1°×1.1°	Yukimoto et al. (2019)
12.	NorESM2-LM	Norway	2.5°×1.9°	Seland et al. (2020)
13.	NorESM2-MM	Norway	0.9×1.25	Seland et al. (2020)

4.6.2 Selection of best-suited GCM model

Climate models are intricate systems of equations and parameterizations that produce varying predictions for different regions and variables. It is crucial to assess the reliability and accuracy of these models by comparing their results with observed data, using statistical equations classified as frequency-based and time series-based metrics. The process of evaluating climate models is necessary to determine their dependability and trustworthiness and multiple criteria are available to judge the fitness of a GCM with concurrent observed data. In

the present study, Nash-Sutcliffe efficiency (NSE), percentage bias (PBIAS), and coefficient of determination (R^2) were used and described here.

4.6.2.1 Nash-Sutcliffe efficiency (NSE)

The Nash-Sutcliffe efficiency can be computed using the following equation:

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_{i,obs} - Q_{i,sim})^2}{\sum_{t=1}^T (Q_{i,obs} - \bar{Q}_O)^2} \quad (4.19)$$

Where, $Q_{i,obs}$ and $Q_{i,sim}$ are the observed and simulated data at time i , and $\bar{Q}_O$ is the mean value of observed data. The NSE ranges from $-\infty$ to 1, with 1 indicating a perfect match between the observed and modeled values, and values less than zero indicating that the model is worse than simply using the mean of the observed values. A value of zero indicates that the model predictions are as accurate as using the mean value of the observed data. In general, a higher NSE value indicates a better fit between the observed and modeled values, although the interpretation of what constitutes a good NSE value depends on the context and the specific application. Further, the performance of the model can be assessed based on the ranges of efficiencies given in **Table 4.6**.

Table 4.6 Performance of the model based on NSE values (Vishwakarma, et.al, 2020)

Performance	NSE values
Very good	0.75 to 1.00
Good	0.65 to 0.75
Satisfactory	0.50 to 0.65
Unsatisfactory	Less than 0.5

4.6.2.2 Pbias (Percentage bias)

The PBIAS or percentage bias represents the cumulative difference in observed and simulated values concerning observed data. The PBIAS can be represented by the following equation:

$$PBIAS = \frac{\sum_{i=1}^n (Q_{i,obs} - Q_{i,sim})}{\sum_{i=1}^n Q_{i,obs}} \times 100 \quad (4.20)$$

The optimum value of PBIAS is 0 whereas, the permissible range for a good performance model is between +15 to -15% (Shrestha et al, 2017; Sanchez, et al, 2017; Padhiary, et al, 2019). The model's positive value explains underestimation, and vice versa. The range of performance as per the PBIAS values is shown in **Table 4.7** (Sanchez, et al., 2017).

Table 4.7 Ranges of performance depending on PBIAS values Source: (Sanchez, et al, 2017).

Performance	PBIAS values range (%)
Very good	$\leq \pm 10$
Good	$\leq \pm 15$
Satisfactory	$\leq \pm 25$
Unsatisfactory	$\geq \pm 25$

PBIAS represents the average tendency of the modeled values to be larger or smaller than the observed values. A PBIAS value of 0% indicates that the model has no systematic bias, i.e., the modeled values are on average as likely to be larger as smaller than the observed values. A positive PBIAS value indicates that the model tends to overestimate the observed values, while a negative value indicates that the model tends to underestimate the observed values. In general, a PBIAS value within +/-10% is considered acceptable for hydrological or environmental modeling applications. However, the interpretation of what constitutes an acceptable PBIAS value depends on the context and the specific application.

4.6.2.3 R^2 (Coefficient of determination)

The coefficient of determination (R^2) can be computed by the following equation:

$$R^2 = \left(\frac{\sum_{i=1}^n (Q_{i,obs} - \overline{Q_o})(Q_{i,sim} - \overline{Q_{sim}})}{\sqrt{\sum_{i=1}^n (Q_{i,obs} - \overline{Q_o})^2 (Q_{i,sim} - \overline{Q_{sim}})^2}} \right) \quad (4.21)$$

Where, $\overline{Q_{sim}}$ is the mean of simulated data. The value of R^2 value ranges from 0 to 1. Where a value nearer to 0 means very low correlation whereas a value close to 1 represents the highest correlation (Padhiary, et al., 2019; Vishwakarma, et al., 2020). The range of performance of the model based on coefficient of determination values is presented in **Table 4.8**.

Table 4.8 Ranges of performance depending on R^2 values.

Performance	Ranges Value
Very good correlation	0.80 to 1.00
Good correlation	0.65 to 0.80
Satisfactory correlation	0.50 to 0.65
Unsatisfactory correlation	Less than 0.5

4.7 Application of CROPWAT 8.0 for Estimation of Future Irrigation Demand

4.7.1 CROPWAT 8.0

CROPWAT 8.0 is a computer program developed by the Food and Agriculture Organization of the United Nations (FAO) that is used to estimate water requirements for crop production. It is a powerful tool that helps farmers, irrigation planners, and water managers to optimize water use and improve crop yields. CROPWAT 8.0 uses a water balance approach to estimate the water requirements of crops, taking into account various factors such as climate, soil, and crop characteristics. It provides estimates of crop water requirements based on historical climate data and allows users to modify input parameters such as crop type, planting date, and irrigation method to simulate different scenarios. The software provides estimates of crop water requirements at different growth stages and calculates the amount of irrigation water required to meet these needs. CROPWAT 8.0 also provides estimates of crop yield based on water availability and allows users to evaluate the impact of different water management strategies on crop production. CROPWAT 8.0 is a user-friendly software that is easily downloaded from the FAO website. It includes a comprehensive user manual that provides step-by-step instructions on how to use the software and also includes a database of climate data for different regions of the world.

4.7.2 Data Acquisition

Metrological data (Rainfall, Maximum, and Minimum Temperature, Humidity, Sunshine Hours & Wind Speed) are used for the determination of Irrigation Water Requirements from CROP WAT 8.0 software, in which Climatic rainfall and temperature data for the past 30 years (1991-2020) is taken from India Metrological Department official website,

4.7.3 Rainfall & Temperature Data

Rainfall and Maximum & Minimum Temperature data of the latitude and longitude of the study area is collected and extracted from the official India Meteorological Department from the years 1991-2020.

For arrangement and computation of these data Microsoft Excel is used. The India Meteorological Department (IMD) provides rainfall and temperature data in the form of grids. These grids represent a spatial distribution of the data across different regions in India & we can use ARC GIS for creating the shape file which depicts these rainfall and temperature grid in that map.

4.7.4 Agro Meteorological Data

Humidity, Wind speed & Sunshine hours are collected from Agro Meteorological Department, Raipur Station which are used for the computation of Evapotranspiration and ultimately for Irrigation Water Requirement with the help of CROP WAT 8.0 software. Humidity refers to the amount of moisture present in the air. It is an essential parameter in agro meteorology as it influences plant growth, evapotranspiration rates, and disease development. The Agro meteorological Department provides data on humidity levels, typically represented as relative humidity (RH). Relative humidity indicates the amount of moisture in the air relative to its maximum capacity at a given temperature and is expressed as a percentage. Sunshine hours represent the duration of time during which sunlight is received in a specific area. It is a critical parameter for agriculture as it affects crop photosynthesis, growth, and development. The Agro meteorological Department provides information on the number of hours of sunshine received in a day or over a specific period. Wind speed refers to the rate at which air moves horizontally. It plays a significant role in agro meteorology as it affects factors like evaporation, transpiration, and pollination. The Agro meteorological Department offers data on wind speed, typically measured in meters per second (m/s) or kilometres per hour (km/h).

4.7.5 Crop Data

Crop data which include name of the crop (Rice), planting and harvesting date of crop, crop coefficient value, stages of crop, rooting depth, critical depletion, yield response and crop height require for the computation for Irrigation Water Requirement. **Figure 4.22** provides essential information about the stages of a paddy crop, including the number of days required for each stage. It shows that the crop progresses from an initial stage with root development to a development stage characterized by rapid vegetative growth. The mid-season stage represents active growth, with high water and nutrient demands. The late season stage signifies maturation and senescence, with reduced water and nutrient requirements. The figure also presents crop coefficients (K_c) for estimating water needs, distinguishing between wet and dry periods. Rooting depth affects water and nutrient availability, while critical depletion indicates the threshold for water stress. Yield response relates to crop productivity, and crop height influences light interception and management practices.

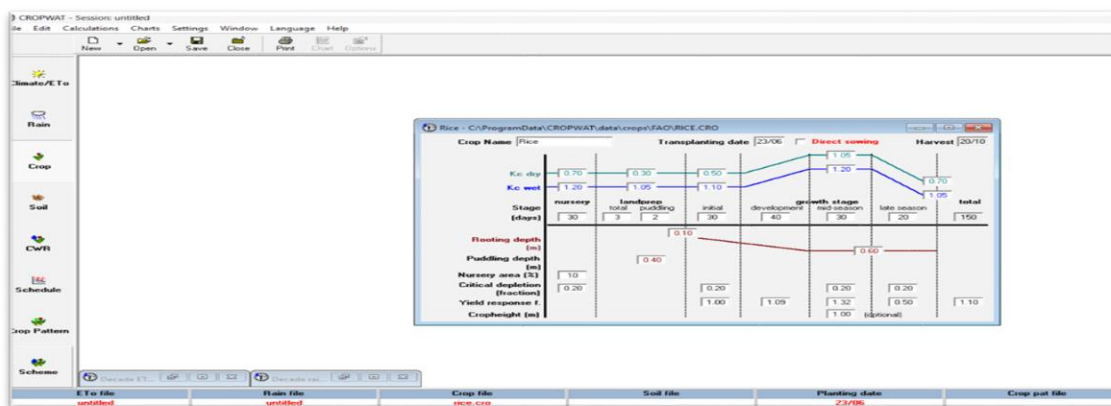


Figure 4.22 Crop coefficient values for different stages.

4.7.6 Soil Data

Soil data include the name of the soil, total available soil moisture, maximum rain infiltration rate, maximum rooting depth, initial soil moisture depletion, initial available soil moisture, drainable porosity, critical depletion for puddle cracking, and maximum percolation rate after puddling, water availability at planting and maximum water depth. Generally, Red Sandy loam soil is found in the study area (Jangre *et al.*, 2022)

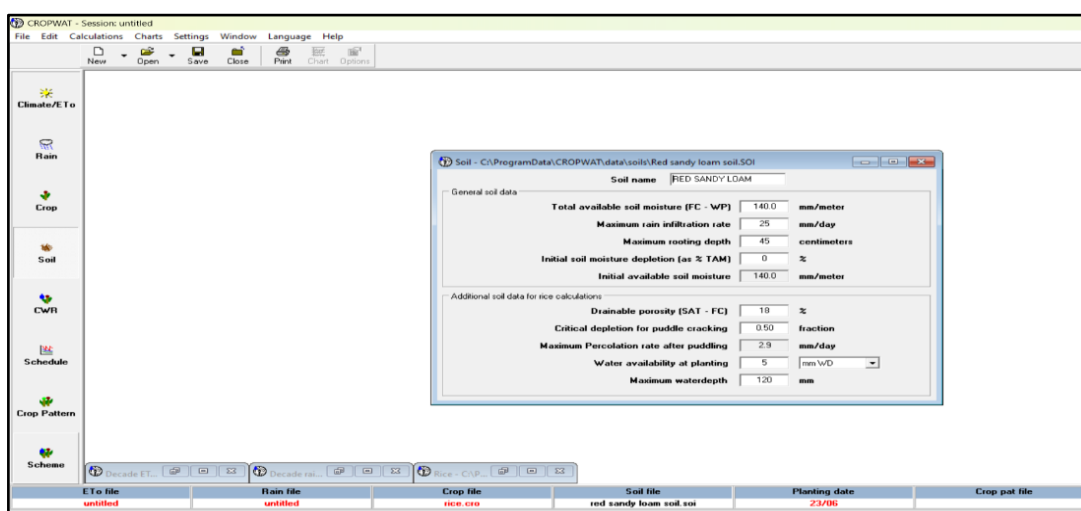


Figure 4.22 Soil input data file.

Figure 4.22 presents key soil-related data points. Total available soil moisture denotes the maximum water capacity for plant uptake, influenced by soil properties. Maximum rain infiltration rate indicates the highest rate at which water can enter the soil. Maximum rooting depth represents the deepest point roots can access for water and nutrients. Initial soil moisture depletion signifies the reduction from field capacity at the start of a crop's growth stage. Initial available soil moisture refers to the readily available water fraction. Drainage porosity characterizes the soil's ability to facilitate water

movement. Critical depletion for puddle cracking indicates moisture levels leading to surface cracking. Maximum percolation rate after puddling denotes vertical water movement post-pudding. Water availability at planting affects germination and early growth. Maximum water depth signifies the capacity for water retention. These factors impact water management, irrigation, and crop establishment.

4.7.7 Computation of Irrigation Water Requirement

Irrigation water requirement refers to the amount of water needed to irrigate crops to achieve optimum growth and yield. Irrigation Water Requirement is computed from rainfall data, maximum and minimum temperature data, humidity, sunshine hour and wind speed data, and crop data which includes the name of the crop, planting, and harvesting date of crop, crop coefficient value, stages of crop, rooting depth, critical depletion, yield response and crop height, & soil data include name of the soil, total available soil moisture, maximum rain infiltration rate, maximum rooting depth, initial soil moisture depletion, initial available soil moisture. The amount of water required depends on various factors such as crop type, growth stage, climate, soil type, and irrigation system efficiency. There are several methods for calculating irrigation water requirements, including:

Crop water requirement method: This method estimates the amount of water needed by the crop based on its evapotranspiration (ET), which is the amount of water lost through both evaporation from the soil and transpiration from the plant.

$$ET_c = K_c * ET_0 \quad (4.22)$$

Where:

ET_0 - The reference evapotranspiration (mm/day)

ET_c - Crop evapotranspiration,

K_c - Crop coefficient.

The computation of the Irrigation water requirement (IWR_c) is given in FAO Irrigation & Drainage paper 56 using crop evapotranspiration (ET_c) and effective rainfall (ER).

$$IWR_c = ET_c - ER \quad (4.23)$$

4.7.8 FAO Penman-Monteith Equation:

The FAO Penman-Monteith equation is a widely used method for estimating potential evapotranspiration (ET) from weather data. The equation takes into account the physical processes of both vegetation transpiration and soil evaporation, as well as meteorological

variables such as temperature, humidity, wind speed, and solar radiation. This equation is used for the simulation of Irrigation water requirements in CROP WAT 8.0 software.

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (4.24)$$

Where:

ET_0 = reference evapotranspiration [mm day⁻¹],

R_n = net radiation at the crop surface [MJ m⁻² day⁻¹],

G = soil heat flux density [MJ m⁻² day⁻¹],

T = mean daily air temperature at 2 m height [°C],

U_2 = wind speed at 2 m height [m s⁻¹],

e_s = saturation vapor pressure [kPa],

e_a = actual vapor pressure [kPa],

$e_s - e_a$ = saturation vapor pressure deficit [kPa],

Δ = slope vapor pressure curve [kPa °C⁻¹],

$\Delta = 4098 \times e (T_{\text{mean}} + 237.3)^{-2}$

γ = psychrometric constant [kPa °C⁻¹].

Figure 4.24 provides a clear visualization of the methodology has been used to project future irrigation demand, helping to understand the data inputs, modeling processes, and projected outcomes. This comprehensive view aids in planning for future water resource management.

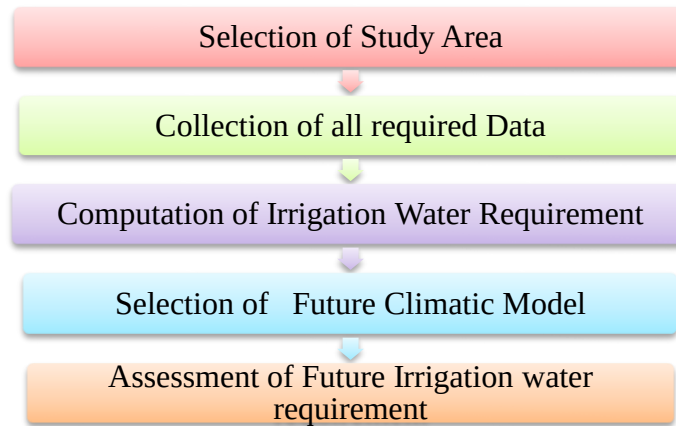


Figure 4.24 Adopted methodology for computation of future irrigation demand.

4.8 Population Forecasting for Mahanadi Command District

Demand of water supply is based on the projected population of Dhamtari, Raipur and Durg city, estimated for the future period. Any underestimated value will make system

inadequate for the purpose intended; similarly overestimated value will make it costly. Change in the population of the city over the year occurs, and the system should be estimated taking into account of the population at the end of the projected or design period.

Factors affecting changes in population are:

- Increase due to births
- Decrease due to deaths
- Increase/ decrease due to migration
- Increase due to annexation.

The present and past population record for the city can be obtained from the census population records. After collecting these population figures, the population at the end of design period is predicted using various method as suitable for that city considering the growth pattern followed by the city. In the present study Geometric increase method has been used for estimation of future population growth rate.

4.8.1 Geometric Increase Method

In this method, the percentage increase in population from the decade is assumed to remain constant. The geometric mean increase is used to find out the future increment in population. This method gives higher values and hence should be applied for a new industrial town at the beginning of development for only decades. The population at the end of n^{th} decade 'P_n' can be estimated as:

$$P_n = P(1 + \frac{I_G}{100})^n \quad (4.25)$$

Where I_G = geometric mean (%)

P = Present population

N = no. of decades

4.9 Performance indicators

The performance of different users has been evaluated using the two different performance indicators based on demand and deficits.

4.9.1 Demand (Dem) and Deficit (Def)

The demand and deficit are the important criteria used to adjudge the performance of any water resource project that influences crop yield and economic benefits to farmers. The total demand of irrigation command and other users is the amount of water required in a hydrological year to meet all temporally varied demands considering losses (conveyance and

application losses) and gains (rainfall and moisture etc.). Similarly, the total deficit is the amount of water in a year that the source is unable to meet under present efficiency, operation, climatic conditions, etc. In the study, the simulation results of NIH_ResyP containing demand and deficit on 10 daily time scale were used to compute average yearly, monthly, and Ten daily demand and deficit for all users in the system i.e. irrigation commands of Sondhur, Dudhawa, and Ravishankar reservoirs, and RSR as industrial users, domestic supply, and Power demand.

4.9.2 Reliability (Rel)

Two indices are generally followed in reservoir regulation. Time or occurrence-based reliability is the probability that the system state lies in the set of satisfactory states

$$r_t = 1 - \left(\frac{f_p}{n} \right): \quad 0 \leq r_t \leq 1, f_p \leq n \quad (4.26)$$

Where r_t is the time reliability and f_p is the number of failure periods out of total n periods. Volume or quantity-based reliability r_v is expressed as:

$$r_v = \frac{V_s}{V_d} \quad (4.27)$$

Where V_s The volume of water is supplied and V_d is the volume of water demanded during a given period.

Let N be the total number of failure events. Moving from time step t to $(t + 1)$, the system will either remain in the same state or switch to the other state. The duration of the j th failure event is denoted by d_j and V_j is the corresponding deficit volume calculated by:

$$V_j = \sum_{t=1}^{d_j} [D_t - R_t] \quad (4.28)$$

Where D_t is the target demand and R_t is the release from the reservoir for the month t . Note that during period of high inflows, water may have to be spilled from the reservoir to ensure the safety of the dam. This extra outflow which does not serve any useful purpose is not considered to be a release; the release used in Eq. (4.28) is always less than or equal to the demand ($R_t \leq D_t$). Therefore, the vulnerability will be zero in the periods when a spill occurs.

The present study has been carried out for the Mahanadi Reservoir Project complex (MRP complex) with the objective of the estimation of revised capacities of the reservoir using different techniques, water balancing of reservoir, hydrological model application for computation long-term hydrological series, development of a model for integrated operation of the reservoir, optimization of reservoir using management tools, application of remote sensing data for irrigation planning, Irrigation water requirement and development of the management model for optimal utilization of resources. The results are presented below.

5.1 Water Balance of Reservoir

Estimating the volume of water stored in controlled water bodies relies on computing all inflow and outflow components to maintain the water balance. Assessing water availability from catchments, particularly for medium and small projects, poses a significant challenge in water resource management, especially in developing nations. Runoff from catchments serves as crucial input for hydrological and water management models. However, measuring discharge entails substantial costs and manpower, thus typically reserved for major Rivers in developing countries. During project design, runoff data is either calculated using empirical formulas or extrapolated from nearby catchments. Furthermore, if gauging is conducted for project design, runoff measurement typically ceases after reservoir commissioning. In such instances, the reservoir's water balance aids in determining runoff from the catchment. This balance operates on the principle of mass conservation, wherein all inflows and outflows are utilized to determine an unknown variable in the equation.

The water balance analysis for Sondhur, Dudhawa, Murumsilli, and Ravishankar Sagar reservoirs involved determining daily inflows from these catchments utilizing reservoir levels, canal outflows, spillway, and inflows from other catchments, rainfall, and evaporation. This analysis was conducted daily, applying Module 1, which employed various input and output variables in a water balance model to compute inflows from the catchments. Specific water balance models adjusted to each reservoir were developed using Excel programming, considering reservoir levels, outflows, and transfers of water from other reservoirs. The analysis spanned from Jun 1991 to May 2020 for the Sondhur, Dudhawa, Murumsilli, and Ravishankar Sagar reservoirs. All positive and negative components of the water balance were computed

daily and applied in a mass conservation equation to determine catchment inflow. To validate the water balance, yearly percentage errors were calculated using changes in storage derived from the water balance, and reservoir levels for each water year period (June 01 to May 31). The yearly water balance results for Sondhur, Dudhawa, Murumsilli, and Ravishankar Sagar reservoirs are presented in **Tables 5.1(a) to 5.1(d) and in Figure. 5.1.**

From the analysis, it has been observed that percentage errors in water balance varied in the range of -6.38 to -7.21 % for the Sondhur reservoir, -6.09 to 6.40 %, for Dudhawa reservoir for Murumsilli reservoir -1.98 to 0.425 and -7.72 to 8.36 % for Ravishankar Sagar reservoir. As percentage errors in different water years came out reasonably well within the range (less than 10% of inflow), the inflow computed from the water balance of reservoirs can be used in the rainfall-runoff modeling. The seepage and evaporation are the major losses in these reservoirs depending on the area of contact and water spread respectively. The results of water balance for reservoirs indicated average annual inflow may be 272.58 ± 188.629 MCM from Sondhur, 522.52 ± 214.95 MCM from Dudhawa, 216.74 ± 112.65 MCM from Murumsilli catchment, and 2995.74 ± 1980.76 from Ravishankar Sagar reservoir. Through water balancing excel sheet, the computed inflow was obtained by quantifying the various inputs and outputs within the system. This calculated inflow was used as an input (observed inflow) in the MIKE 11 NAM model, a hydrological simulation tool, to analyse and calibrate the model. The goal of this calibration process was to identify the optimal parameters that would allow the model to accurately predict future inflow scenarios for the MRP complex. By fine-tuning these parameters, the model can simulate potential future water conditions and assist in effective water resource management for the MRP complex.

5.2 Results of the MIKE-11 NAM Rainfall-Runoff Model

The NAM model for Sondhur, Dudhawa, Murumsilli and Ravishankar Sagar catchment has been developed to model rainfall-runoff processes which can be used to compute inflows for developing a decision support system. The MIKE-11 NAM is a rainfall-runoff (RR) model created by the Danish Hydraulic Institute (DHI) as part of the MIKE-11 module. MIKE11 NAM can also be used to model lateral flows to a River basin from several contributing catchments (DHI 2017). The Nedbor Afstromnings Model (NAM) is a deterministic, lumped, and conceptual rainfall-runoff model that works by continually compensating moisture content in three separate and directly interconnected storages that depict overland flow, interflow, and base flow (DHI, 2008).

Table 5.1 (a) Water balance of Sondhur reservoir (All values in MCM).

Year	Inflow (MCM)	Release (MCM)					Change in Storage in the reservoir	Total incoming (MCM)	Total Outgoing (MCM)	ΔS	% Error
		Irrigation Kharif (MCM)	Irrigation Rabi (MCM)	Dudhawa SFC (MCM)	Nistari (MCM)	ET (MCM)					
2003-04	306.709	40.75	38.64	3.59	3.48	34.780	46.369	306.709	86.46	220.25	3.75
2004-05	232.053	29.09	9.53	3.44	1.41	41.559	46.545	232.053	43.47	188.58	3.05
2005-06	112.642	4.20	0.11	10.01	1.59	37.943	-47.854	112.642	15.92	96.72	-3.02
2006-07	206.142	2.60	4.97	2.72	0.06	40.988	-56.591	206.142	10.35	195.80	-4.46
2007-08	288.949	30.06	74.11	69.28	4.25	38.066	-20.641	288.949	177.70	111.25	-6.39
2008-09	332.262	6.66	12.52	88.40	26.26	32.572	43.180	332.262	133.83	198.43	3.60
2009-10	215.333	45.78	0.00	94.58	11.59	28.459	-46.029	215.333	151.95	63.38	-2.38
2010-11	489.900	23.12	92.52	107.40	0.00	29.050	44.899	489.900	223.04	266.86	4.94
2011-12	185.804	35.65	0.00	28.84	9.23	28.680	61.660	185.804	73.72	112.08	0.82
2012-13	246.601	31.52	86.51	42.21	0.73	28.914	-81.606	246.601	160.97	85.64	-2.05
2013-14	364.838	22.97	82.54	73.04	0.24	28.852	29.364	364.838	178.80	186.04	5.34
2014-15	249.035	31.28	78.89	56.24	0.05	31.654	10.796	249.035	166.46	82.57	6.65
2015-16	212.481	49.89	0.00	113.07	6.69	29.064	-10.141	212.481	169.66	42.82	-5.22
2016-17	297.753	28.23	85.85	90.44	0.00	34.886	11.348	297.753	204.52	93.24	7.22
2017-18	208.509	37.52	0.00	74.09	6.57	28.771	11.515	208.509	118.18	90.33	6.84
2018-19	408.172	0.00	74.24	91.07	201.48	28.011	-52.103	408.172	366.79	41.38	-1.79
2019-20	250.483	0.00	0.00	95.57	0.00	29.865	109.560	250.483	95.57	154.92	0.41
2020-21	298.806	0.00	0.00	188.17	0.00	36.274	-20.619	298.806	188.17	110.64	-6.37

Table 5.1 (b) Water balance of Dudhawa reservoir (All values in MCM).

Year	Inflow Sondhur (MCM)	Inflow Dudhawa (MCM)	Release (MCM)				Change in Storage	Total incoming (MCM)	Total Outgoing (MCM)	ΔS	% Error
			Spillway	LBC	RBC	ET (MCM)					
2003-04	3.53	668.54	411.90	0.00	0.00	71.72	248.54	672.07	411.90	260.17	0.05
2004-05	3.36	518.62	660.46	0.00	7.23	48.95	-145.58	521.98	667.69	-145.71	0.00
2005-06	7.37	335.52	113.62	0.00	24.40	59.25	178.06	342.89	138.02	204.87	0.15
2006-07	2.35	548.61	573.34	0.00	23.26	67.07	-151.65	550.96	596.61	-45.65	-0.70
2007-08	61.59	638.93	522.31	0.00	28.81	56.42	-40.28	700.53	551.11	149.41	-4.71
2008-09	76.39	592.11	548.18	0.00	8.46	49.57	39.74	668.50	556.64	111.86	1.81
2009-10	82.35	455.38	377.91	3.43	7.15	27.67	-68.79	537.73	388.49	149.24	-3.17
2010-11	94.72	524.29	400.05	4.48	11.59	46.99	109.05	619.01	416.12	202.89	0.86
2011-12	45.65	314.88	334.43	5.16	12.09	48.19	-73.92	360.53	351.68	8.85	-1.12
2012-13	30.64	312.47	325.59	25.19	21.36	36.81	-8.94	343.11	372.14	-29.03	2.25
2013-14	64.35	397.16	220.14	27.47	2.06	49.45	28.62	461.51	249.68	211.83	6.40
2014-15	49.19	681.80	647.63	4.79	6.34	47.64	-40.64	730.99	658.76	72.23	-2.78
2015-16	98.56	226.96	218.73	3.90	1.06	22.48	-20.37	325.52	223.69	101.82	-6.00
2016-17	75.01	617.35	455.48	8.10	15.35	60.57	118.85	692.36	478.93	213.44	0.80
2017-18	64.74	236.36	257.01	8.77	19.41	44.79	-66.36	301.10	285.19	15.91	-1.24
2018-19	91.07	384.36	284.60	0.00	17.68	41.09	-34.06	475.43	302.28	173.15	-6.08
2019-20	0.00	416.25	234.71	0.00	23.41	57.69	106.82	416.25	258.12	158.13	0.48
2020-21	0.00	684.77	640.70	0.00	24.51	71.74	-48.44	684.77	665.21	19.56	-1.40

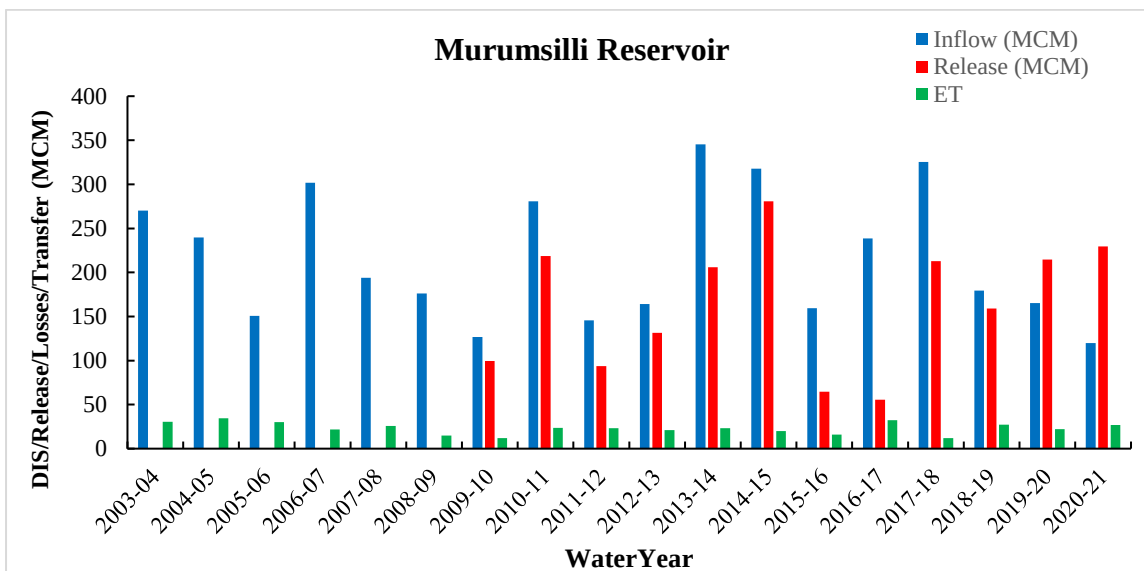
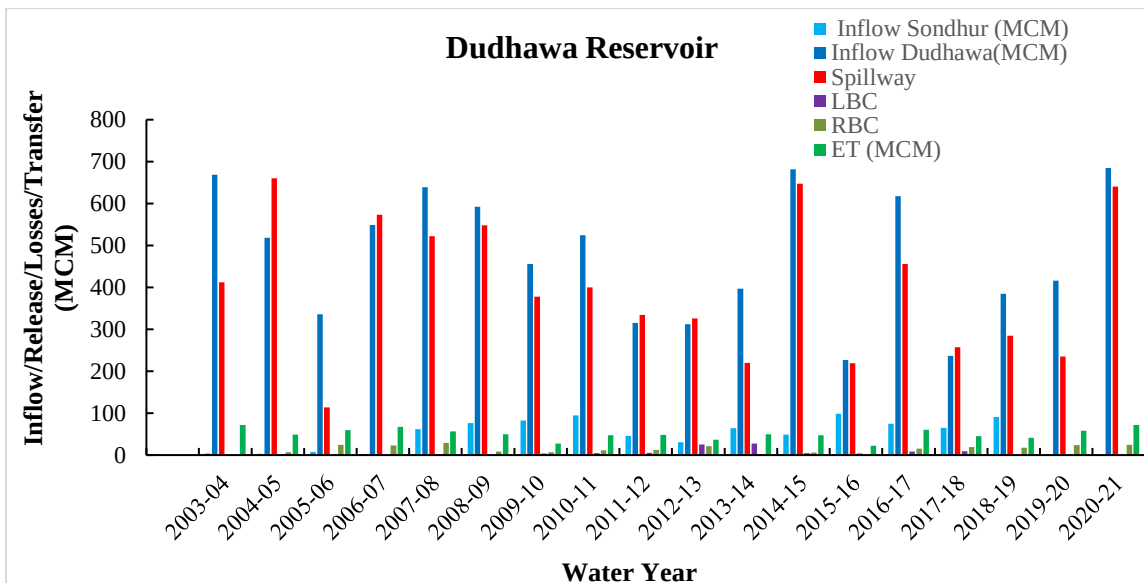
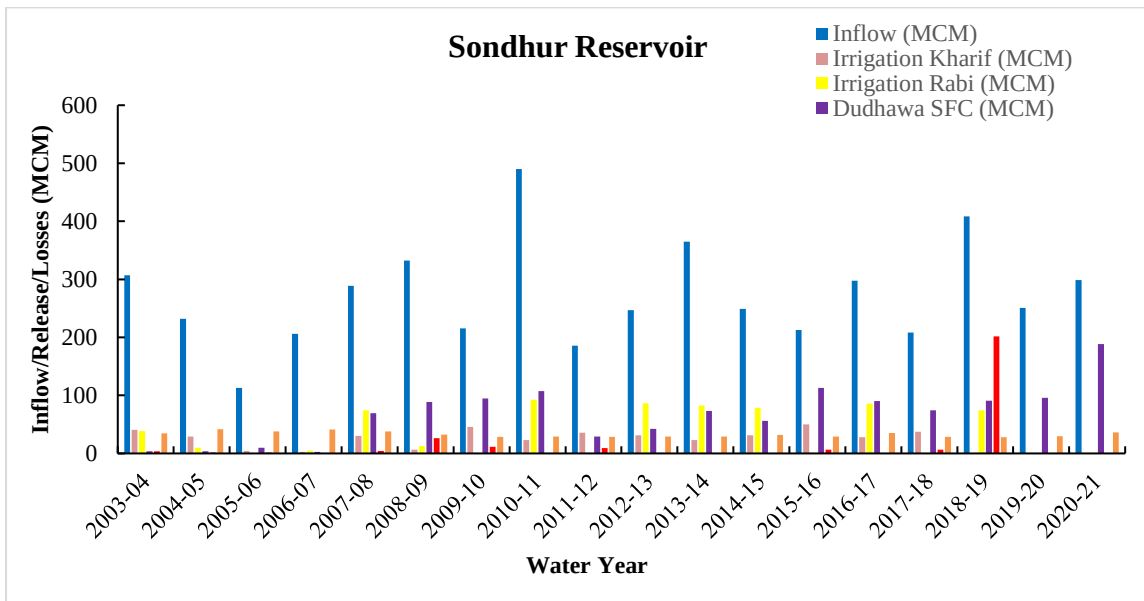
Table 5.1 (c) Water balance of Murumsilli reservoir (All values in MCM).

Year	Inflow (MCM)	Release (MCM)	Change in storage in the reservoir	ET (MCM)	Total incoming (MCM)	Total Outgoing (MCM)	ΔS	% Error
2003-04	270.360	0.000	115.432	30.530	270.360	0.000	270.360	-0.573
2004-05	239.809	0.000	-72.619	34.529	239.809	0.000	239.809	-1.303
2005-06	150.623	0.000	-3.160	30.162	150.623	0.000	150.623	-1.021
2006-07	301.881	0.000	-63.762	21.818	301.881	0.000	301.881	-1.211
2007-08	193.943	0.000	0.929	25.749	193.943	0.000	193.943	-0.995
2008-09	176.127	0.000	-0.929	14.834	176.127	0.000	176.127	-1.005
2009-10	126.872	99.515	0.000	12.109	126.872	99.515	27.357	-1.000
2010-11	280.580	218.435	0.000	23.678	280.580	218.435	62.145	-1.000
2011-12	145.771	93.756	13.140	23.172	145.771	93.756	52.015	-0.747
2012-13	164.209	131.620	-13.140	21.042	164.209	131.620	32.589	-1.403
2013-14	345.204	205.994	0.000	23.132	345.204	205.994	139.210	-1.000
2014-15	317.769	280.831	0.000	19.884	317.769	280.831	36.938	-1.000
2015-16	159.451	64.563	2.486	16.022	159.451	64.563	94.888	-0.974
2016-17	238.747	55.582	95.932	32.433	238.747	55.582	183.165	-0.476
2017-18	325.426	212.695	-96.583	12.054	325.426	212.695	112.731	-1.857
2018-19	179.365	158.985	29.046	27.152	179.365	158.985	20.381	0.425
2019-20	165.201	214.763	48.673	22.043	165.201	214.763	-49.562	-1.982
2020-21	119.907	229.483	-17.503	26.939	119.907	229.483	-109.576	-0.840

Table 5.1 (d) Water balance of Ravishankar Sagar reservoir (All values in MCM).

Year	Inflow from Dudhawa (MCM)	Inflow from Murumsilli (MCM)	Inflow from Mahanadi (MCM)	Release (MCM)			ET (MCM)	Change in Storage in reservoir (MCM)	Total incoming (MCM)	Total Outgoing (MCM)	ΔS	% Error
				MFC+ MMC	Spillway	Hydropower						
1991	336.56	339.19	1408.70	132.14	703.20	0.00	76.09	437.83	2084.45	911.44	1173.01	1.68
1992	508.87	263.03	1021.81	308.86	853.19	0.00	106.58	-207.09	1793.72	1268.63	525.09	-3.54
1993	564.15	297.01	842.35	219.00	702.12	0.00	89.64	219.38	1703.51	1010.77	692.74	2.16
1994	710.57	358.58	3016.44	158.31	3431.30	0.00	103.64	-47.57	4085.59	3693.25	392.34	-9.25
1995	451.05	235.03	1754.97	722.05	1177.83	0.00	89.42	129.95	2441.05	1989.30	451.75	2.48
1996	524.91	245.89	836.18	336.40	1280.61	0.00	83.66	-482.49	1606.97	1700.67	-93.70	-0.81
1997	336.56	184.01	1117.05	233.79	650.09	17.17	90.21	404.39	1637.62	991.26	646.35	0.60
1998	508.87	319.50	635.58	358.40	1038.67	14.64	94.12	-431.92	1463.95	1505.83	-41.88	-0.90
1999	564.15	204.20	1033.80	128.41	514.27	24.57	60.68	600.12	1802.16	727.92	1074.24	0.79
2000	710.57	223.04	1691.98	987.12	1595.23	0.00	73.68	-621.05	2625.58	2656.03	-30.45	-0.95
2001	451.05	339.19	5305.71	1111.79	2623.76	0.00	65.23	436.29	6095.96	3800.79	2295.16	4.26
2002	524.91	263.03	785.32	726.04	520.08	0.00	98.78	-293.68	1573.25	1344.90	228.35	-1.78
2003	216.09	296.94	1180.81	437.43	181.86	0.00	101.69	514.08	1693.84	720.98	972.86	0.89

2004	613.88	358.65	2004.59	1205.49	1126.19	139.39	156.61	-179.51	2977.13	2627.69	349.44	-2.95
2005	390.08	235.03	1815.53	1032.52	764.00	225.66	139.48	29.79	2440.63	2161.66	278.97	8.36
2006	612.05	245.89	4255.85	1232.93	2015.24	322.91	149.98	890.00	5113.79	3721.06	1392.73	0.56
2007	663.57	184.01	3431.52	1549.38	1226.30	709.84	134.73	140.49	4279.09	3620.26	658.83	3.69
2008	801.32	319.50	2140.22	1854.96	700.90	597.52	101.99	-154.16	3261.04	3255.38	5.67	-1.04
2009	499.94	204.20	2176.11	1281.94	575.96	435.46	108.55	-71.13	2880.24	2401.91	478.34	-7.72
2010	580.65	222.97	3116.68	954.69	1106.36	432.25	104.64	363.33	3920.30	2597.94	1322.36	2.64
2011	391.11	203.23	1929.65	1292.6	445.77	595.72	96.81	-188.94	2523.99	2430.97	93.02	-1.49
2012	423.09	223.04	2303.92	1039.90	760.61	523.72	128.00	63.07	2950.05	2452.23	497.81	6.89
2013	336.15	310.98	3639.90	1262.67	963.42	841.20	116.95	119.28	4287.03	3184.25	1102.78	8.25
2014	896.52	474.76	4054.18	1752.54	1403.99	905.26	125.52	638.50	5425.47	4187.30	1238.17	0.94
2015	268.46	108.53	1613.32	1037.94	507.82	495.08	88.11	-390.72	1990.31	2128.95	-138.63	-0.65
2016	653.37	352.37	3211.26	1163.22	1254.48	463.02	102.04	393.28	4217.01	2982.76	1234.25	2.14
2017	341.18	386.66	1320.82	1000.01	441.24	354.84	88.65	-323.83	2048.65	1884.74	163.92	-1.51
2018	429.52	229.22	3604.35	1254.55	1112.08	307.95	101.89	418.23	4263.09	2776.46	1486.63	2.55
2019	484.32	196.98	3426.47	1549.38	1226.30	457.51	94.02	120.21	4107.77	3327.21	780.55	5.49
2020	732.87	194.02	2652.13	1854.96	700.90	504.70	129.73	65.68	3579.02	3190.30	388.72	4.92



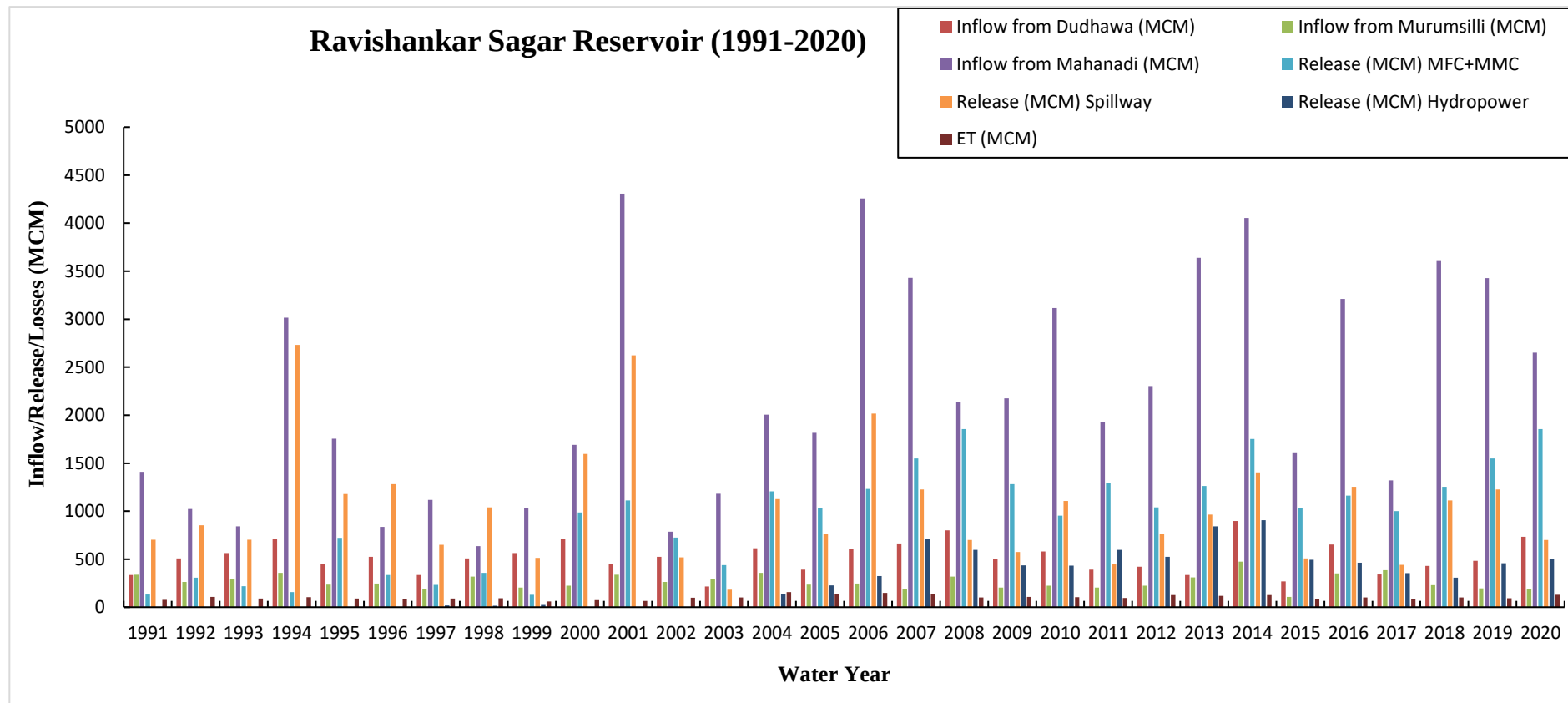


Figure 5.1 Graphical representation of different components of water balance in Sondhur, Dudhawa, Murumsilli & Ravishankar sagar reservoir.

5.2.1 Model setup

To work effectively in the MIKE11 NAM tool, input data must be arranged in the form of a “Time Series”. To calibrate and validate the model, meteorological data, discharge data, catchment parameters, and initial conditions are required as input. Before importing data into the model, it is necessary to create the time series of all three parameters i.e. rainfall, potential evapotranspiration, and discharge data in dfso format, which can be created using MIKE ZERO software. MIKE11 NAM model simulates runoff in a lumped manner therefore it is decided to take the weightage of precipitation from all individual catchments. The areal precipitation was estimated by multiplying the rainfall at each station and their calculated percentage weight. The weightage rainfall has been calculated for all four reservoir catchments. This rainfall has been used in MIKE -11 NAM for development parameters for all four reservoir catchments. The MIKE -11 NAM model has been calibrated and validated for all reservoir catchments.

5.2.1.1 Model calibration

The main goal of the model calibration is to obtain a set of parameters for all four catchments that provides the best possible fit between the simulated and observed runoff for the calibration period. Calibration is the process of finding correction factors that can be used to standardize predicted values. Such empirical corrections are widely used in modeling, and it is acknowledged that every hydrological model should be tested against observed data to ensure the model’s reliability. In the MIKE-11 NAM model, initial calibration can be done through auto-calibration mode and later fine-tuned by manual calibration.

The calibration of the MIKE-11 NAM Model was done by inserting daily rainfall, potential evaporation, and observed discharge time series for the periods of 13 years from Jun 2003 to May 2016 for Sondhur, Dudhawa and Murumsilli Catchment and 21 years from 1991 to 2011 for Ravishankar Sagar Catchment. Catchment definitions such as catchment name and area were specified. After importing the time series, the model was run under auto-calibration mode by taking the surface, root zone, and groundwater storage parameters as default. The model output simulation results during calibration were checked for R^2 (coefficient of determination) value and graphically analyzed for the degree of agreement between simulated and observed runoff. Then the model was run several times by adjusting these parameters one by one using the trial-and-error method until the gap between observed and simulated discharge was reduced to an acceptable limit. The trial giving the best result is

selected as the best-fit model and parameters are considered as the final parameters of model calibration. The model parameters thus obtained after refinement of the model were then used in the validation of the model.

5.2.1.2 Model validation

Model validation tests the ability of the model to estimate runoff for periods outside that used to calibrate the model. Once the calibration of a model is completed, it becomes necessary to check the calibrated parameter values to simulate events for a period other than those used for the calibration (Sorooshian et. al., 1983). In the process of validation, the model parameters were kept constant as obtained during model calibration and runoff was simulated for the remaining period of 5 years from Jun 2016 to May 2021 for Sondhur, Dudhawa and Murumsilli reservoirs and from 2012 to 2020 for Ravishankar Sagar reservoir.

In the present study, MIKE -11 NAM has been applied for the Sondhur, Dudhawa, Murumsilli and Ravishankar Sagar catchments. The model has been calibrated and validated for each catchment. The results of each catchment have been shown in the below section.

5.2.2 Results of MIKE-11 NAM model of Sondhur reservoir

The MIKE -11 NAM model has been created for the Rainfall-Runoff modeling which utilized the daily rainfall time series, potential evapotranspiration, and observed discharge data of the Sondhur catchment for the period from Jun 2003 to May 2016. The area of the catchment upstream at the dam is 512 sq. km. First, MIKE 11 NAM has been used to simulate the runoff by using the auto-calibration mode, and a set of model parameters for the period of Jun 2003 to May 2016. After that, the model was calibrated by modifying the model parameters to reduce the error between observed and simulated stream flow data. To obtain the best match between observed and simulated runoff, the model has been refined. Throughout the model calibration, nine parameters have been determined and the range of these parameters and the best-fit values of the Sondhur catchment have been given in **Table 5.2**.

Table 5.2 Final calibrated model parameter value and their range for Sondhur Catchment.

S.No.	Parameter	Parameter range	Best-fit value
1	U_{max}	5 - 20	18.5

2	L_{max}	100 - 300	182
3	$CQOF$	0.1 – 1.0	0.495
4	$CKIF$	100 - 1000	294.5
5	CK_{12}	3 - 72	10
6	TOF	0 – 0.99	0.0296
7	TIF	0 – 0.99	0.446
8	TG	0 – 0.99	0.944
9	$CKBF$	200 - 4000	3915

S. No.	YEAR	Q-obs	Q-Sim	% Diff	RF	PET	AET	GWR	OF	IF	BF
1	2003-04	862.5	857.9	0.5	1832.1	2222.7	904.8	392.7	412.2	122. 2	323.5
2	2004 -05	526.9	480.5	8.8	1329.5	2134.1	885.6	143.5	232	67.4	181.1
3	2005 -06	444	389.6	12.3	1106.5	2136.4	723.3	130.2	197.4	56.6	135.7
4	2006-07	731.2	675.4	7.6	1363.8	2199.8	661.5	301.1	327.5	74.1	273.8
5	2007 -08	624	587.1	5.9	1295	2126.7	718.9	223.5	264	88.6	234.6
6	2008-09	445.3	389	12.6	944.5	1849.8	566	138.4	173.9	66.1	148.9
7	2009-10	525.1	487.2	7.2	1197	1992.9	708.3	178.3	248.4	61.8	177
8	2010-11	653.6	609.6	6.7	1288	1679.5	661.8	256	274.9	94.7	240
9	2011 -12	620	542.7	12.5	1122	1657.3	577.8	240.8	249.9	54	238.8
10	2012-13	481.6	440.9	8.4	1095	1697.3	673.6	153.5	182.8	84.8	173.4
11	2013 -14	622	622	0	1276	1529.6	643.1	243.5	282.3	107. 2	232.6
12	2014-15	719.5	716.3	0.4	1295	1694.8	564.7	317.1	345.4	67.9	303.1
13	2015-16	187.2	103.2	44.9	589	1804.9	536.6	0	43.1	9.8	50.3
	Total	7443	6901.4	7.3	15733	24726	8826	2719	3233. 7	955. 1	2712. 6

Table 5.3 presented various components of the hydrological cycle simulated during model calibration for the Sondhur catchment including runoff, actual evapotranspiration, groundwater recharge, overland flow, interflow, and base flow. Model calibration showed a coefficient of determination of 0.73, indicating a synergistic relation between observed and simulated runoff in terms of timing, rate, and volume. The difference between observed and simulated flows is 7.3 %, which is reasonable and indicates a good relation between observed and simulated runoff. During the calibration period, the simulated discharge is 6901.4 mm out of total precipitation of 15733.4 mm, of which 3233.7 mm is overland flow, 32.6 mm was inter-flow, 955.1 mm is base flow, and 2712.6 mm is groundwater recharge.

Table 5.3 Statistics of model calibration result for Sondhur Catchment

Q-obs=Obs. Runoff, Q-Sim=Sim. Runoff, RF=Rainfall, PotEvap=Potential Evapotranspiration, ActEvap=Actual Evapotranspiration, GWR=Ground Water Recharge, OF=Overland Flow, IF=Inter Flow and BF=Base Flow)

Figure 5.2 represents the cumulative graph of observed and simulated discharge over the calibration period. A double mass curve suggests a good match between observed and simulated accumulated flow volume and model accuracy **Figure 5.3**. **Figure 5.4** shows a comparison of the observed and simulated annual runoff depth during calibration. The overall comparison showed the MIKE11 NAM Model as a suitable model for the Sondhur catchment and predicting runoff with a high degree of accuracy.

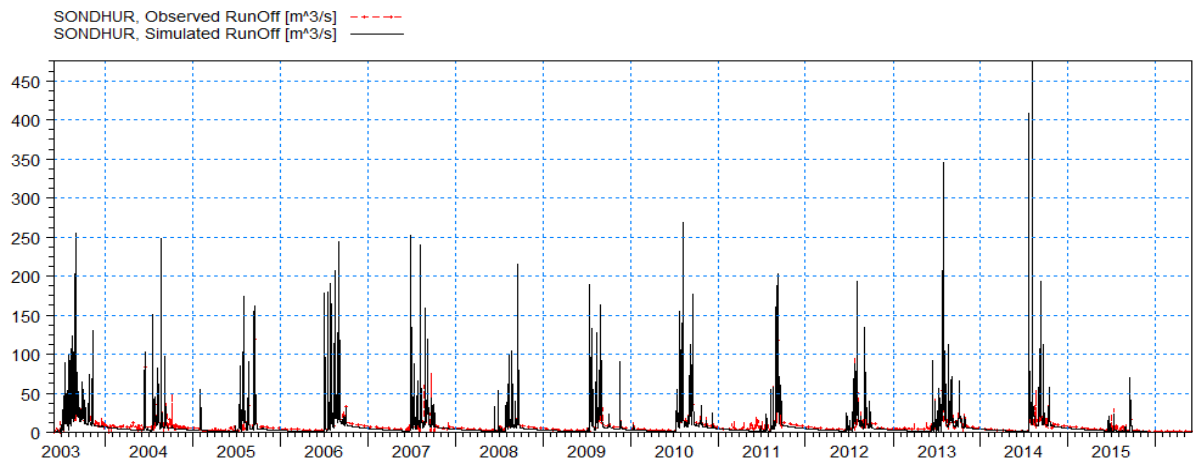


Figure 5.1 Comparison between observed and simulated discharge for Sondhur catchment during calibration.

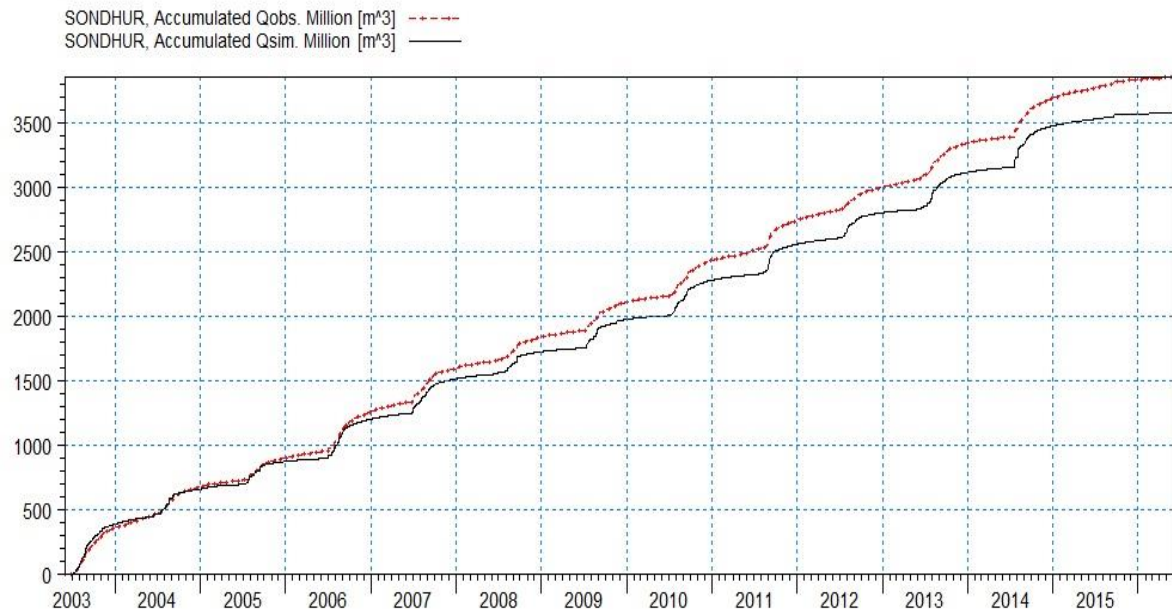


Figure 5.2 Double Mass Curve for Sondhur catchment during the calibration period.

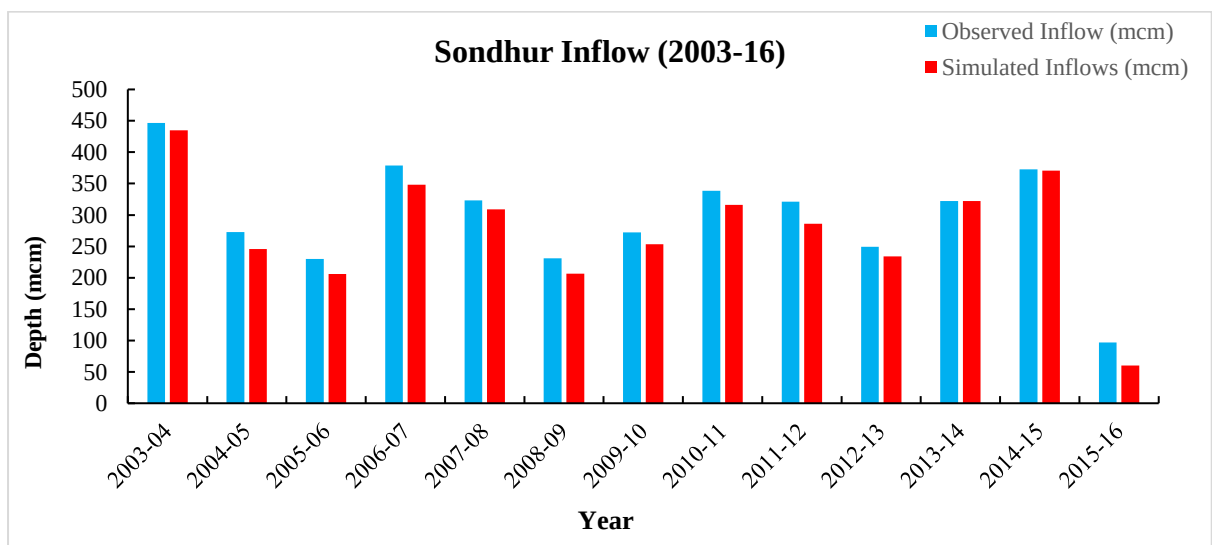


Figure 5.3 Observed and simulated annual runoff depth of Sondhur during calibration.

In the process of validation, the model parameters have been kept constant as obtained during model calibration and runoff has been simulated for the remaining period of 5 years from Jun 2016 to May 2021 for Sondhur catchment. **Figure 5.5** shows the graphical representation of the results obtained during model validation. From the analysis of the results of model validation, it can also be concluded that the developed NAM model for the Sondhur catchment performed well and appears to be capable of generating or forecasting runoff time

series for an extended period with good accuracy. A double mass curve suggests a good match between observed and simulated accumulated flow volume and model accuracy shown in **Figure 5.6**. The statistics of the output and observed and simulated runoff have been compared. This process is supportive for the prediction of runoff for the remote River basin like the modeled basin or the data of different periods for the same basin. **Table 5.4** represents the various components of the hydrological cycle during model validation.

Table 5.4 Statistics of model validation results during 2016-2020 for Sondhur (All values in mm).

S. No.	YEAR	Q-obs	Q-Sim	% Diff	RF	PET	AET	GWR	OF	IF	BF
1	2016-17	228.5	131.2	42.6	765	1788	631.8	7.6	73.3	52	5.8
2	2017-18	130.8	67.7	48.2	640	1692	573.7	0	48.4	17.7	1.6
3	2018-19	318	222.7	30	875	1633	638.4	76.6	122.4	37.2	63.1
4	2019-20	212	173.1	18.3	916	1556	747.1	21.6	90.4	53	29.7
5	2020-21	168	154.6	8	731	1684	583.1	14.7	94.4	43.1	17.1
	Total	1057.3	749.5	29.1	3927	8353	3174.1	120.6	429.1	203.1	117.3
Coefficient of Determination = 0.73											

The coefficient of determination for the validation process of the model has been observed as 0.73, indicating good agreement between the simulated and observed catchment runoff in terms of the peak flows with respect to timing, rate, and volume. The statistical analysis given in **Table 5.4** shows a difference in Q-observed and Q-simulated has reasonable i.e. 29.1% which is again within acceptable limits. **Figure 5.7** shows a comparison of the observed and simulated annual runoff depth during validation.

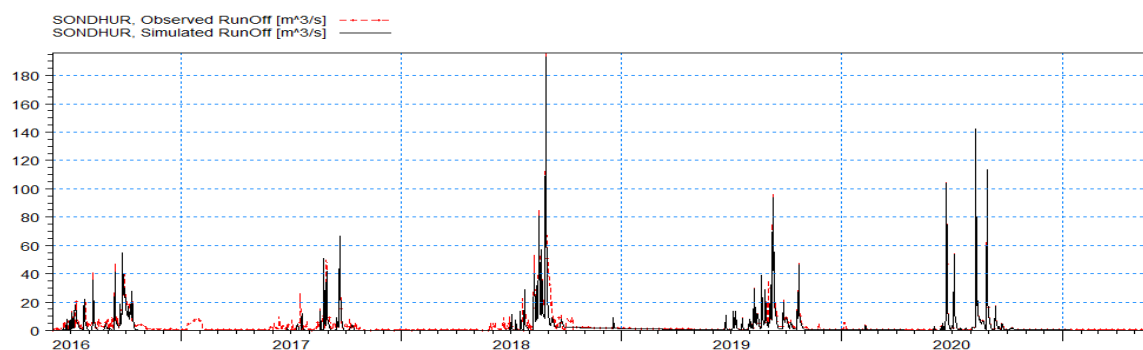


Figure 5.4 Comparison between observed and simulated discharge for Sondhur reservoir during validation.

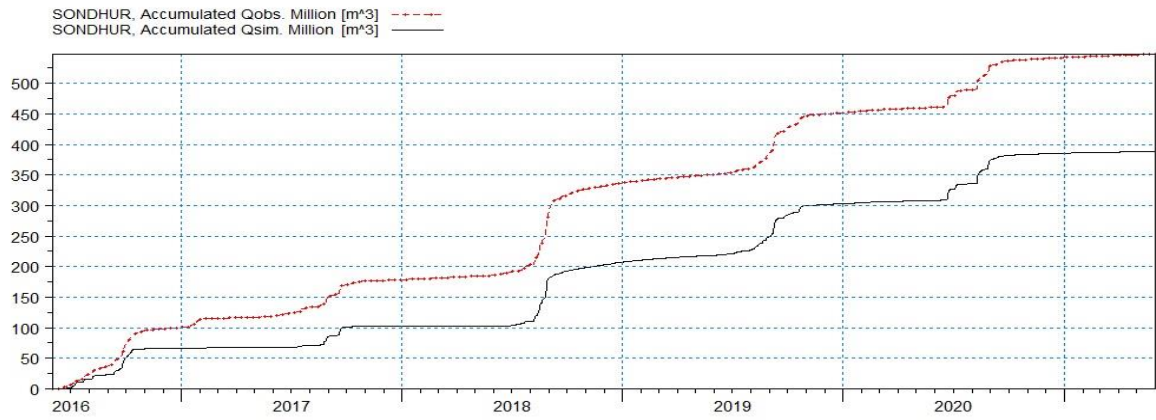


Figure 5.5 Double Mass Curve for Sondhur during the validation period.

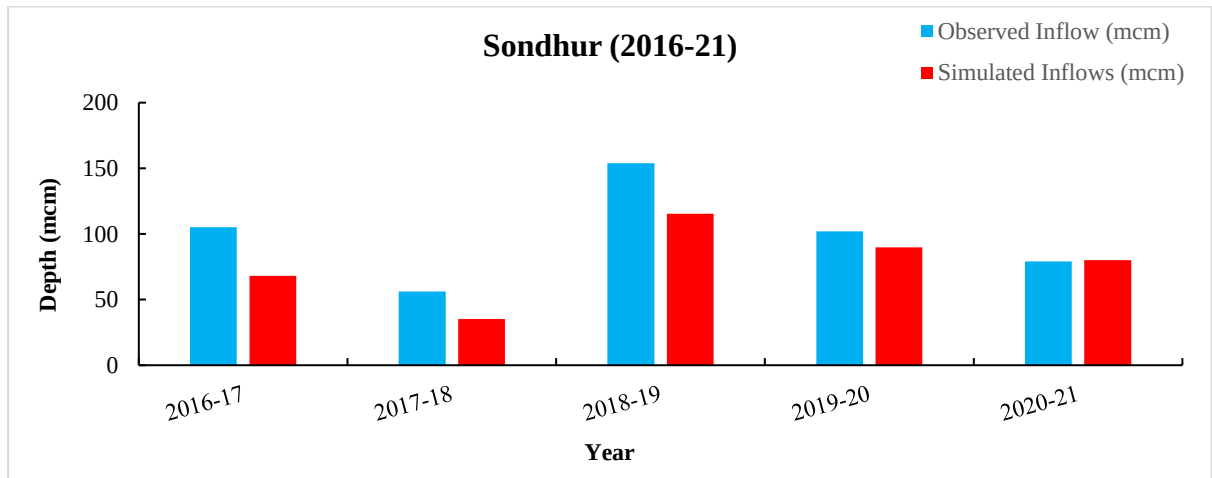


Figure 5.6 Observed and simulated annual runoff depth for Sondhur during validation.

5.2.3 Result of MIKE-11 NAM model of Dudhawa reservoir

The MIKE -11 NAM model has been also created for the Rainfall-Runoff modeling which utilized the daily rainfall time series, potential evapotranspiration, and observed discharge data of the Dudhawa catchment for the period from Jun 2003 to May 2016. The area of the catchment upstream at the dam is 625.27 sq. km. First, MIKE 11 NAM has been used to simulate the runoff by using the auto-calibration mode, and a set of model parameters for the period of Jun 2003 to May 2016. After that, the model was calibrated by modifying the model parameters to reduce the error between observed and simulated stream flow data. To obtain the best match between observed and simulated runoff, the model has been refined. Throughout the model calibration, nine parameters have been determined and the range of these parameters and best-fit values has been given in **Table 5.5**.

Table 5.5 Final calibrated model parameter value and their range for Dudhawa Catchment.

S.No	Parameter	Parameter range	Best-fit value
1	U_{max}	5 – 20	11
2	L_{max}	100 – 300	221
3	$CQOF$	0.1 – 1.0	0.895
4	$CKIF$	100 - 1000	861
5	CK_{12}	3 – 72	26.3
6	TOF	0 – 0.99	0.3
7	TIF	0 – 0.99	0.00791

8	TG	0 – 0.99	0.00641
9	CKBF	200 – 4000	1201

Table 5.6 illustrates various aspects of the hydrological cycle as simulated during model calibration for the Dudhawa catchment, encompassing runoff, actual evapotranspiration, groundwater recharge, overland flow, interflow, and base flow. The calibration of the model revealed a coefficient of determination of 0.76, indicating a strong correlation between observed and simulated runoff in terms of timing, rate, and volume. The deviation between observed and simulated flows is merely 8.2%, indicating a good agreement between observed and simulated runoff. Throughout the calibration period, the simulated discharge amounted to 8349.7 mm, derived from a total precipitation of 17507 mm. Within this context, 4782.4 mm has been attributed to overland flow, 253.2 mm to interflow, 3314.2 mm to base flow, and 3314.9 mm to groundwater recharge.

Table 5.6 Statistics of model calibration result for Dudhawa Catchment from Jun 2003- May 2016 (All values in mm).

S. No.	YEAR	Q-obs	Q-Sim	% Diff	RF	PET	AET	GWR	OF	IF	BF
1	2003-04	801.1	747	6.8	1450	2222.7	701.5	277	448.9	22.2	275.8
2	2004 -05	668.6	529.8	20.8	1335.6	2134.1	804.3	251.8	263.7	15.1	251
3	2005 -06	602.6	517.8	14.1	1339.7	2136.4	782.8	237.2	267.2	16.2	234.4
4	2006-07	1093.1	1084.1	0.8	1848.9	2199.8	805.4	377.6	682.7	20.2	381.3
5	2007 -08	748.6	732.9	2.1	1480.3	2126.7	747.9	273.5	437.2	21.7	274
6	2008-09	517.8	444.7	14.1	1064	1849.8	619.3	191.1	233.7	19.8	191.3
7	2009-10	430.7	386	10.4	1095	1992.9	681.2	185.5	189.5	13.3	183.3
8	2010-11	888.1	854.3	3.8	1595	1679.5	759.1	310.5	519.7	24	310.6
9	2011 -12	618.7	598.9	3.2	1197.6	1657.3	607.2	229.9	348.4	18.7	231.9
10	2012-13	637.4	632.2	0.8	1293.6	1697.3	660.9	241.7	366.5	23.9	241.7
11	2013 -14	701	662.7	5.5	1335.2	1529.6	671.9	260.4	377.4	25	260.3
12	2014-15	885.4	663.2	25.1	1314.7	1694.8	651.4	253.4	390.3	19.5	253.4
13	2015-16	498.9	496.3	0.5	1157.4	1804.9	662.8	225.4	257.1	13.7	225.4
	Total	9092	8349.7	8.2	17507	24725.9	9155.9	3314.9	4782.4	253.2	3314.2
Coefficient of Determination = 0.76											

(Q-obs=Obs. Runoff, Q-Sim=Sim. Runoff, RF=Rainfall, PotEvap=Potential Evapotranspiration,

ActEvap=Actual Evapotranspiration, GWR=Ground Water Recharge, OF=Overland Flow, IF=Inter Flow and BF=Base Flow)

Figure 5.8 represents the cumulative graph of observed and simulated discharge over the calibration period. A double mass curve suggests a good match between observed and simulated accumulated flow volume and model accuracy (**Figure 5.9**). **Figure 5.10** shows a comparison of the observed and simulated annual runoff depth during calibration. The overall comparison showed the MIKE11 NAM Model as a suitable model for the Dudhawa catchment and predicting runoff with a high degree of accuracy.

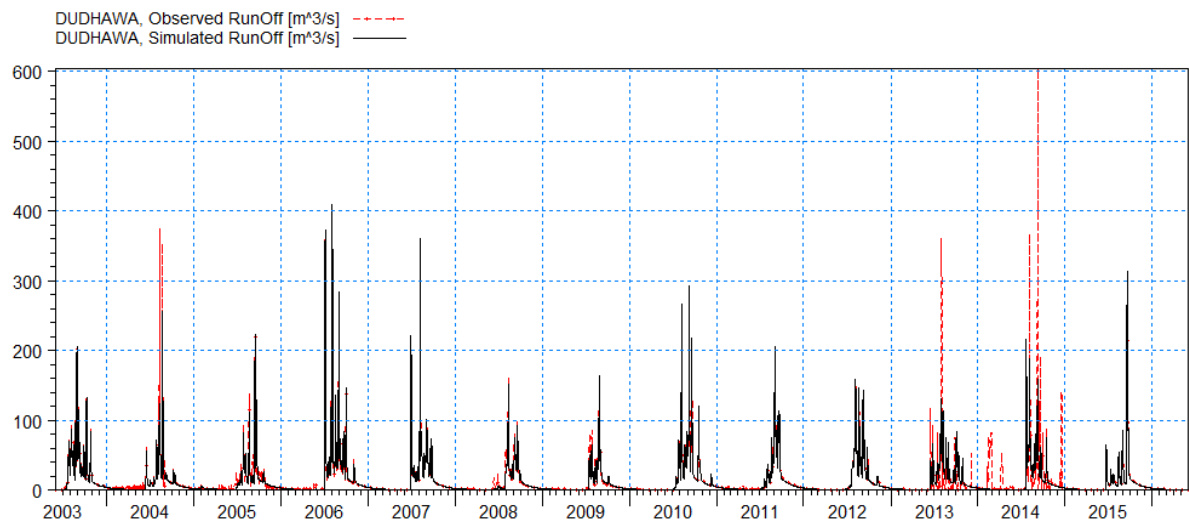


Figure 5.7 Comparison between observed and simulated discharge for Dudhawa catchment during calibration.



Figure 5.8 Double Mass Curve for Dudhawa catchment during the calibration period.

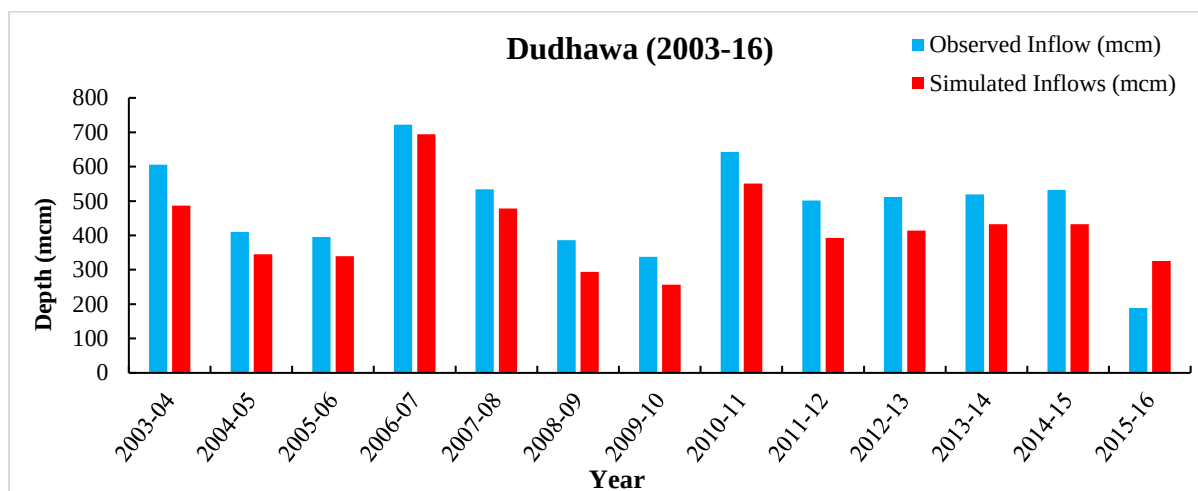


Figure 5.9 Observed and simulated annual runoff depth of Dudhawa during calibration.

In the process of validation, the model parameters have been kept constant as obtained during model calibration and runoff has been simulated for the remaining period of 5 years from 2016 to 2020. **Figure 5.11** shows the graphical representation of the results obtained during model validation. From the analysis of the results of model validation, it can also be concluded that the developed NAM model for the Dudhawa catchment performed well and appears to be capable of generating or forecasting runoff time series for an extended period with satisfactory accuracy. A double mass curve suggests a good match between observed and simulated accumulated flow volume and model accuracy shown in **Figure 5.12**.

The statistics of the output and observed and simulated runoff were compared. This process is supportive for the prediction of runoff for the remote River basin like the modeled basin or the data of different periods for the same basin. **Table 5.7** represents the various components of the hydrological cycle during model validation.

Table 5.7 Statistics of model validation result during 2016-2020 for Dudhawa (All values in mm).

S. No.	YEAR	Q-obs	Q-Sim	% Diff	RF	PET	AET	GWR	OF	IF	BF
1	2016-17	830	778.1	6.3	1445.8	1788.1	666.1	281.5	473	24.5	280.6
2	2017-18	557.1	541.1	2.9	1292.1	1691.8	746.5	222.3	298.1	20.6	222.5
3	2018-19	651.4	543.9	16.5	1186.8	1632.9	646.1	234.3	295.3	14.6	233.9

4	2019-20	616.9	604	2.1	1440.4	1555.6	829.7	234.9	343.4	25.5	235.1
5	2020-21	678.4	545.2	19.6	1355.3	1684.2	790.8	222.6	304.9	21.2	219.1

Coefficient of Determination = 0.69

($Q_{\text{-obs}} = \text{Obs. Runoff}$, $Q_{\text{-Sim}} = \text{Sim. Runoff}$, $RF = \text{Rainfall}$, $PotEvap = \text{Potential Evapotranspiration}$, $ActEvap = \text{Actual Evapotranspiration}$, $GWR = \text{Ground Water Recharge}$, $OF = \text{Overland Flow}$, $IF = \text{Inter Flow}$ and $BF = \text{Base Flow}$)

The coefficient of determination for the validation process of the model has been observed as 0.69, indicating good agreement between the simulated and observed catchment runoff in terms of the peak flows with respect to timing, rate, and volume. The statistical analysis given in **Table 5.7** shows a difference in $Q_{\text{-observed}}$ and $Q_{\text{-simulated}}$ was reasonable i.e. 9.6% which is again within acceptable limits. **Figure 5.13** shows a comparison of the observed and simulated annual runoff depth during validation.

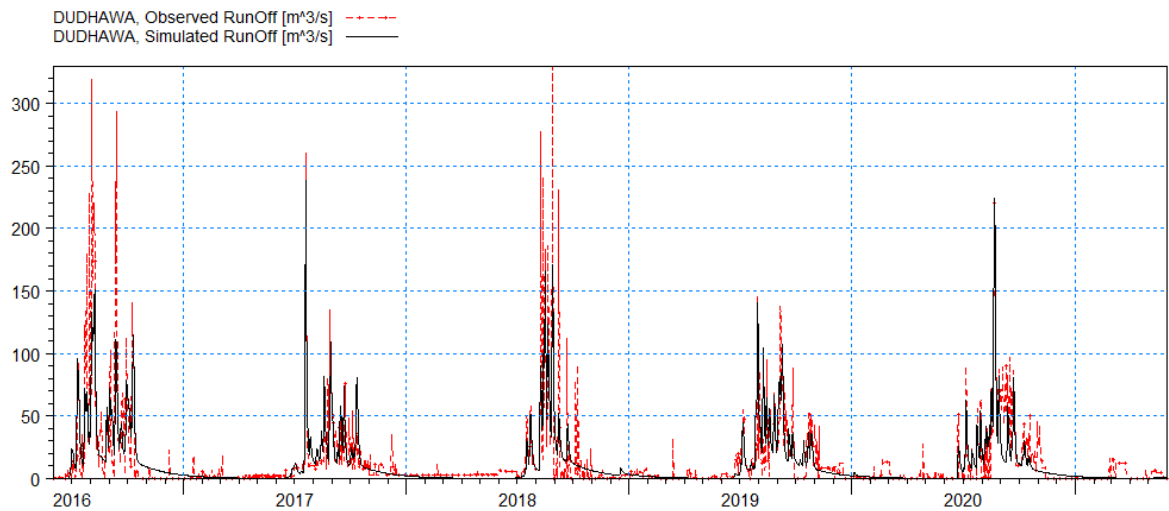


Figure 5.10 Comparison between observed and simulated discharge for Dudhawa during validation.

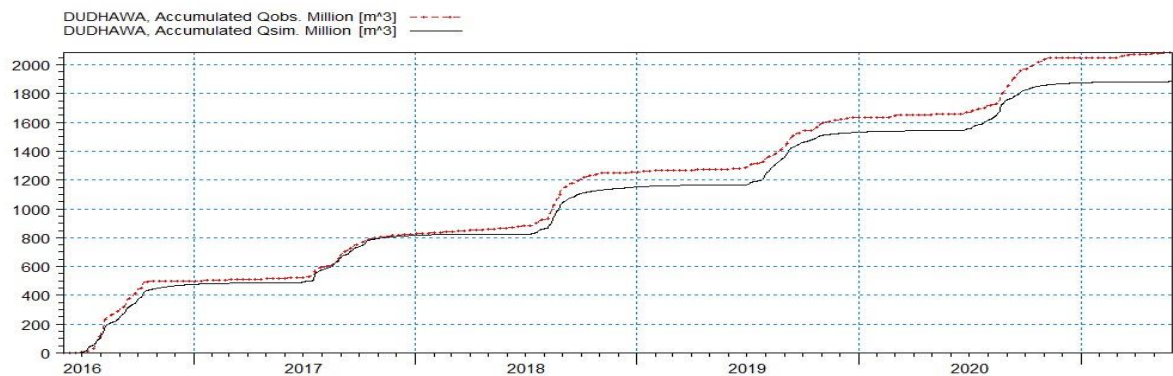


Figure 5.11 Double Mass Curve for Dudhawa during validation period.

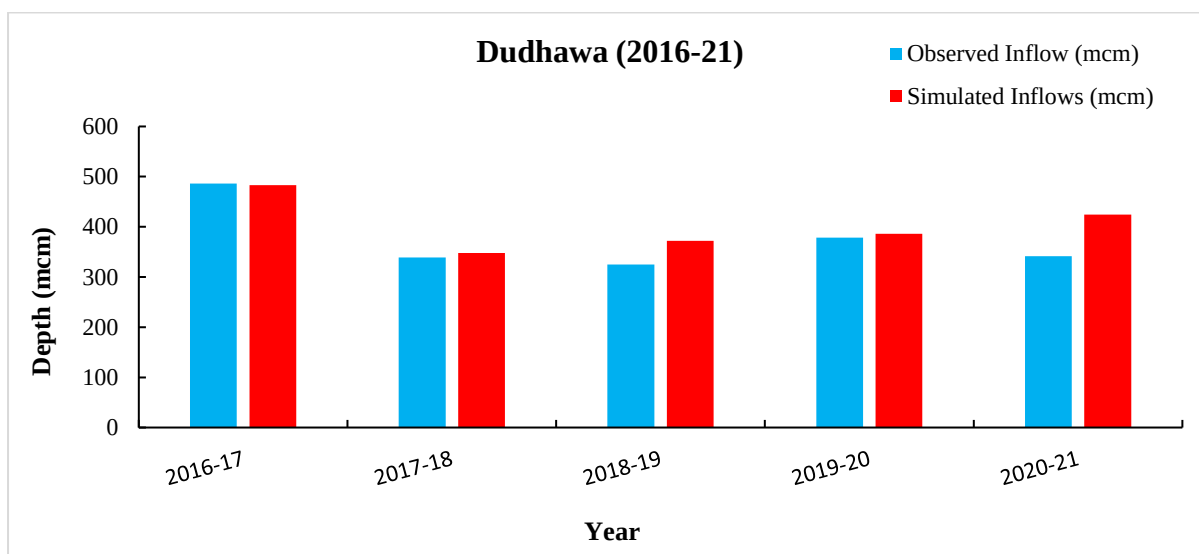


Figure 5.12 Observed and simulated annual runoff depth for Dudhawa during validation.

5.2.4 Results of MIKE-11 NAM model of Murumsilli reservoir

The MIKE -11 NAM model has been created for the Rainfall-Runoff modeling which utilized the daily rainfall time series, potential evapotranspiration, and observed discharge data of the Murumsilli catchment for the period from Jun 2003 to May 2016. The area of the catchment upstream at the dam is 484.33 sq. km. First, MIKE 11 NAM has been used to simulate the runoff by using the auto-calibration mode, and a set of model parameters for the period of Jun 2003 to May 2016. After that, the model was calibrated by modifying the model parameters to reduce the error between observed and simulated stream flow data. To obtain the best match between observed and simulated runoff, the model has been refined. Throughout the model calibration, nine parameters have been determined and the range of these parameters and best-fit values have been given in **Table 5.8** for Murumsilli Catchment, including runoff, actual evapotranspiration, groundwater recharge, overland flow, interflow, and base flow. The model calibration yielded a coefficient of determination of 0.70, indicating a good correlation between observed and simulated runoff concerning timing, rate, and volume. The disparity between observed and simulated flows was only 4.8%, suggesting a strong alignment between observed and simulated runoff. Over the calibration period, the total simulated discharge was 6103.6 mm, derived from total precipitation of 15733.4 mm. In this context, overland flow accounted for 703.4 mm, interflow for 593.4 mm, base flow for 4806.4 mm, and groundwater

recharge for 4816.6 mm.

Table 5.8 Final calibrated model parameter value and their range for Murumsilli

S.No	Parameter	Parameter range	Best-fit value
1	U_{max}	5 - 20	19.6
2	L_{max}	100 - 300	255
3	$CQOF$	0.1 - 1.0	0.129
4	$CKIF$	100 - 1000	538.7
5	CK_{12}	3 - 72	21.6
6	TOF	0 - 0.99	0.539
7	TIF	0 - 0.99	0.243
8	TG	0 - 0.99	0.552
9	$CKBF$	200 - 4000	3649

catchment

Table 5.9 Statistics of model calibration result for Murumsilli Catchment from Jun 2003- May 2016 (All values in mm).

S. No.	YEAR	Q-obs	Q-Sim	% Diff	RF	PET	AET	GWR	OF	IF	BF
1	2003-04	750.1	766	-2.1	1832.1	2222.7	949.4	703.4	103.2	74.5	588.4
2	2004 - 05	466.2	438	6.1	1329.5	2134.1	950.6	292.3	42.5	41.4	354.1
3	2005 - 06	358.1	336	6.2	1106.5	2136.4	781.2	257.2	37.2	33.1	265.7
4	2006-07	626.1	600.1	4.2	1363.8	2199.8	730.4	514.6	75.4	44.7	480
5	2007 - 08	551.7	523	5.2	1295	2126.7	786.9	397.3	57.9	52.7	412.4
6	2008-09	370	330.3	10.7	944.5	1849.8	632.1	237.5	34.6	40.1	255.6
7	2009-10	412.8	411.3	0.4	1197	1992.9	776.2	331.3	48.1	40.2	323
8	2010-11	540.6	535.8	0.9	1288	1679.5	729.7	431.3	63.1	60.9	411.8
9	2011 - 12	512.1	476.3	7	1122	1657.3	650.8	384.1	56.2	33.5	386.6
10	2012-13	414.2	379.7	8.3	1095	1697.3	740.7	259.1	37.7	56	285.9
11	2013 - 14	570.2	551.8	3.2	1276	1529.6	700.5	445.7	65.2	64.6	422.1
12	2014-15	669.3	654.6	2.2	1295	1694.8	620.9	552.6	80.8	40.9	532.9

13	2015-16	172	100.8	41.4	589	1804.9	569.5	10	1.5	11	88.3
	Total	6413.4	6104	4.8	15733	24726	9618.9	4816.4	703.4	593.6	4806.8
Coefficient of Determination = 0.70											

(*Q-obs= Obs. Runoff, Q-Sim= Sim. Runoff, RF=Rainfall, PotEvap=Potential Evapotranspiration, ActEvap=Actual Evapotranspiration, GWR=Ground Water Recharge, OF=Overland Flow, IF=Inter Flow and BF=Base Flow*)

Figure 5.14 represents the cumulative graph of observed and simulated discharge over the calibration period. A double mass curve suggests a good match between observed and simulated accumulated flow volume and model accuracy **Figure 5.15**. **Figure 5.16** shows a comparison of the observed and simulated annual runoff depth during calibration. The overall comparison showed the MIKE11 NAM Model as a suitable model for the Murumsilli catchment and predicting runoff with a high degree of accuracy.

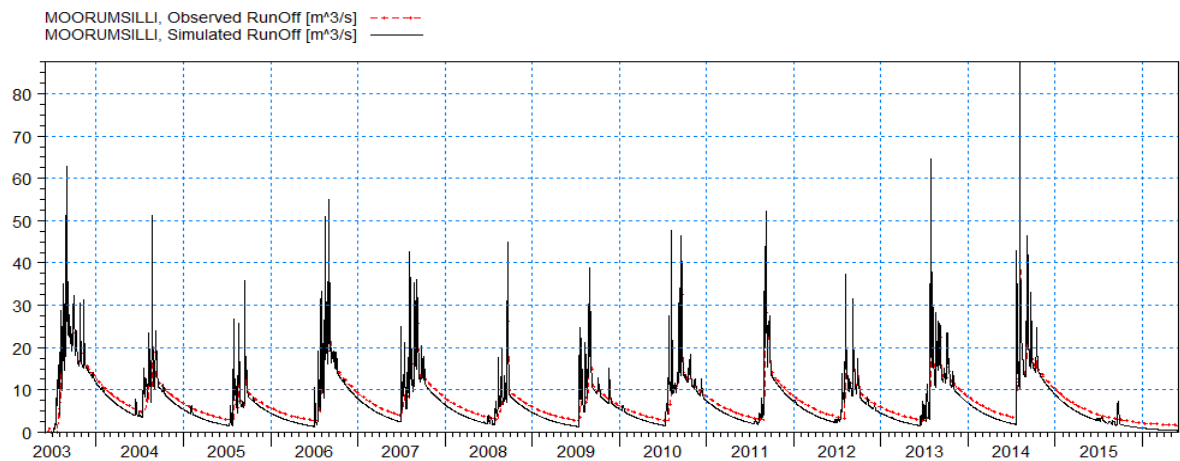


Figure 5. 13 Comparison between observed and simulated discharge for Murumsilli catchment during calibration.

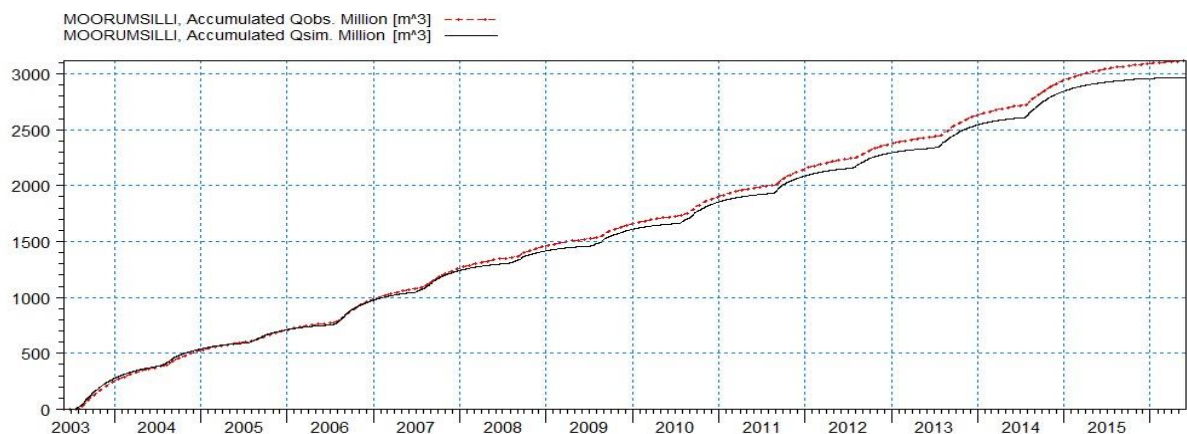


Figure 5. 14 Double Mass Curve for Murumsilli catchment during the calibration

period.

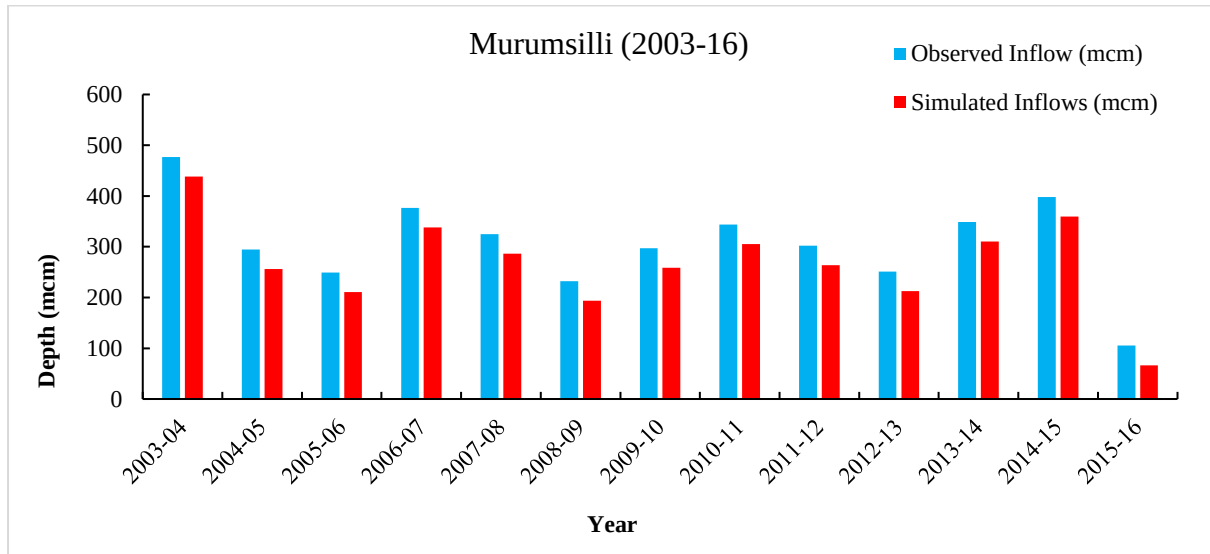


Figure 5. 15 Observed and simulated annual runoff depth of Murumsilli during calibration.

In the process of validation, the model parameters have been kept constant as obtained during model calibration and runoff has been simulated for the remaining period of 5 years from 2016 to 2020. **Figure 5.17** shows the graphical representation of the results obtained during model validation. From the analysis of the results of model validation, it can also be concluded that the developed NAM model for the Murumsilli catchment performed well and appears to be capable of generating or forecasting runoff time series for an extended period with satisfactory accuracy. A double mass curve suggests a good match between observed and simulated accumulated flow volume and model accuracy shown in **Figure 5.18**.

The statistics of the output and observed and simulated runoff have been compared. This process is supportive for the prediction of runoff for the remote River basin like the modelled basin or the data of different periods for the same basin. **Table 5.10** represents the various components of the hydrological cycle during model validation.

Table 5.10 Statistics of model validation results during 2016-2020 for Murumsilli (All values in mm).

S. No.	YEAR	Q-obs	Q-Sim	% Diff	RF	PET	AET	GWR	OF	IF	BF
1	2016-17	94.2	82	12.9	765	1788.1	671.1	52.5	7.6	32.1	42.3
2	2017-18	89.6	38.7	56.8	640	1691.8	606.7	18	2.7	12	24

3	2018-19	179.8	157.2	12.6	875	1632.9	699.6	130.9	18.9	23.9	114.4
4	2019-20	154.5	128.8	16.7	916	1555.6	783.8	78.4	11.3	34.5	83
5	2020-21	180.8	119.2	34.1	731	1684.2	625.3	78.5	11.3	26.1	81.8
	Total	698.9	525.8	24.8	3927	8352.5	3387	358.4	51.8	128.5	345.5
Coefficient of Determination = 0.69											

The coefficient of determination for the validation process of the model has been observed as 0.69, indicating good agreement between the simulated and observed catchment runoff in terms of the peak flows with respect to timing, rate, and volume. The statistical analysis given in **Table 5.10** shows a difference in Q-observed and Q-simulated was reasonable i.e. 24.8 % which is again within acceptable limits. **Figure 5.19** shows a comparison of the observed and simulated annual runoff depth during validation.



Figure 5.16 Comparison between observed and simulated discharge for Murumsilli during validation.

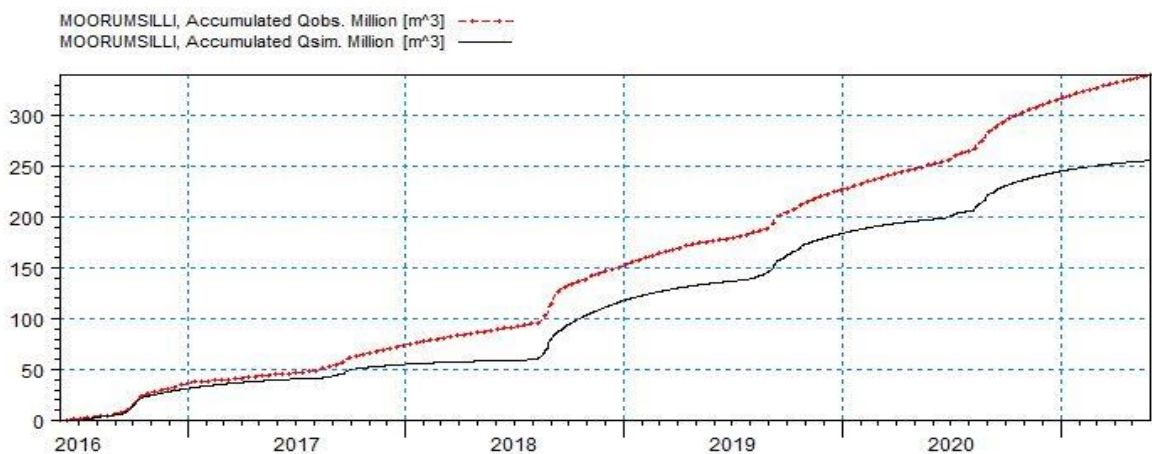


Figure 5.17 Double Mass Curve for Murumsilli during the validation period.

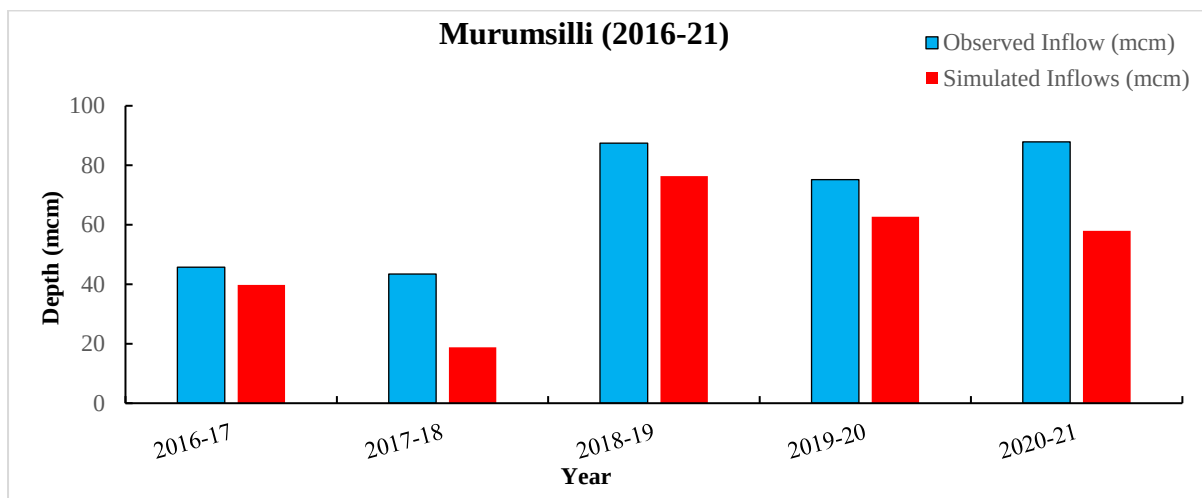


Figure 5.18 Observed and simulated annual runoff depth for Murumsilli during validation.

5.2.5 Results of MIKE-11 NAM model of Ravishankar Sagar reservoir

The MIKE -11 NAM model has been created for the Rainfall-Runoff modeling which utilized the daily rainfall time series, potential evapotranspiration, and observed discharge data of the Ravishankar Sagar catchment for the period from Jan 1991 to Dec 2020. The area of the catchment upstream at the dam is 2509 sq. km. First, MIKE 11 NAM has been used to simulate the runoff by using the auto-calibration mode, and a set of model parameters for the period of 1991 to 2011. After that, the model was calibrated by modifying the model parameters to reduce the error between observed and simulated stream flow data. To obtain the best match between observed and simulated runoff, the model has been refined. Throughout the model calibration, nine parameters have been determined and the range of these parameters and best-fit values have been given in **Table 5.11**.

Table 5.11 Final calibrated model parameter value and their range for Ravishankar Sagar Catchment.

S.NO	Parameter	Parameter range	Best-fit value
1	U_{max}	5 - 20	11
2	L_{max}	100 - 300	109
3	$CQOF$	0.1 -1.0	0.525
4	$CKIF$	100 - 1000	287.3

5	<i>CK₁₂</i>	3 - 72	21.2
6	<i>TOF</i>	0 - 0.99	0.0701
7	<i>TIF</i>	0 - 0.99	0.419
8	<i>TG</i>	0 - 0.99	0.0266
9	<i>CKBF</i>	200 - 4000	1154

Table 5.12 demonstrates various facets of the hydrological cycle as modeled during the calibration process for the Ravishankar Sagar catchment. This includes runoff, actual evapotranspiration, groundwater recharge, overland flow, interflow, and base flow. The model calibration yielded a coefficient of determination of 0.74, indicating a strong correlation between observed and simulated runoff concerning timing, rate, and volume. The variation between observed and simulated flows was only 31.1 %, indicating a satisfactory agreement between observed and simulated runoff. Throughout the calibration period, the simulated discharge was 14864.2 mm, derived from a total precipitation of 14864.2 mm. Within this framework, overland flow accounted for 5569.4 mm, interflow for 1220.8 mm, base flow for 8074.1mm, and groundwater recharge for 4248.2 mm.

Table 5.12 Statistics of model calibration result for Ravishankar Sagar Catchment from 1991- 2011 (All values in mm).

S. No.	YEAR	Q-obs	Q-Sim	% Diff	RF	PET	AET	GWR	OF	IF	BF
1	1991	1297.1	1049.3	19.1	1843.2	1440.2	703.6	562.8	431.8	97.6	519.9
2	1992	1431.1	826.4	42.3	1292	1501.9	517.3	429.9	311.7	60.6	454
3	1993	674.4	530.9	21.3	1070.2	1501.1	529.7	290.4	182.6	54.4	293.9
4	1994	1358.3	1264.7	6.9	1885.7	1414.9	591.4	673.4	527.8	81.3	655.6
5	1995	879.4	717.1	18.5	1390.9	1379.3	710.2	390.1	260.5	48.8	407.8
6	1996	598.7	427.2	28.6	913.4	1497.3	495.1	234.3	144.1	45.7	237.3
7	1997	791.8	620.2	21.7	1424.9	1788	773.6	368.5	214.1	44.4	361.6
8	1998	584.4	367.3	37.1	1047.5	1798.1	706.4	189.1	107.1	62.1	198.2
9	1999	813	784	3.6	1332.5	1329.1	508.6	415.5	290.1	89	404.8
10	2000	410.2	393.3	4.1	812	1342.2	471.8	213.9	125.1	41.1	227.1
11	2001	1409.7	1342.3	4.8	1945.5	1263.5	562.3	715.6	565.5	78.1	698.7
12	2002	701.4	522.9	25.4	1017.3	1426.5	524.1	290.7	173.9	49.2	299

											.9
13	2003	799.2	682.4	14.6	1426	1698.2	726.2	376.9	262.3	54.9	365.2
14	2004	510.5	456.3	10.6	976.1	1609.6	560.5	251.5	147.9	39.8	268.6
15	2005	615.8	528.6	14.2	1208.7	1636.6	667.1	307	176.9	53.3	298.4
16	2006	1166.1	979.3	16	1659.1	1661.3	677.1	531	394.1	59.7	525.5
17	2007	992.6	831.3	16.2	1454.8	1666.9	631.8	436.6	314.1	73.1	444.1
18	2008	1713.3	677.5	60.5	1307.8	1697.2	624.7	377.5	251.8	54.7	371
19	2009	1480.5	495	66.6	978.4	1848.1	494.9	284.8	168.9	29.8	296.3
20	2010	1703.1	725.9	57.4	1454	1662.3	700.7	410.8	279.9	51.8	394.1
21	2011	1634.3	642.3	60.7	1252.8	1579.8	625.8	346.3	239.1	51.2	352
	Total	21564.8	14864.2	31.1	27692.9	32742.1	12802.8	8096.5	5569.4	1220.8	807.4
Coefficient of Determination = 0.74											

(Q-Obs= Obs. Runoff, Q-Sim= Sim. Runoff, RF=Rainfall, PotEvap=Potential Evapotranspiration, ActEvap=Actual Evapotranspiration, GWR=Ground Water Recharge, OF=Overland Flow, IF=Inter Flow and BF=Base Flow)

Figure 5.20 represents the cumulative graph of observed and simulated discharge over the calibration period. A double mass curve suggests a good match between observed and simulated accumulated flow volume and model accuracy **Figure 5.21**. **Figure 5.22** shows a comparison of the observed and simulated annual runoff depth during calibration. The overall comparison showed the MIKE11 NAM Model as a suitable model for the Ravishankar Sagar catchment and predicting runoff with a high degree of accuracy.

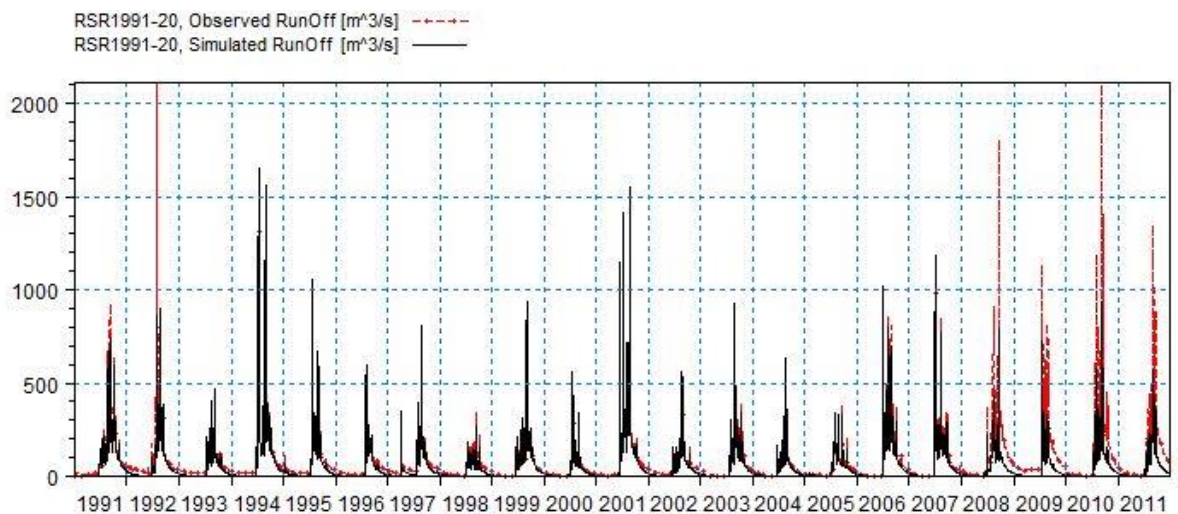


Figure 5.19 Comparison between observed and simulated discharge for Ravishankar Sagar catchment during calibration.



Figure 5.20 Double Mass Curve for Ravishankar Sagar catchment during calibration period.

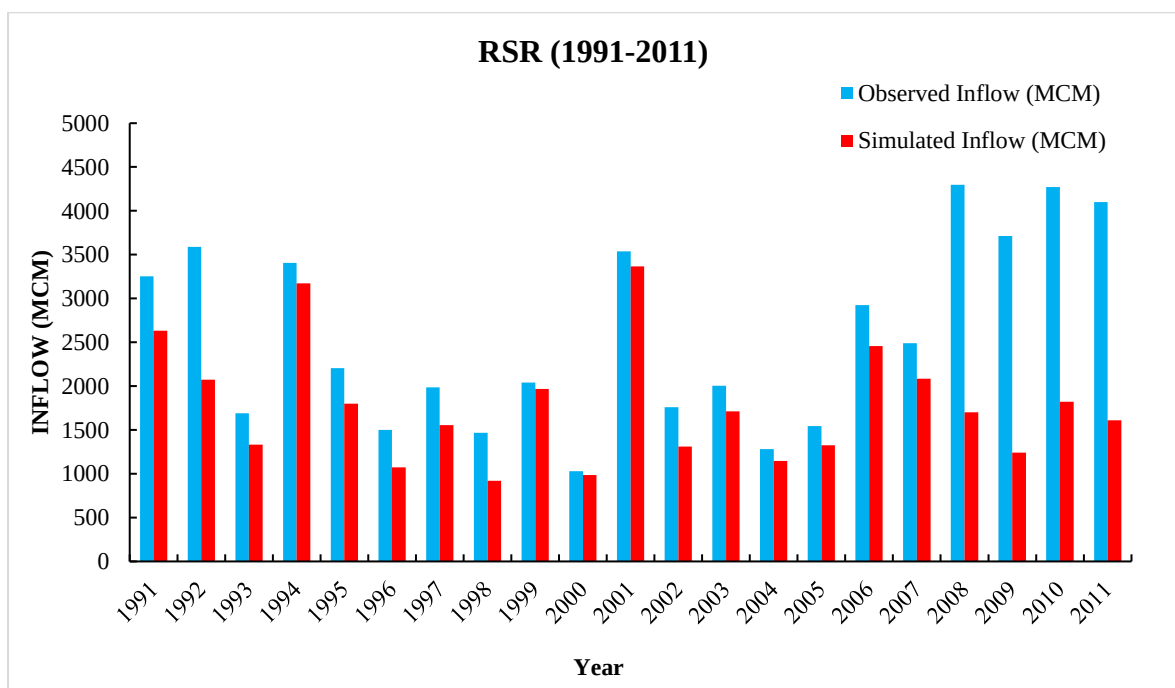


Figure 5.21 Observed and simulated annual runoff depth of Ravishankar Sagar during calibration.

In the process of validation, the model parameters have been kept constant as obtained during model calibration and runoff has been simulated for the remaining period of 9 years from 2012 to 2020. **Figure 5.23** shows the graphical representation of the results obtained during model validation. From the analysis of the results of model validation, it can also be concluded that the developed NAM model for the Ravishankar Sagar catchment performed well and appears to be capable of generating or forecasting runoff time series for an extended

period with satisfactory accuracy. A double mass curve suggests a good match between observed and simulated accumulated flow volume and model accuracy shown in **Figure 5.24**.

The statistics of the output and observed and simulated runoff has been compared. This process is supportive for the prediction of runoff for the remote River basin like the modeled basin or the data of different periods for the same basin. The **Table 5.13** represented the various components of hydrological cycle during model validation.

Table 5.13 Statistics of model validation results during 2012-2020 for Ravishankar Sagar (All values in mm).

S. No.	YEAR	Q-obs	Q-Sim	% Diff	RF	PET	AET	GWR	OF	IF	BF
1	2012	1297.1	1049.3	19.1	1843.2	1440.2	703.6	562.8	431.8	97.6	519.9
2	2013	1431.1	826.4	42.3	1292	1501.9	517.3	429.9	311.7	60.6	454
3	2014	674.4	530.9	21.3	1070.2	1501.1	529.7	290.4	182.6	54.4	293.9
4	2015	1358.3	1264.7	6.9	1885.7	1414.9	591.4	673.4	527.8	81.3	655.6
5	2016	879.4	717.1	18.5	1390.9	1379.3	710.2	390.1	260.5	48.8	407.8
6	2017	598.7	427.2	28.6	913.4	1497.3	495.1	234.3	144.1	45.7	237.3
7	2018	791.8	620.2	21.7	1424.9	1788	773.6	368.5	214.1	44.4	361.6
8	2019	584.4	367.3	37.1	1047.5	1798.1	706.4	189.1	107.1	62.1	198.2
9	2020	813	784	3.6	1332.5	1329.1	508.6	415.5	290.1	89	404.8
	Total	8428.1	6586.9	21.8	12200.4	13649.9	5535.9	3554	2469.7	584	3533.2
	Coefficient of Determination = 0.83										

(Q-Obs= Obs. Runoff, Q-Sim= Sim. Runoff, RF=Rainfall, PotEvap=Potential Evapotranspiration, ActEvap=Actual Evapotranspiration, GWR=Ground Water Recharge, OF=Overland Flow, IF=Inter Flow and BF=Base Flow)

The coefficient of determination for the validation process of the model has been observed as 0.83, indicating good agreement between the simulated and observed catchment runoff in terms of the peak flows concerning timing, rate, and volume. The statistical analysis given in **Table 5.13** shows a difference in Q-observed and Q-simulated was reasonable i.e. 21.8% which is again within acceptable limits. **Figure 5.25** shows a comparison of the observed and simulated annual runoff depth during validation.

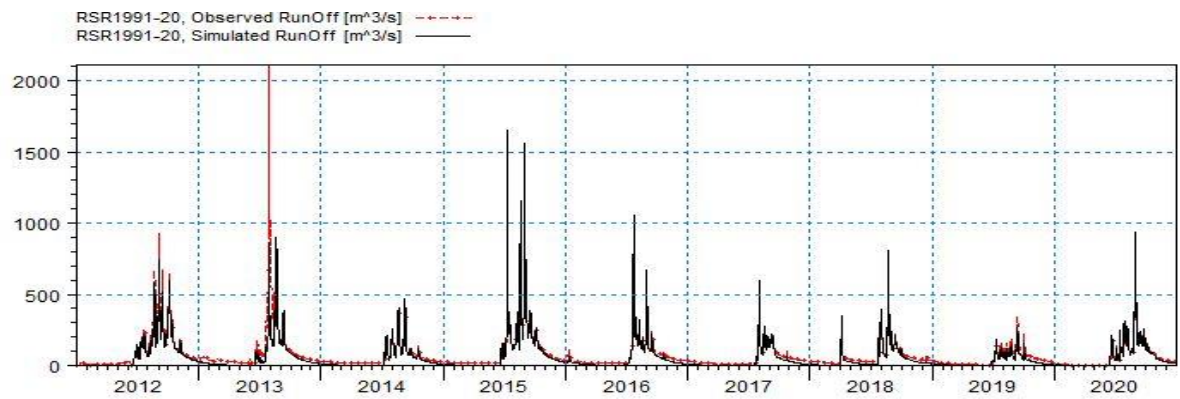


Figure 5.22 Comparison between observed and simulated discharge for Ravishankar Sagar during validation.



Figure 5.23 Double Mass Curve for Ravishankar Sagar reservoir during validation period.

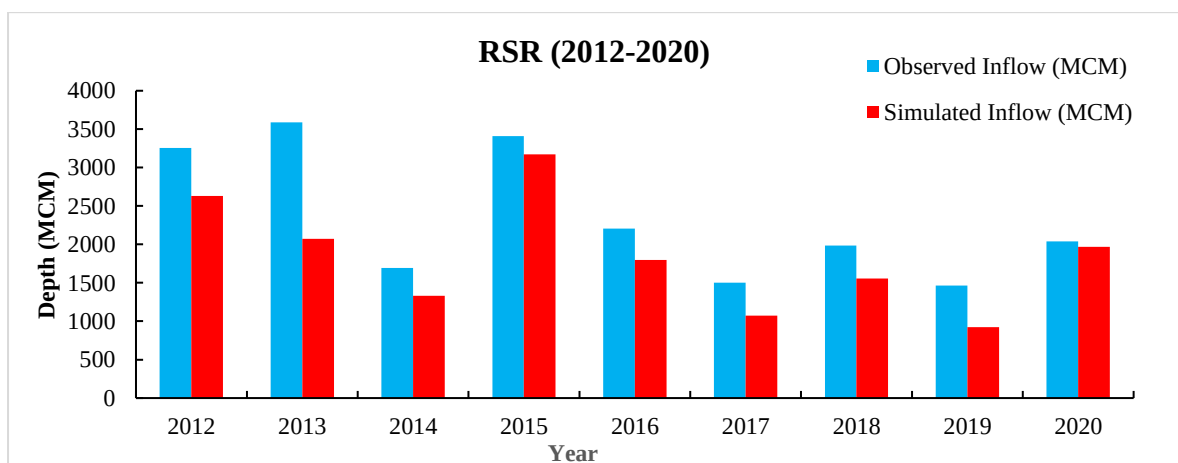


Figure 5.24 Observed and simulated annual runoff depth for Ravishankar Sagar during validation.

After calibrating and validating the MIKE NAM model for all catchments within the MRP complex, the calibrated parameters has been applied to simulate inflows from 1991 to 2020 for the Sondhur, Murumsilli, and Dudhawa catchments. The simulated inflows has been used in NIH_ResyP to develop rule curves for all the dams.

5.3 Efficient Segment Algorithm for Estimation of Revised Reservoir Capacity in GEE

The computation of the revised capacity of the reservoir is essential for efficient operation and needs assessment of soil conservation measures in the catchment of the reservoir. Bathymetric surveys cannot be conducted frequently due to high cost; presently, digital image analysis of optical remote sensing data is commonly used to assess revised capacities. The presentstudy suggested Otsu, an efficient technique for the segmentation of SAR images that can be automated through GEE. Ravishankar Sagar, Murumsilli, Sondhur and Dudhawa reservoirs of MRP have been selected in this study. The results of the analysis have been compared with the bathymetric survey of the year 2021 for three reservoirs (RS Sagar, Murumsilli, and Sondhur reservoirs) conducted in the study area.

5.3.1 The revised capacity of Ravishankar Sagar reservoir

The Ravishankar Sagar reservoir is the biggest reservoir that started functioning in the year 1979 having year gross storage of 909.32 MCM at FSL of 348.70 m and dead storage capacity of 143 MCM at DSL of 336.21 m.

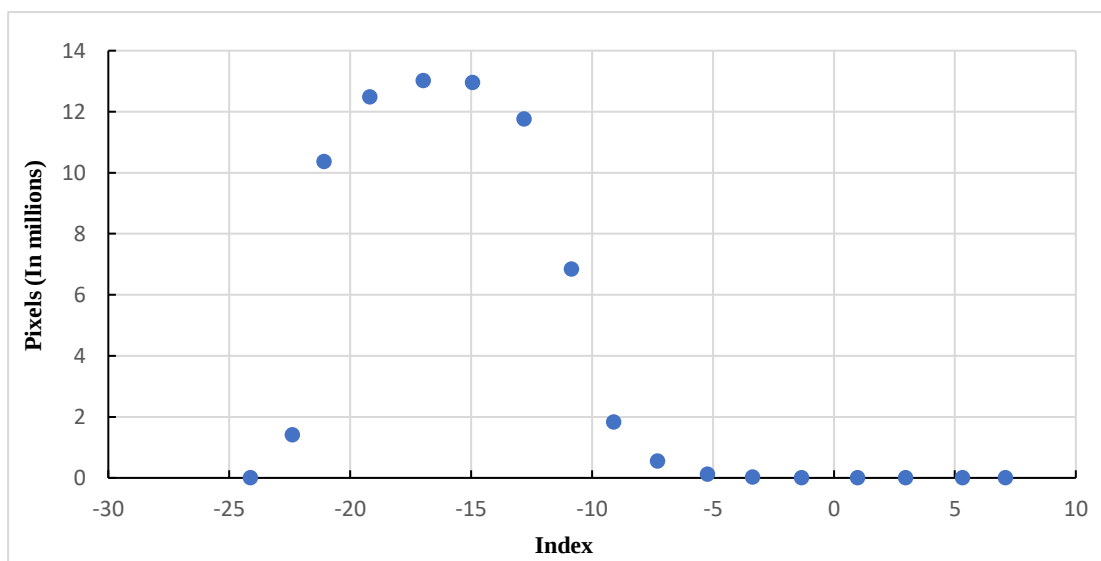


Figure 5.25 Segmentation graph using the Otsu technique for Ravishankar Sagar reservoir.

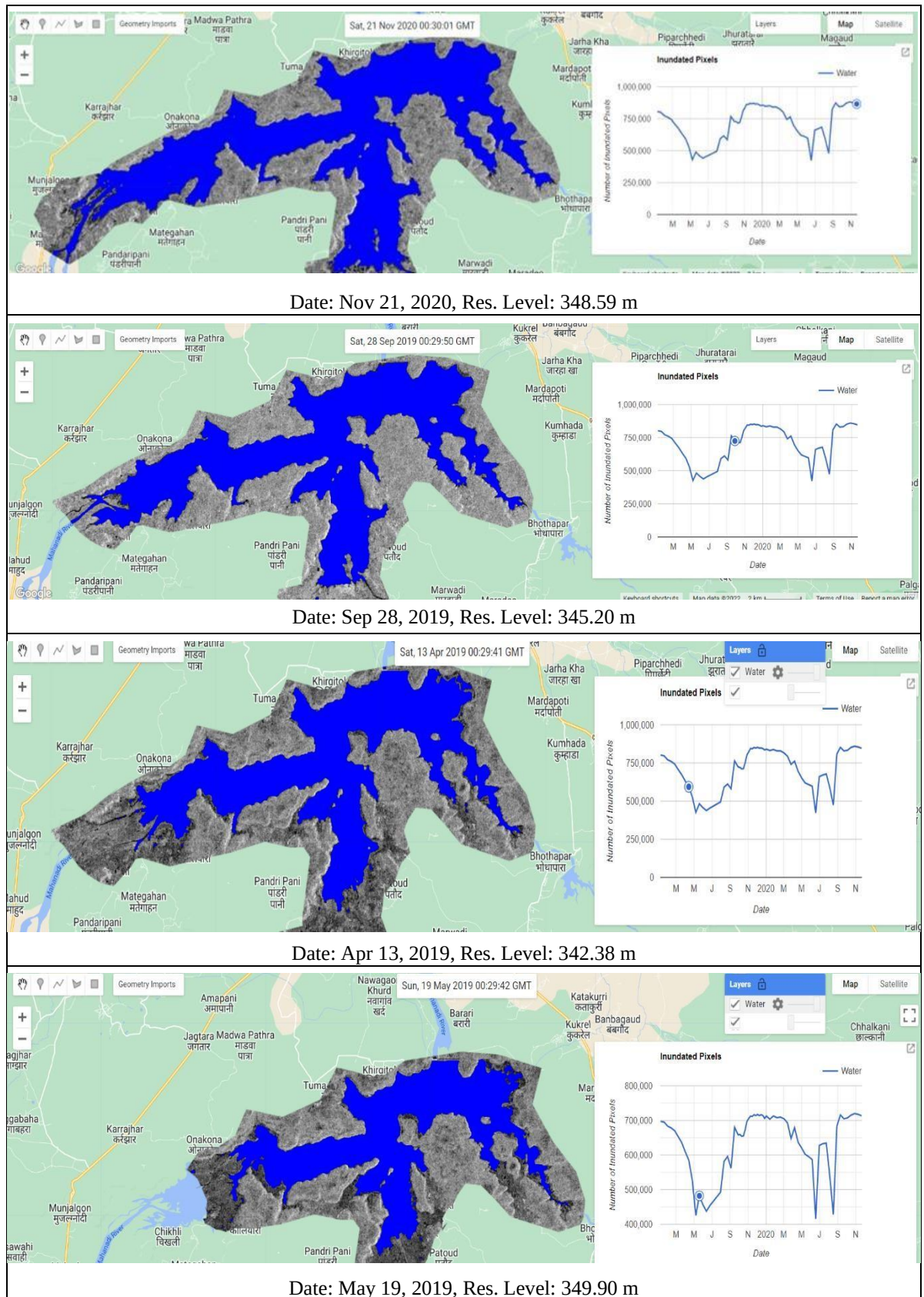


Figure 5.26 Revised water spread using Otsu technique in GEE for RS Sagar

reservoir.

The total catchment area of River Mahanadi up to Ravishankar Sagar dam is about 3620 sqkm. Nine different dates during the period 2019-21 were selected and the Otsu value - 16.9 (**Figure.5.26**) was found suitable to classify water pixels from the rest of the image. A few water spread areas on different dates obtained through the application of the Otsu technique for RS Sagar are presented in **Figure 5.27**. The revised water spread at different elevations was used to fit the best-fitcurve and the revised water spread of 29.67 sq km was found at the DSL of 336.21 m. Similarly, the curve was extrapolated to the FSL of 348.70 m with a revised water spread of 89.28 sq km. The computation of revised capacities and its comparison with original capacities at different levels are presented in **Figure 5.28** and **Table 5.14**. From the analysis, it has been found that nearly 25.31 MCM (17.65%) of dead storage and 85.44 (9.38%) of gross storage of RS Sagar have been lost in 40 to 41 years (1979 to 2019).

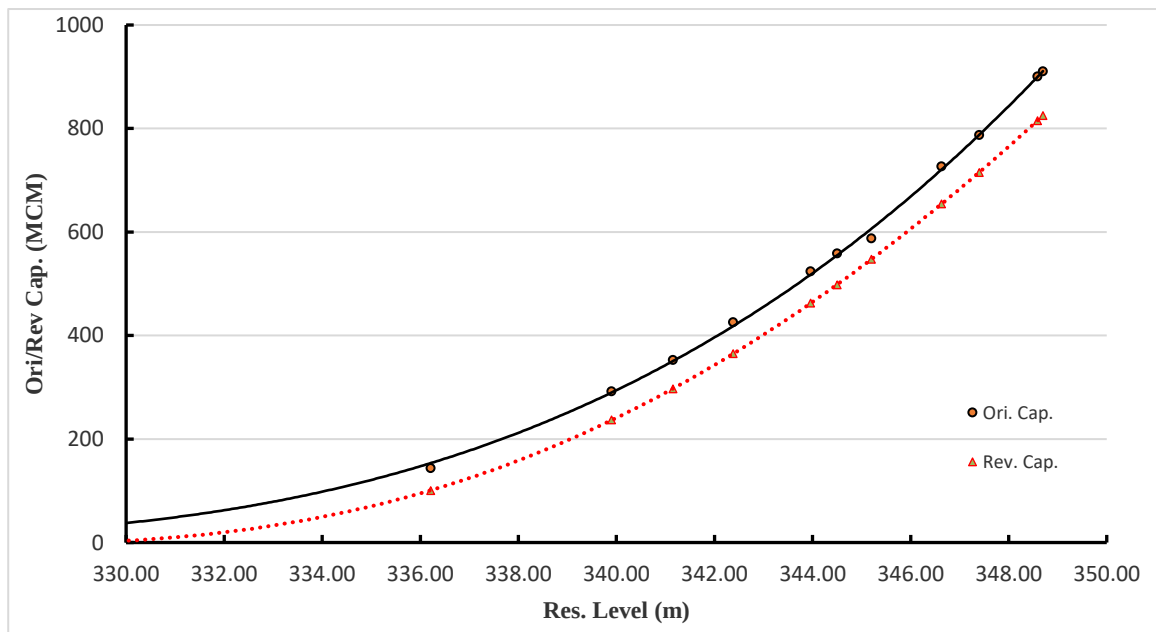


Figure 5.27 Original and revised capacities at different levels of RS Sagar reservoir.

Table 5.14 Original and revised capacities at different levels of RS Sagar reservoir.

Date of Pass	Reservoir Elevation (meter)	Original Capacity (MCM)		Revised Capacity (MCM)		Loss in Capacity (MCM)	Loss in Capacity (%)
		Volume	Cum. Capacity	Volume	Cum. Capacity		

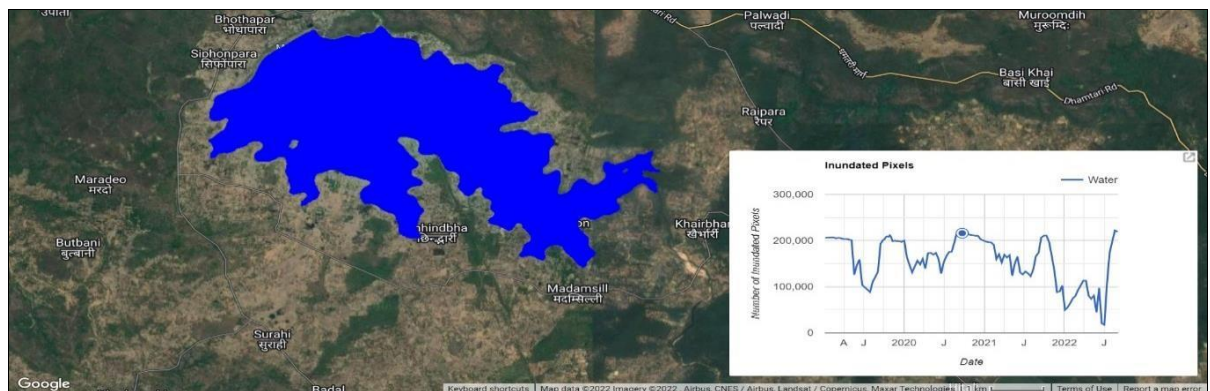
Or.	322.47	0	0		0	0.000	-
River bed							
Rev.	324.25		18.629		0	18.629	100.00
Riverbed*							
DSL	336.21	124.971	143.600	100.300	100.300	43.300	30.15
19-May-19	339.90	148.500	292.100	136.840	237.140	54.960	18.82
25-Apr-19	341.15	60.150	352.250	59.821	296.961	55.289	15.70
13-Apr-19	342.38	73.200	425.450	67.738	364.699	60.751	14.28
20-Mar-19	343.96	98.200	523.650	97.793	462.492	61.158	11.68
08-Mar-19	344.50	34.660	558.310	35.641	498.134	60.176	10.78
28-Sep-19	345.20	29.060	587.370	49.209	547.343	40.027	6.81
14-Mar-20	346.63	139.292	726.662	106.903	654.246	72.416	9.97
29-Aug-20	347.40	60.538	787.200	60.493	714.739	72.461	9.20
21-Nov-20	348.59	112.910	900.110	100.553	815.292	84.818	9.42
FSL	348.70	10.400	910.510	9.780	825.072	85.438	9.38

DSL: Dead storage level, FSL: Full supply level, Or: Original, Res: Reservoir, MCM: Million cubic meter

* Revised water spread was extrapolated on this level

5.3.2 Revised capacity of Murumsilli reservoir

Murumsilli reservoir started functioning in the year 1922 having a gross storage capacity of 164.54 MCM, water spread of 25 sq km, and live storage capacity of 161.91 MCM. The ten different scenes were during 2020-22 (mean 2021). The Otsu segmentation technique yielded a threshold value of -15.03 to segregate water pixels from the rest of the image. A few selected revised water spreads for the Murumsilli reservoir on different dates are presented in **Figure 5.29**. The revised water spread at different levels was used to fit a non-linear curve to determine the new zero elevation for the reservoir and found that sediment had filled all the space upto 359.95 m in Murumsilli reservoir. The revised capacities and loss of capacities at different levels are presented in **Figure 5.30** and **Table 5.15**. From the analysis, it has been observed that nearly 94.1% of the dead and 10.33% of gross storage of the Murumsilli reservoir was lost in 99 years with an average rate of 0.17 MCM/year.



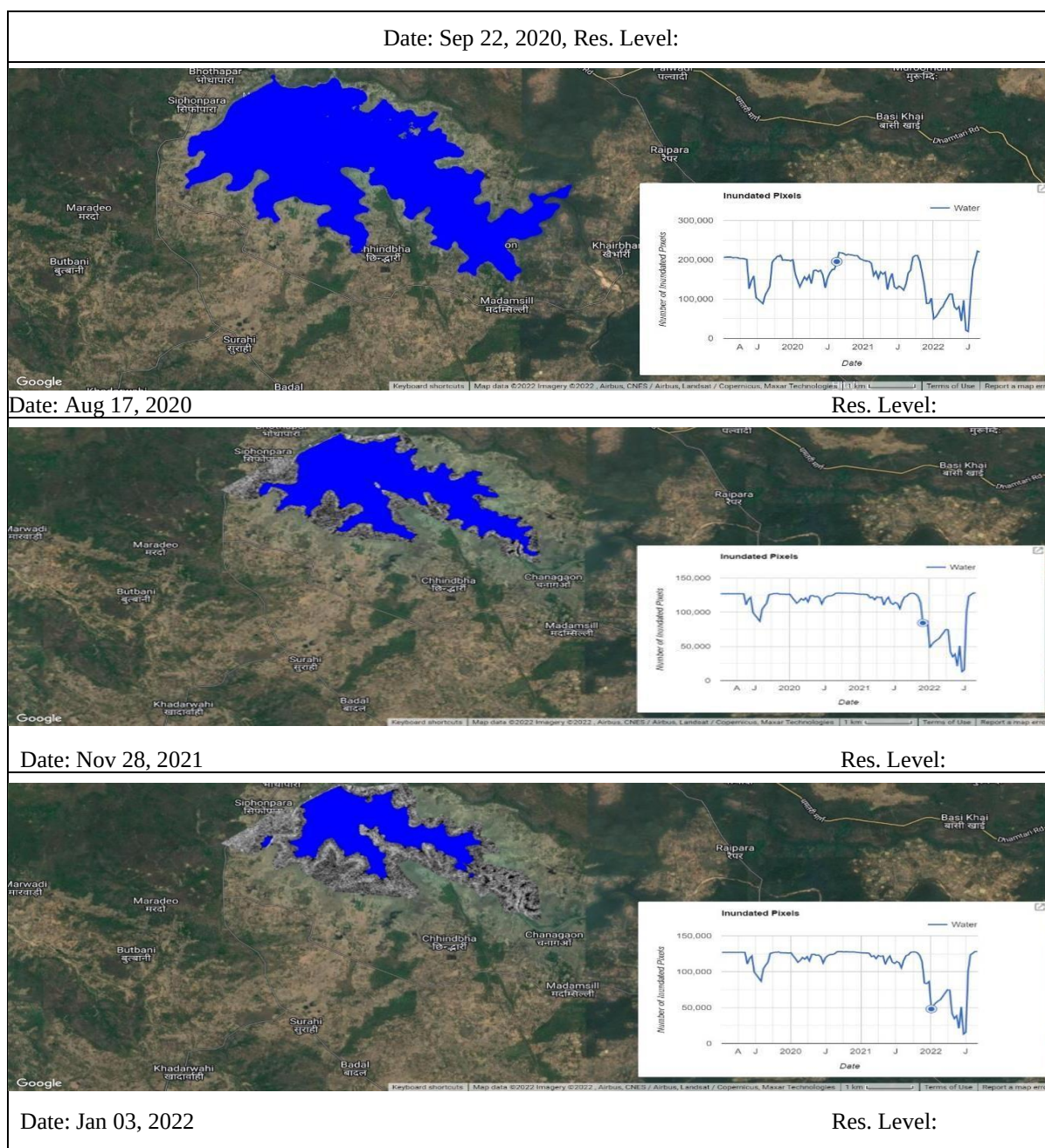


Figure 5.28 Revised water spread using Otsu technique in GEE for Muramsilli Reservoir.

Table 5.15 Original, revised, and loss of capacities for Muramsilli reservoir.

Date of Pass	Res. Elevation (meter)	Original Capacity (MCM)		Revised Capacity (MCM)		Loss in Capacity (MCM)	Loss in Capacity (%)
		Volume	Cum. Capacity	Volume	Cum. Capacity		
Or. River bed	359.50		0.000		0.000		

Rev. River bed*	359.95	1.08	1.08	0.00	0.00	1.08	100.00
DSL*	360.20	0.27	1.348	0.080	0.080	1.26	94.07
08.06.22	361.17	2.05	3.130	1.206	1.286	1.84	58.91
03.01.22	365.74	15.79	18.920	14.161	15.447	3.47	18.35
28.11.21	368.58	20.02	38.940	17.996	33.444	5.49	14.11
11.08.19	369.77	11.44	50.380	11.166	44.610	5.77	11.45
23.08.19	370.50	8.53	58.910	8.357	52.967	5.94	10.09
25.06.21	371.01	6.85	65.760	6.246	59.213	6.54	9.96
24.08.21	372.63	24.44	90.200	22.077	81.290	8.91	9.88
17.08.20	374.43	33.13	123.330	30.173	111.463	11.86	9.62
11.10.21	375.80	29.91	153.240	26.766	138.230	15.01	9.80
22.09.20	376.29	12.12	165.36	10.091	148.320	17.04	10.30
FSL*	376.31	0.530	165.89	0.428	148.748	17.14	10.33

DSL: Dead storage level, FSL: Full supply level, Or: Original, Res: Reservoir, MCM: Million cubic meter

* Revised water spread was extrapolated on this level

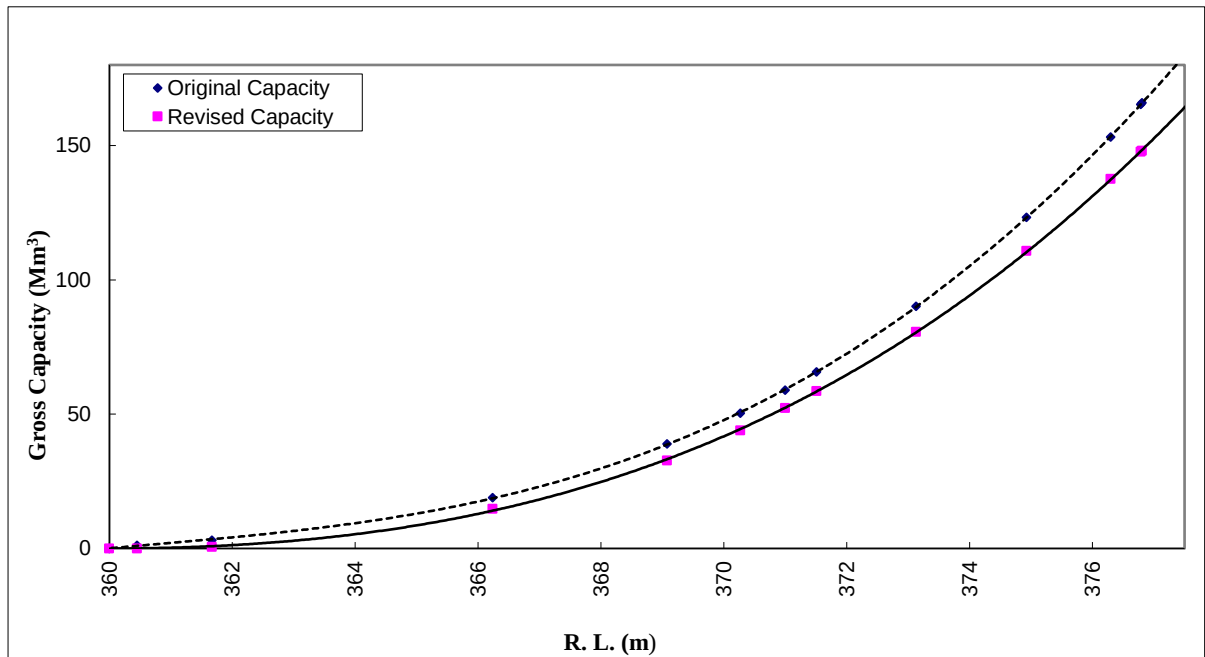


Figure 5. 29 Original and revised capacities at different levels of Muramsilli reservoir.

5.3.3 Revised capacity of Sondhur reservoir

To assess the revised capacities of the Sondhur reservoir ten different dates were selected to cover the whole range of live storage from 455.19 m to 471.07 m. The threshold value to distinguish water pixels from the rest of the image was found as -14.93 and used to determine revised water spread areas on ten different dates to cover the whole live storage zone (Figure 5.31). The revised capacities based on revised water spreads are depicted in

Figure 5.32 and **Table 5.16**. From the analysis, it can be concluded that 13.12% of gross storage (Original storage: 198.10 MCM & Revised storage: 172.11 MCM) has been lost with a silt index of 10.24 ha-m/sq km/year.

Table 5.16 Original, revised, and loss of capacities for Sondhur reservoir.

Date of Pass	Reservoir Elevation (meter)	Original Capacity (MCM)		Revised Capacity (MCM)		Loss in Capacity (MCM)	Loss in Capacity (%)
		Volume	Cumulative Capacity	Volume	Cumulative Capacity		
Or. River bed	447.07		0.00		0.00		
Revised River bed*	450.15	2.09	2.09	0.00	0.00	2.09	100.00
DSL*	455.10	4.11	6.20	2.01	2.01	4.19	67.53
12.06.19	460.25	19.80	26.00	17.24	19.25	6.74	25.93
14.05.19	460.59	2.91	28.90	2.34	21.59	7.31	25.29
13.07.19	463.45	30.37	59.27	24.21	45.80	13.46	22.72
20.04.19	463.70	3.23	62.50	2.57	48.37	14.13	22.61
04.11.21	464.56	11.88	74.38	10.08	58.45	15.93	21.42
08.03.19	466.18	25.16	99.54	21.20	79.64	19.89	19.98
11.08.19	467.01	14.26	113.79	11.98	91.62	22.17	19.48
02.04.20	468.43	26.69	140.48	22.17	113.80	26.69	19.00
25.07.20	470.07	34.45	174.94	26.54	140.33	34.60	19.78
11.09.19	470.39	7.70	182.64	5.24	145.57	37.07	20.29
FSL*	471.07	57.62	198.10	26.54	172.11	25.99	13.12

DSL: Dead storage level, FSL: Full supply level, Or: Original, Res: Reservoir, MCM: Million cubic meter

* Revised water spread was extrapolated on this level

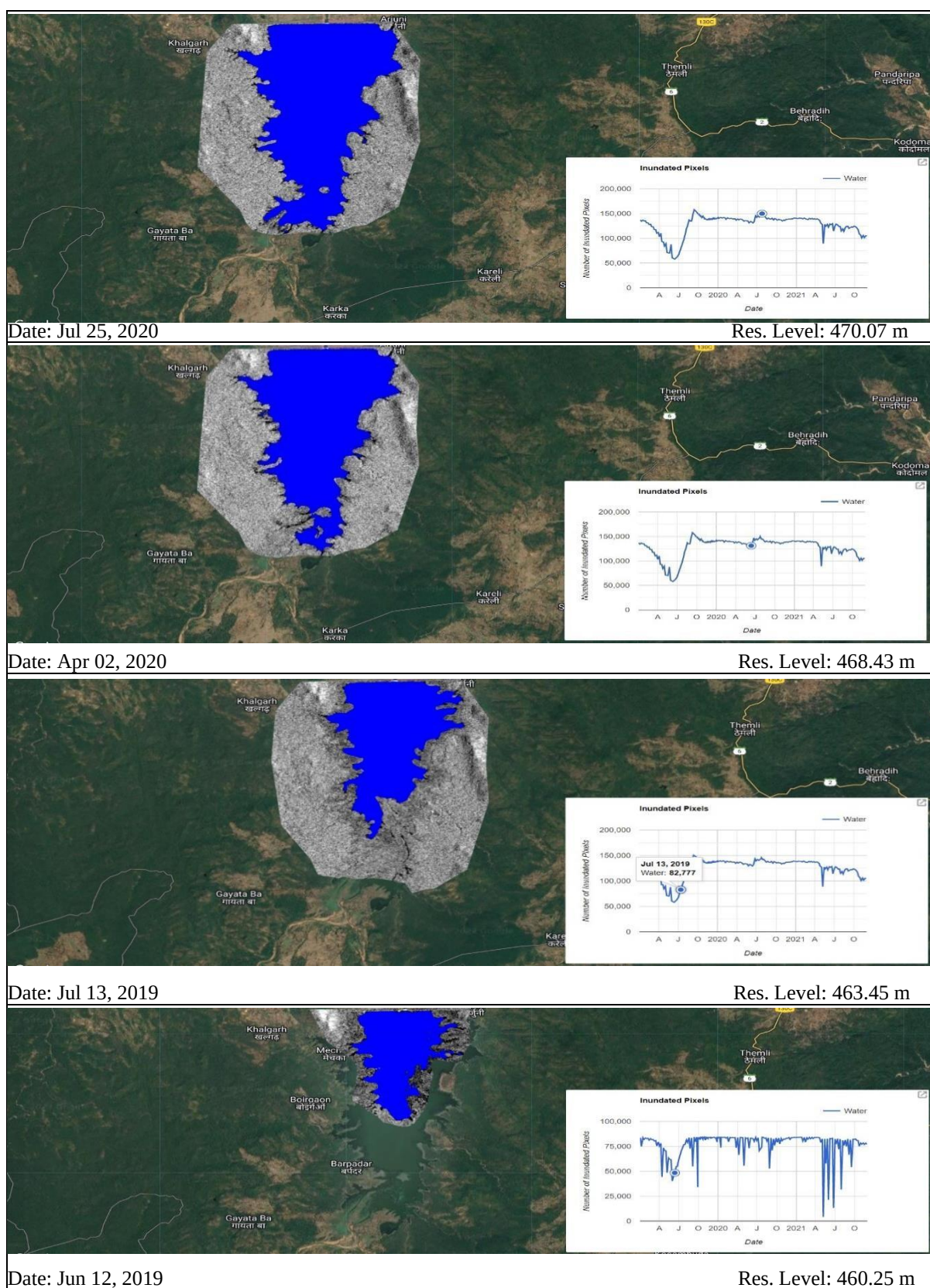


Figure 5.30 Revised water spread using Otsu technique in GEE for Sondhur reservoir.

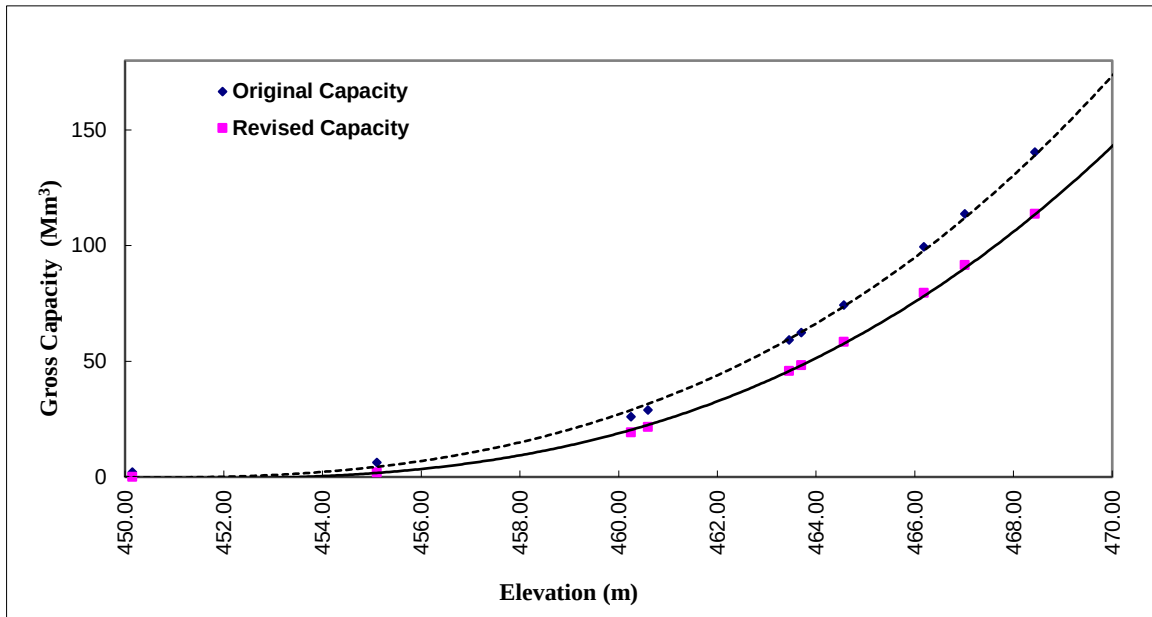


Figure 5.31 Original and revised capacities at different levels of the Sondhur reservoir.

5.3.4 Revised capacity of Dudhawa reservoir

Dudhawa Dam was constructed on the Mahanadi River in the village of Dudhawa and started its operation in 1964. The catchment area of the Dudhawa reservoir is 625.27 sq. km. The gross and live storage capacities of the Dudhawa reservoir are 4.79 MCM (DSL: 409.96 m) and

288.61 MCM (FSL: 425.12 m) respectively. In the study, nine different SAR scenes were used in the Otsu segmentation in GEE and -14.98 was found as the threshold value to classify water and other features. A few scenes of SAR data and revised water spreads of the Dudhawa reservoir are presented in **Figure 5.33**. The revised water spreads on different levels were plotted with reservoir levels and the revised bed of the Dudhawa reservoir was found as 407.37 m. The revised water areas at different levels were used to compute revised volume, revised cumulative capacities, and loss in capacities for the Dudhawa reservoir **Figure 5.34 & Table 5.17**. From the analysis, it has been found that the 2.31 MCM which is 48.23% of storage at DSL (409.96 m), and 35.70 MCM of storage amount to 12.37% of total gross storage at FSL (425.12 m) have been lost in 57 years (1964 to 2020). The average rate of sedimentation can be considered for the Dudhawa reservoir is about 0.63 MCM/year.

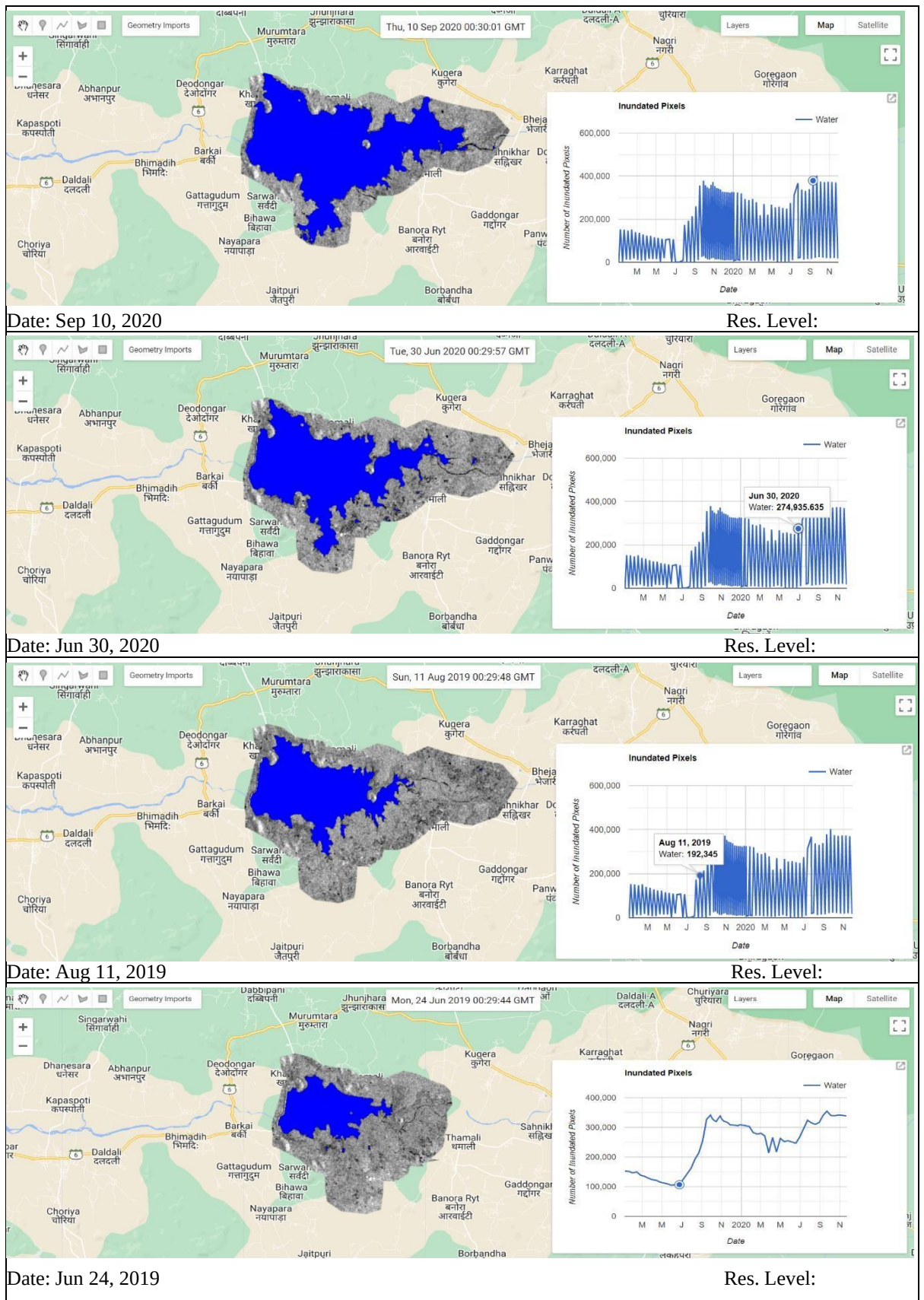


Figure 5.32 Revised water spread using Otsu technique in GEE for Dudhawa

reservoir.

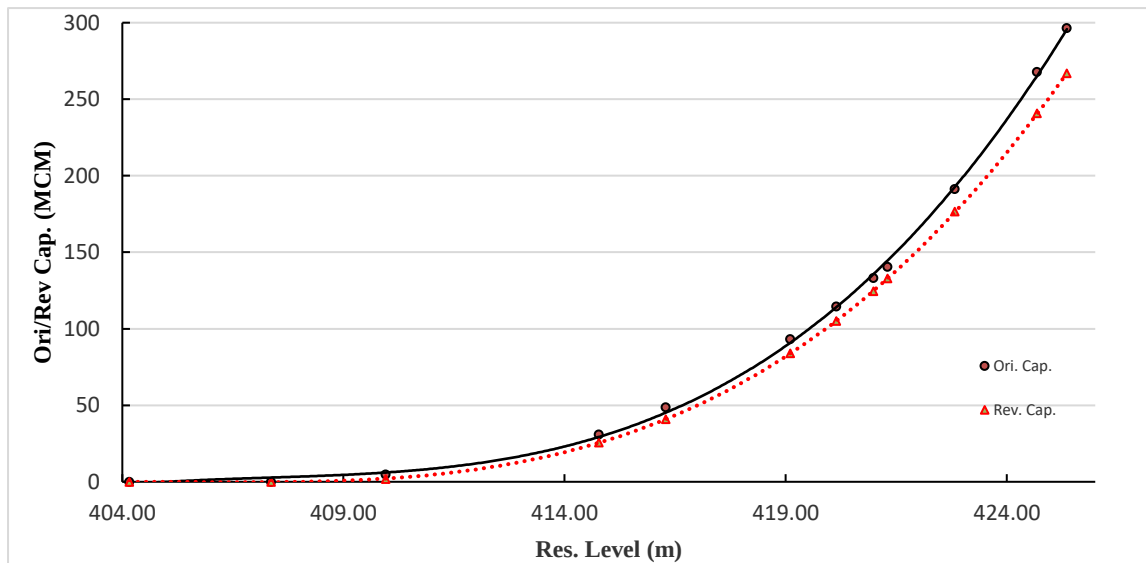


Figure 5.33 Original and revised capacities at different levels of the Dudhawa reservoir.

Table 5.17 Original, revised, and loss of capacities for Dudhawa reservoir.

Res. Level	Reservoir Elevation (meter)	Original Capacity (MCM)		Revised Capacity (MCM)		Loss in Capacity (MCM)	Loss in Cumulative Capacity
		Volume	Cum. Capacity	Volume	Cum. Capacity		
Or. River bed	404.16	0	0		0	0.000	-
Rev. Riverbed	407.37		0.00		0	0.000	0.00
DSL*	409.96	4.79	4.7	2.48	2.48	2.31	48.23
24/06/2019	414.78	26.07	30.86	26.47	28.95	1.91	6.18
08/03/2019	416.29	17.85	48.71	15.22	44.17	4.54	9.32
11/08/2019	419.11	44.57	93.28	41.71	85.88	7.40	7.93
23/08/2019	420.15	21.30	114.58	20.08	105.96	8.62	7.53
06/06/2020	420.99	18.53	133.11	18.64	124.60	8.51	6.40
30/06/2020	421.31	7.35	140.46	8.08	132.68	7.78	5.54
12/07/2020	422.83	50.82	191.28	43.77	176.45	14.83	7.75
10/09/2020	424.69	76.60	267.88	62.34	238.79	29.09	10.86
22/09/2020	425.36	28.66	296.54	24.51	263.30	33.24	11.21

FSL*	425.12	-7.93	288.61	-10.39	252.91	35.70	12.37

DSL: Dead storage level, FSL: Full supply level, or: Original, Res: Reservoir, Rev: Revised Cum: Cumulative

* Extrapolate

5.4 LULC Change Detection and Forecasting using GEE and Hybrid Markov CA Model(TerrSet)

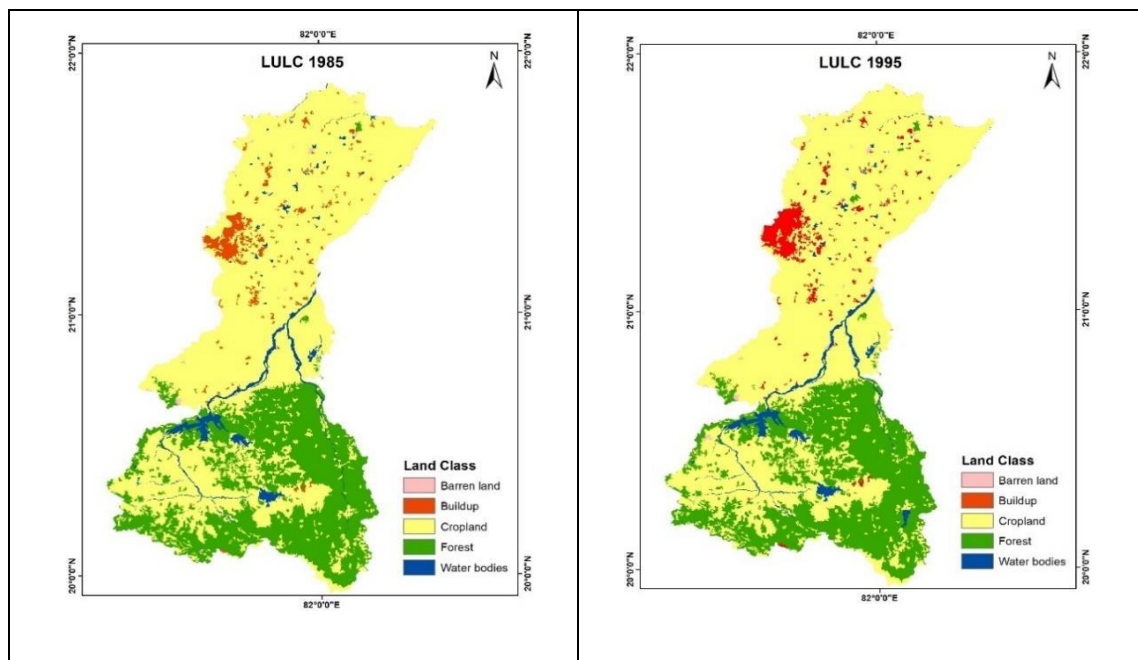
A tree-based classifier called RF is flexible enough to handle both random and systematic categorization. The study area was divided into five different land cover classes Forest, Cropland, Built-up area, Barren land, and Waterbodies using the RF machine learning classifier in Google Earth Engine (GEE). **Figure 5.35** displays the classified output maps for each LANDSAT image. For the classified LULC maps, an accuracy evaluation was done. Overall classifier accuracy (OA) shows that nearly all reference sites were accurately identified. The Kappa coefficient (KC), which is a recommended method in the literature for measuring and comparing picture categorization accuracy, is used. Calculated Overall classifier accuracy (OA) and the Kappa coefficient (KC) values of each land cover class are shown in **Table 5.18**.

Table 5.18 Simulated and Predicted Land use classes and their area's accuracy and kappa.

Year land Class	Area (km ²)				Predicted Area (km ²)	
→ ↓	1985	1995	2005	2021	2025	2050
A1	A2	A3	A4	A5	A6	
Forest	3711.11	3649.32	3588.88	3496.9	3474.47	3339.94
Crop	8827.03	8799.48	8851.36	8868.04	8873.37	8897.88
Built-up	355.65	437.5	436.12	498.16	512.68	605.43
Barren	27.84	33.05	36	42.45	43.68	52.34
Water	377.13	379.41	386.4	393.21	394.56	403.17
Overall classifier accuracy(OA)	0.934	0.947	0.907	–	–	–
Kappa coefficient (KC)	0.925	0.778	0.823	–	–	–

From **Table 5.18**, it can observe that the forest area has been decreasing over the years. In 1985, the forest area was 3711.11 sq. km, and it decreased to 3496.9 sq. km in 2021. This decrease in forest area is a cause of concern as forests play a vital role in maintaining the ecological balance. Deforestation results in soil erosion, loss of biodiversity, and climate change. Therefore, efforts must be made to preserve the forest area and prevent further deforestation. On the other hand, the crop area has remained relatively stable over the years,

with a slight increase from 8827.03 sq. km in 1985 to 8868.04 sq. km in 2021. This stability in the crop area is a positive sign as it ensures food security for the growing population. However, it is essential to ensure that this stability does not come at the cost of environmental degradation. Farmers should adopt sustainable farming practices that do not harm the environment. The built-up area has been increasing steadily over the years. In 1985, it was only 355.65 sq km, and it has now increased to 498.16 sq. km in 2021. The increase in the built-up area is an indication of urbanization and industrialization. While urbanization is necessary for economic growth, it also leads to various environmental problems like air and water pollution, solid waste management, and loss of biodiversity. Therefore, urban planning must be done in a way that minimizes its environmental impact.



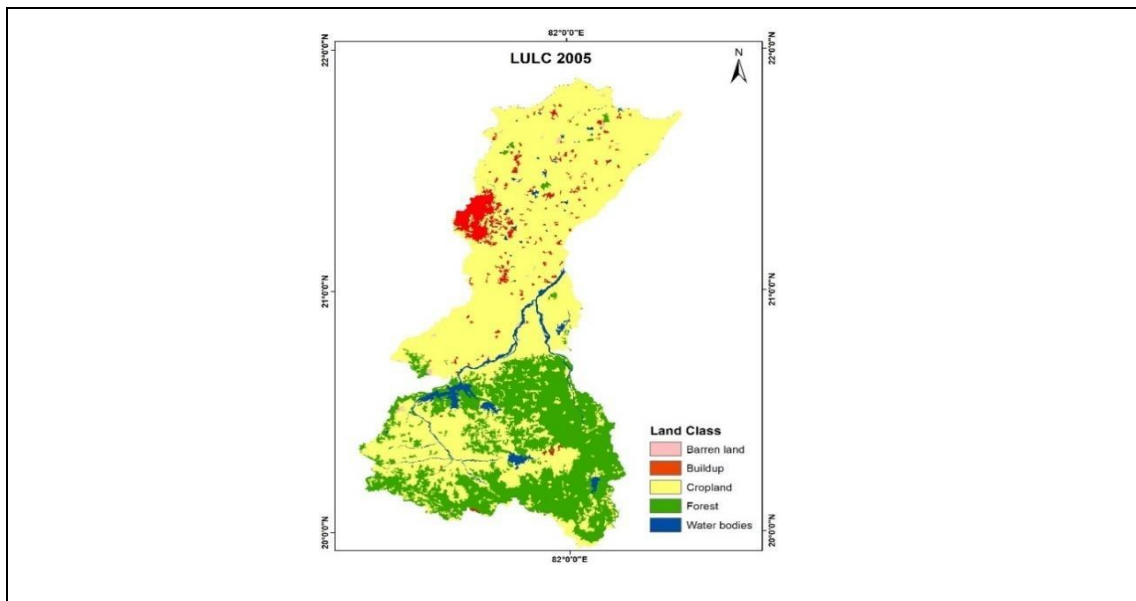


Figure 5.34 LULC maps of years 1985, 1995, and 2005 (GEE).

5.4.1 Validation of the model

In this first of all classified maps of 1985, 1995, and 2005 are obtained by using RF classifier, and the 2021 classified map was obtained from ESRI land cover. To get the transition probability matrix 1985 and 2005 classified maps were used in the Markov chain model. With the help of the 1995 and 2005 classified maps, the 2021 maps were predicted using the CA-Markov chain model. Finally, the 2021 classified maps and the projected map were compared for further validation and testing of the model. After successful validation, the 2025 and 2050 maps were predicted to understand the elements that influence environmental change to take corrective action for land cover changes.

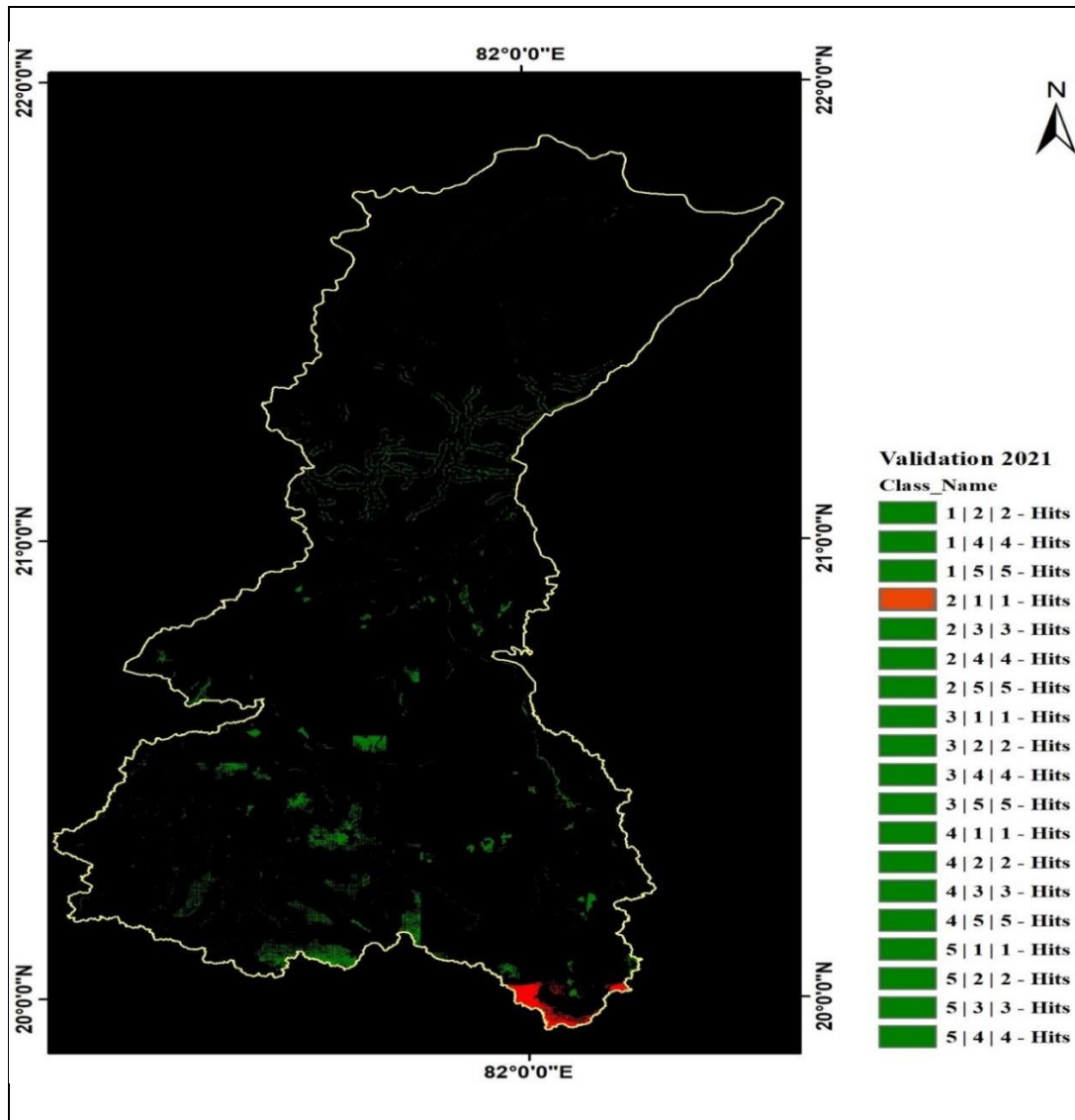


Figure 5.35 Validation of 2021 LU/LC.

The TerrSet Validation panel allows us to determine the quality of the predicted land use map in relation to a map of reality. It does this by running a 3-way crosstabulation between the later landcover map, the prediction map, and a map of reality. The output will illustrate the accuracy of the model results in **Figure 5.36**, where: A | B | B = Hits (green) – Model predicted change and it changed A | A | B = Misses (red) – The model predicted persistence and it changed

A | B | A = False Alarms (yellow) – Model predicted change and it persisted

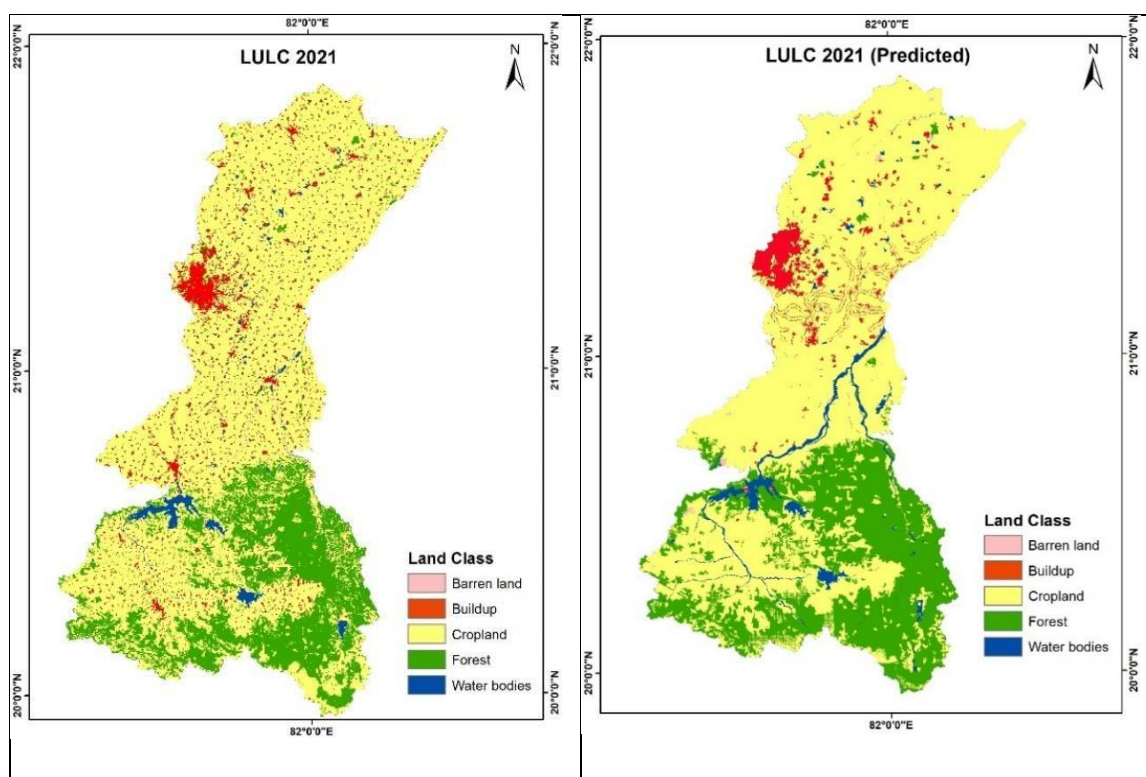


Figure 5.36 ESRI resampled and Predicted LULC of 2021.

5.4.2 Predicted land use/land cover map in 2021, 2025 and 2050

Simulated classified LU/LC maps of 1995 and 2005 were used to predict the 2021 LU/LC map. To further anticipate maps and identify the driving forces linked with the environment, validation is a crucial element. Statistics were used to compare the quality of the predicted 2021 map (**shown in Figure. 5.36**) to the classified 2021 (ESRI resampled and reclassified LU/LC using ArcGIS) map using TerrSet's validation module. The Kappa index was found more than 90%. It indicates classified 2021 map is almost similar to the predicted 2021 map therefore, future maps can be projected. **Figure. 5.37** shows the predicted and classified LU/LC of the year 2021. Finally, the 1985 and 2005 classified maps were used to predict the 2025 and 2050 maps as shown in **Figure 5.3** From **Table 5.18** it can be inferred that there are some noticeable changes in the predicted land use for 2025 and 2050 compared to the land use in 2005. The largest decrease in the land area occurs in the forest class, with a reduction of 114.41 square kilometres (3.19%) from 2005 to 2025, and an additional 134.53 square kilometres (3.87%) from 2025 to 2050. This suggests that deforestation may be an issue in this region, leading to a loss of forested areas over time.

On the other hand, the crop area shows a slight increase of 22.01 square kilometres

(0.25%) from 2005 to 2025 and a further increase of 24.51 square kilometres (0.27%) from 2025 to 2050. This may be due to an increase in agricultural activities or improved farming techniques, leading to more efficient use of land.

Another significant change is seen in the built-up land class, which shows a continuous increase from 436.12 square kilometers in 2005 to 512.68 square kilometers (17.55%) in 2025, and further to 605.43 square kilometers (18.09%) in 2050. This suggests that urbanization and infrastructure development are taking place rapidly in the region, leading to an expansion of built-up areas.

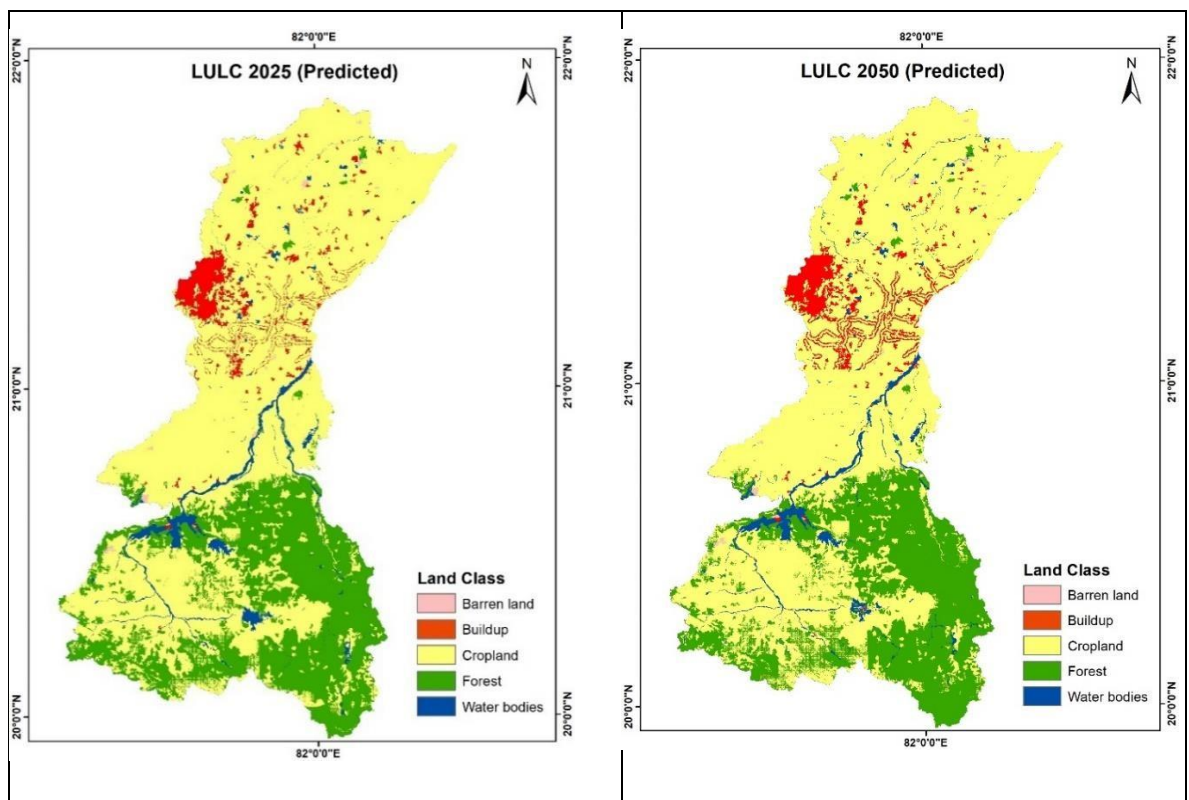


Figure 5.37 Predicted LULC maps of years 2025 & 2050 using TerrSet Land Change Modeler.

The barren land class also shows a slight increase from 36 square kilometers in 2005 to 43.68 square kilometers (21.33%) in 2025, and further to 52.34 square kilometers (19.83%) in 2050. This may be due to natural factors such as erosion or human activities such as mining or quarrying.

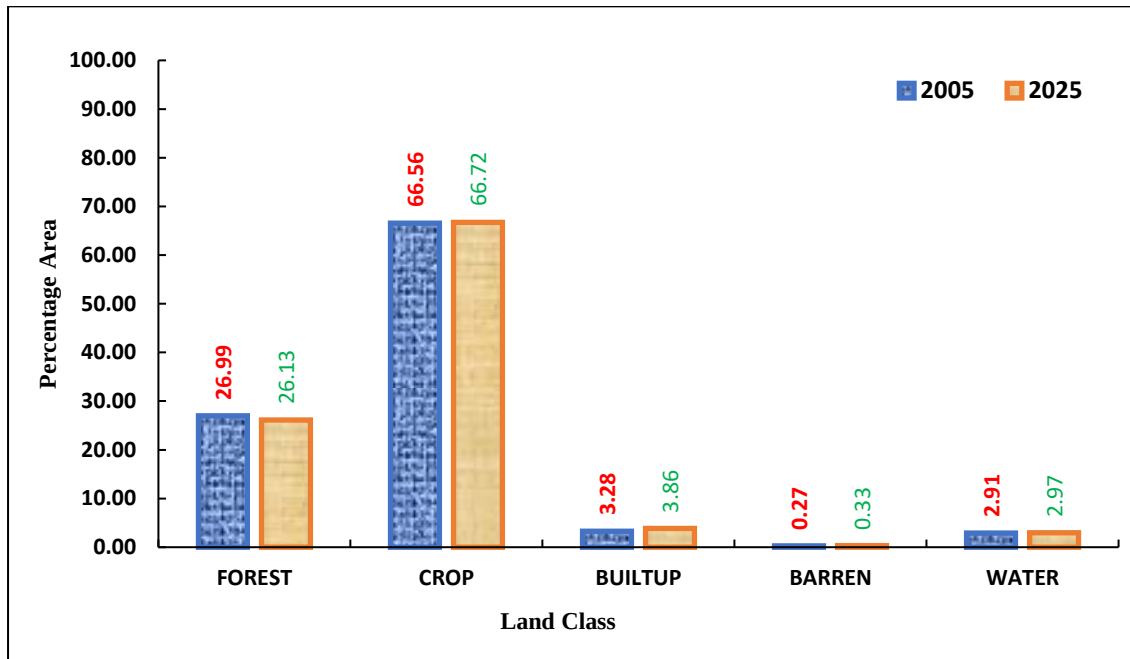


Figure 5.38 Area of LU/LC of years 2005 and 2025 classified map in the study area.

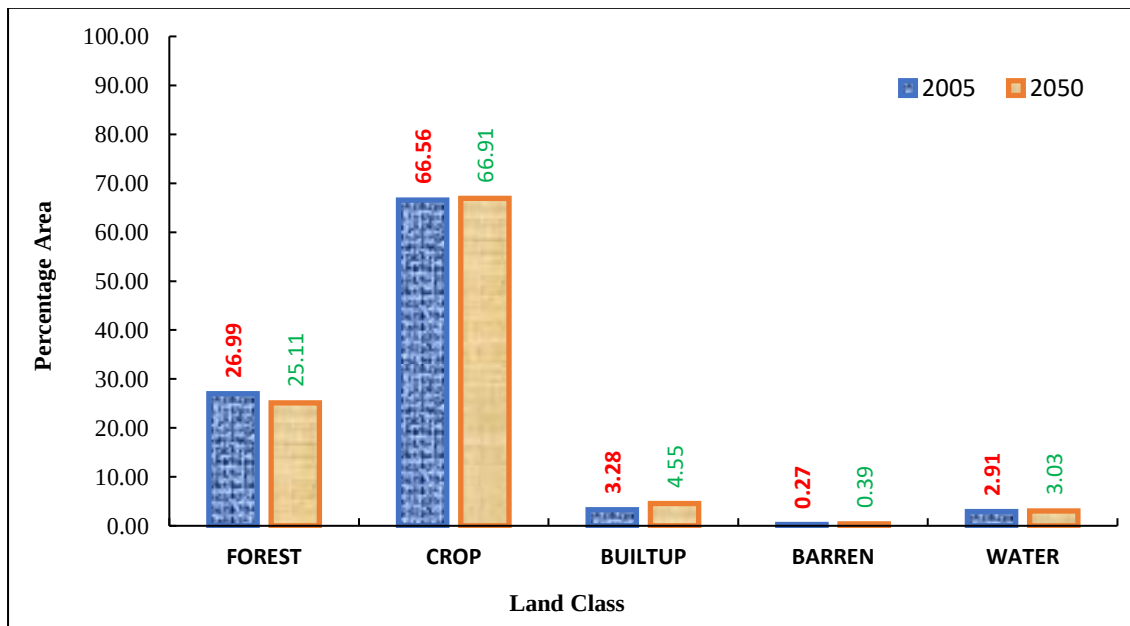


Figure 5.39 Area of LU/LC of years 2005 and 2050 classified map in the study area.

Figure 5.39 & Figure 5.40. shows the changes plot of LU/LC predicted for the years 2025 and 2050 concerning the year 2005. **Figure 5.41 & Figure 5.42** shows the percentage area changes in the LU/LC predicted for the years 2025 and 2050 with respect to the year 2005.

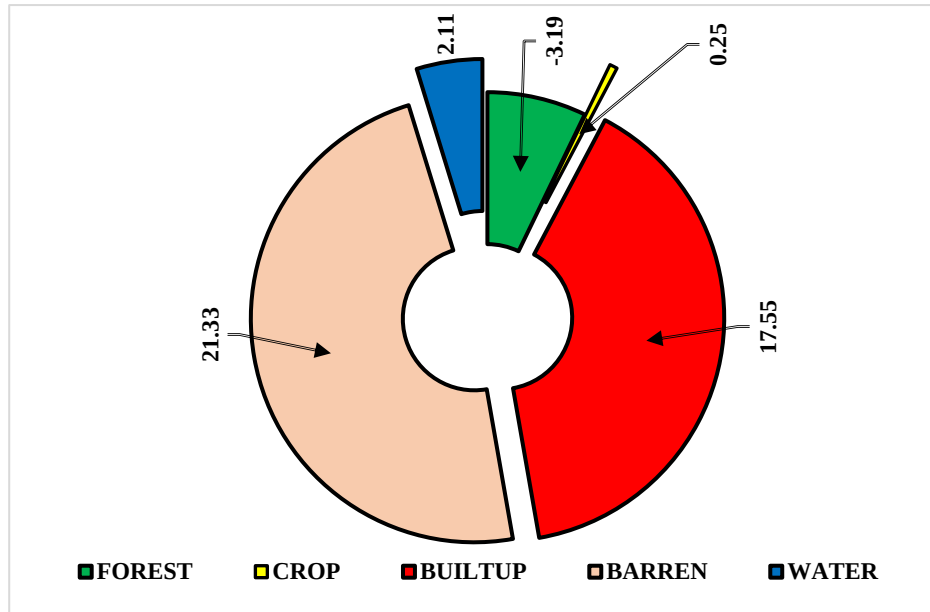


Figure 5.40 Percentage area change in the year 2025 concerning the year 2005.

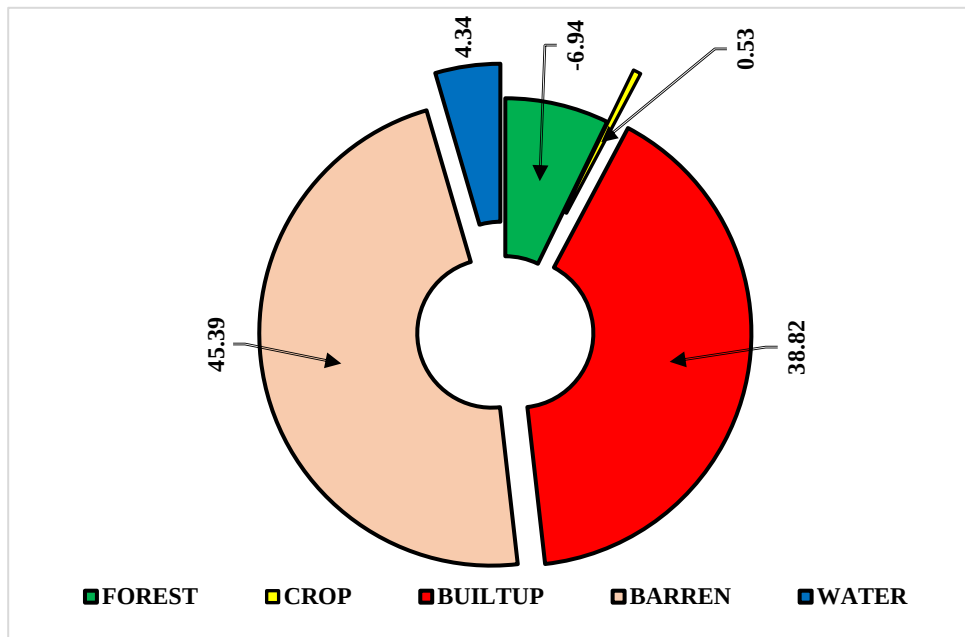


Figure 5.41 Percentage area change in the year 2050 concerning the year 2005.

5.5 Determination of Initial Reservoir Rule Curves

From the net inflow series at a project site, monthly inflows at different dependability levels (50%, 60%, 75% 80% and 90%) are estimated. The estimated percentage dependable flow of Sondhur, Dudhawa, Murumsilli and Ravishankar Sagar

reservoirs have been presented in **Table 5.19(a) to 5.19(d)**. Knowing the dependable inflows, water demands, evaporation depths, and reservoir features (FRL, MDDL, and EAC table), initial trial rule curves have been derived for all reservoirs using a NIH_ReSyP.

Table 5.19 (a) Percentage dependable flow of Sondhur Reservoir.

Month	50%	60%	75%	80%	90%
Jan	4.482	3.040	1.570	1.202	0.587
Feb	4.374	2.754	1.031	0.622	0.084
Mar	3.689	2.317	0.855	0.510	0.062
Apr	3.442	1.952	0.581	0.310	0.024
May	3.720	2.658	1.358	0.986	0.334
Jun	11.860	9.115	6.062	5.204	3.561
Jul	64.839	51.812	34.735	29.333	18.199
Aug	80.601	66.444	48.287	42.574	30.634
Sep	57.111	49.186	37.872	33.976	25.168
Oct	22.915	18.419	12.092	9.974	5.435
Nov	6.546	4.504	2.291	1.715	0.746
Dec	5.190	3.398	1.493	1.022	0.304

Table 5.19 (b) Percentage dependable flow of Dudhawa Reservoir

Month	50%	60%	75%	80%	90%
Jan	4.788	3.882	2.763	2.422	1.726
Feb	3.280	2.546	1.722	1.489	1.038
Mar	2.591	2.068	1.441	1.254	0.881
Apr	2.333	1.757	1.155	0.993	0.690
May	1.979	1.418	0.848	0.701	0.436
Jun	8.897	5.527	2.198	1.437	0.372
Jul	66.945	51.547	32.685	27.071	16.114
Aug	161.468	137.915	103.448	91.356	63.665
Sep	118.057	103.300	81.811	74.272	56.884
Oct	43.976	36.824	27.228	24.098	17.361
Nov	16.120	13.167	9.221	7.946	5.251
Dec	10.062	8.430	6.385	5.748	4.418

Table 5.19 (c) Percentage dependable flow of Murumsilli Reservoir.

Month	50%	60%	75%	80%	90%
Jan	5.088	3.688	2.174	1.767	1.389
Feb	3.868	2.514	1.111	0.769	0.482
Mar	4.515	3.162	1.593	1.164	0.777
Apr	3.420	1.875	0.545	0.296	0.128
May	3.442	1.852	0.520	0.279	0.118
Jun	8.337	5.625	2.521	1.703	0.997
Jul	29.384	22.283	13.369	10.690	8.091
Aug	49.844	38.621	23.289	18.337	13.358
Sep	26.871	19.977	11.267	8.662	6.167
Oct	7.832	5.531	3.114	2.483	1.909
Nov	2.687	2.036	1.360	1.178	1.006
Dec	2.936	2.189	1.431	1.230	1.042

Table 5.19 (d) Percentage dependable flow of Ravishankar Sagar Reservoir.

Month	50%	60%	75%	80%	90%
Jan	15.134	9.171	3.030	1.662	0.102
Feb	16.657	10.799	4.541	3.003	0.741
Mar	32.089	23.158	11.462	7.930	1.700
Apr	40.640	29.024	14.008	9.547	1.879
May	41.940	28.666	12.959	8.697	1.944
Jun	31.076	19.713	8.556	5.953	2.060
Jul	133.107	99.208	62.451	52.408	33.724
Aug	472.780	381.837	253.022	209.592	115.754
Sep	425.017	359.152	266.449	235.014	165.240
Oct	280.703	240.953	178.565	126.941	79.660
Nov	53.292	36.536	26.343	22.370	6.901
Dec	27.606	20.408	5.179	4.781	3.123

For a reservoir, different rule curves can be specified for different water availability and water demand conditions. Monthly demands for each reservoir are given in **Table 5.20**. The position of rule curves for various demands depends on the relative availability of water. Starting upwards from the dead storage level, first lies the rule curve for 75% dependable flow condition. This rule curve is calculated for the case when water is scarce and it is possible to meet only the 75% dependable scenario demands. When the

reservoir level falls below this rule level, it is suggested to meet full/partial 75% dependable scenario demands.

For deriving the rule curves, the monthly inflow series at the project site was analyzed and inflow values corresponding to different probability levels of 50%, 60%, 75%, 80%, and 90% were worked out for each month using a statistical approach. Using these dependable inflow series, the water availability is assumed to correspond to a particular probability of the inflow series. For deriving critical rule levels for different water availability conditions, the water demands at corresponding conditions are assumed. A reservoir is assumed to be empty at the end of a water year. Then, computations of end-of-month reservoir levels are made after allowing for water demands and evaporation losses from the reservoir surface. Rule curves for different water availability conditions are computed separately. First, computations are made for the least water availability condition. The rule curve for a water availability condition is calculated for the case when water is scarce in the reservoir and it is just possible to meet various demands at that condition in full throughout the year. Rule levels are calculated assuming the following conditions:

- i) Reservoir level reaches to intended lowest level by the end of the water year (May end).
- ii) Inflow at a particular water availability condition (75%, 65%, or average) is entering the reservoir.
- iii) Water demands corresponding to that water availability condition are satisfied.

Backward computations were made starting from the end of May. Evaporation loss is considered at a normal monthly rate over the surface area of the reservoir corresponding to a particular elevation. The following formula is used:

$$\text{Storage}_{\text{begin}} = \text{Storage}_{\text{end}} - \text{Inflow} + \text{Release} + \text{Evaporation} + \text{Spill} \quad \dots(5.1)$$

Effort was made to find such a level at which all the demands can be satisfied in full even at that water availability condition. This way, the initial trial rule curve levels for various water availability conditions were computed. It needs to be mentioned that the rule curve level in any month rises with the water availability condition. Thus, the rule curve level for the 65% condition will be higher than the 75% condition and so on.

The rule curves obtained for each reservoir in the system are shown in **Figure**

5.43 to Figure 5.46. Here domestic supply is considered as priority demand, environmental flow is the second priority, irrigation is third and hydropower is considered as fourth priority demand.

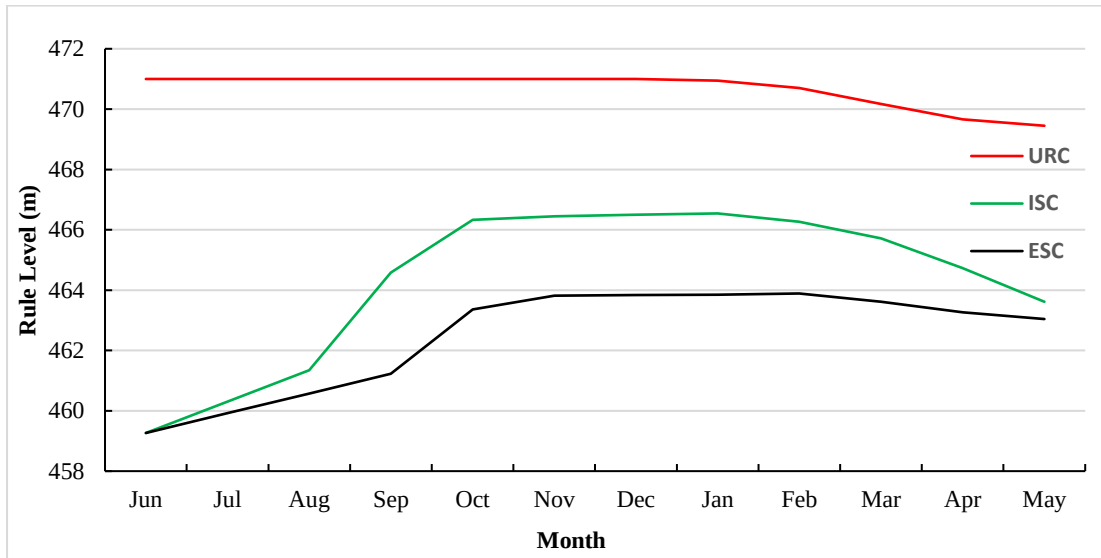


Figure 5.43 Rule curve for Soundur reservoir.

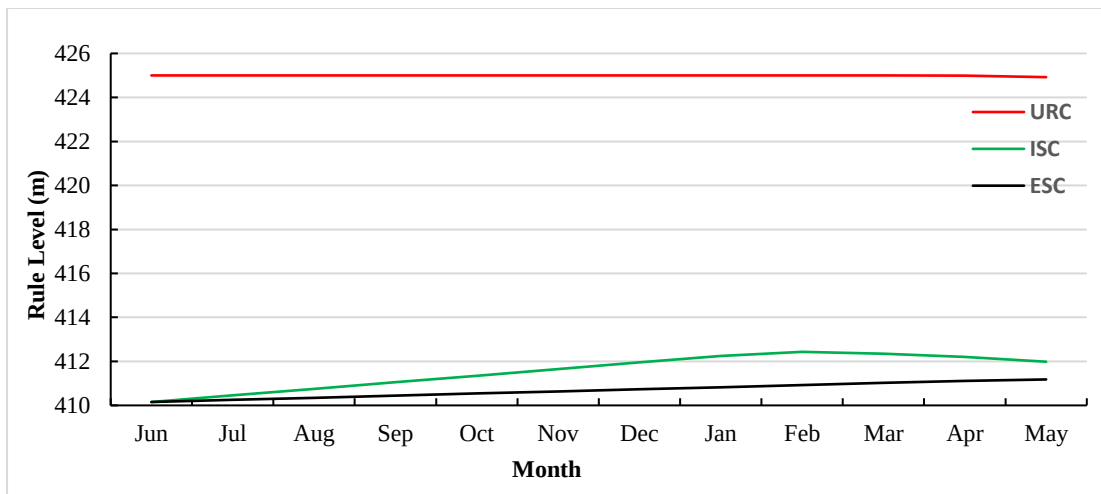


Figure 5.42 Rule curve for Dudhawa reservoir.

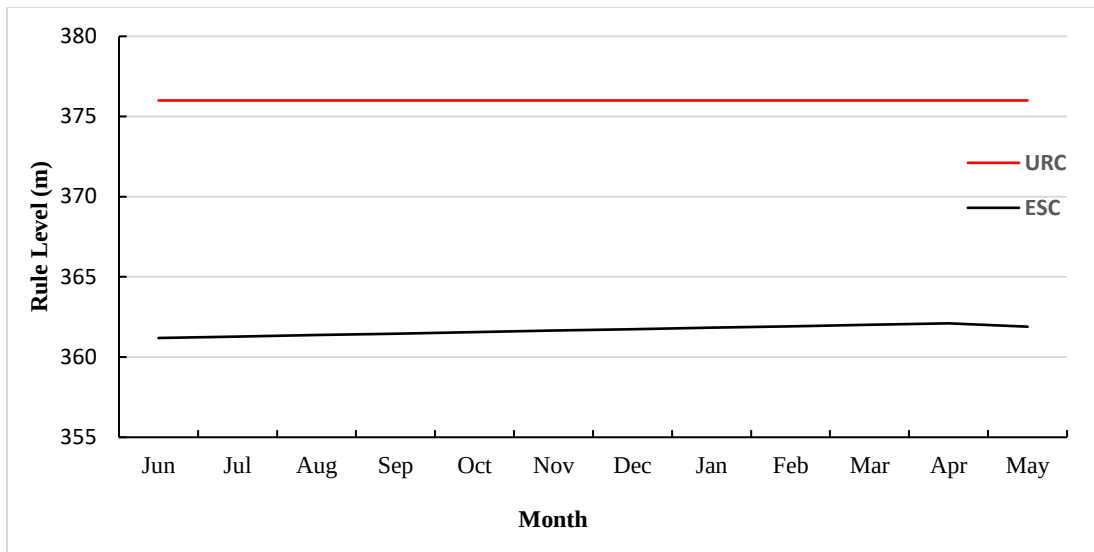


Figure 5.45 Rule curve for Murumsilli reservoir.

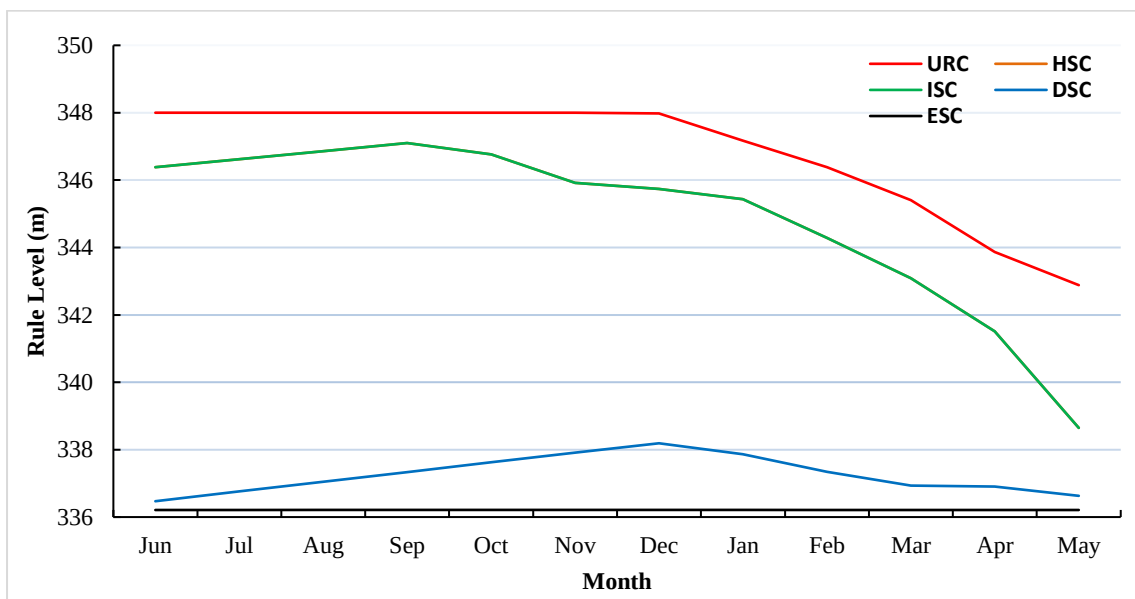


Figure 5.46 Rule curve for Ravishankar Sagar reservoir.

5.5.1 Methodology for integrated operation analysis for MRP system

NIH_ReSyP, a Software developed at NIH was used for the integrated simulation of various projects in the MRP. Each reservoir in the system was simulated as per the water balance approach:

$$S_{t+1} = S_t + \text{Inflow} - \text{Releases} - \text{Spill} - \text{Evaporation} \quad \dots(5.2)$$

The steps involved in the underlying methodology of computations are as follows:

- a) First, all the data for all the structures in the system is read and saved in specified variables.
- b) The simulation is started for a time step and all the projects are simulated as per their connectivity for that time step. The whole system is simulated for subsequent time steps till the end of the simulation period.
- c) In a time step, the projects are simulated from upstream to downstream. For each project, the demands are satisfied in the order of priority as per the water availability and the operating levels. The return flows and spills are transferred as inflow for the downstream projects.
- d) The evaporation is estimated iteratively. For a time step, some final elevation is assumed and the evaporation loss is computed. The project is simulated and the final elevation so obtained is compared with that initially assumed. Several iterations are made till the value converges.
- e) All the variables are recorded and an output file is created which gives a complete glimpse of the simulation analysis at each 10-daily time step for each project.

5.5.2 Operation guidelines suggested by WRD, Chhattisgarh

- 1 Sondhur Reservoir continuously releases water to Dudhawa Reservoir during monsoon after ensuring its own Kharif irrigation demands.
- 2 From the middle of September if required to take up the maintenance of spillway gates and head regulator gates balance storage of the Sondhur reservoir may be transferred to Dudhawa. Simultaneously water from Dudhawa and Murumsilli Reservoirs may be transferred to Ravishankar Sagar Reservoir in case there is adequate storage space even after storing the Rabi and minimum carry-over requirement of the next year.
- 3 The rate of drawdown in all dams will be 10cm/day as per design requirements.
- 4 In the Sondhur Reservoir, during high flow when the reservoir level is at 466 m the incoming water may be passed over the spillway taking care that the rate of outflow does not exceed the rate of inflow in the reservoir.

- 5 In Ravishankar Sagar Reservoir, the operation during the flood period should be done in such a way that the reservoir is not depleted below 348.7 m by August end. It should be filled up to FRL 348.7 m from 1st September onward till the end of the monsoon.
- 6 No release from Murumsilli and Dudhawa is planned from June to September only spills may reach to Ravishankar Sagar Reservoir.

Table 5.20 Monthly demand of all reservoirs (Sondhur, Dudhawa, Murumsilli, and Ravishankar Sagar Reservoir) all value in MCM.

Months	Sondhur reservoir			Dudhawa reservoir		Murumsilli	Ravishankar Sagar reservoir				
	Link Transfer	ENV Demand	Irri Demand	ENV Demand	Irri Demand	ENV Demand	WS Demand	ENV Demand	MMC Irri.	MFC Irri.	HP demand
Jan	0.63	0.018	5.54	0.36	0.11	0.545	19.25	0.05	42.74	21.438	2.28
Feb	1.00	0.014	5.67	0.44	0.31	0.427	17.23	0.05	47.79	16.429	2.15
Mar	0.93	0.012	10.18	0.21	0.28	0.370	8.83	0.07	78.37	18.696	3.30
Apr	1.14	0.015	11.47	0.35	0.26	0.545	18.83	0.09	106.37	25.090	3.53
May	0.70	0.009	7.16	0.30	1.63	0.578	22.99	0.11	72.18	16.741	1.77
Jun	0.15	0.043	0.09	1.06	0.06	0.696	15.12	0.13	16.39	10.271	0.22
Jul	4.59	0.140	2.18	4.95	0.46	2.066	19.26	0.48	28.08	12.320	0.37
Aug	14.39	0.178	6.91	8.91	0.25	3.074	17.68	0.92	119.54	15.393	3.46
Sep	16.01	0.107	8.84	6.47	0.30	1.871	10.00	0.82	256.00	22.134	5.42
Oct	13.63	0.045	7.81	2.70	1.41	0.900	12.95	0.42	224.20	23.083	4.24
Nov	7.47	0.021	0.39	1.00	0.00	0.495	10.95	0.13	58.07	7.573	0.28
Dec	2.34	0.017	0.01	0.72	0.00	0.765	17.31	0.06	2.00	8.738	0.15

5.6 Integrated Operation of the System with SLOP

Integrated operation of the MRP system was first carried out using NIH_ReSyP with Standard Operating Policy (SLOP). The results are presented in the form of tables and graphs. The results in the tables reveal insights into the reliability of the reservoirs, Sondhur, Dudhawa, Murumsilli, and Ravishankar, in meeting different demands using SLOP. **Table 5.21, Table 5.22 and Table 5.23** show the average annual reliability of the projects, average monthly reliability and average ten-daily reliability of the projects. Average volume reliability of various projects is given in **Table 5.24**.

Results show that Ravishankar in general shows lower annual reliability in fulfilling full irrigation and power demands compared to other reservoirs in integrated operation. Specifically, while Sondhur, Dudhawa, and Murumsilli achieve full reliability in municipal, industrial, and irrigation demands, Ravishankar falls short, particularly in meeting full irrigation demands where its reliability is significantly lower. In contrast, Ravishankar performs better in meeting critical water supply demands and critical power demands, showing a higher reliability in these categories.

Over monthly periods, Ravishankar exhibits high reliability in critical water supply and critical municipal and industrial demands, although it has lower reliability for full irrigation and power demands compared to Sondhur and Murumsilli, which generally maintain higher reliability for these demands. Dudhawa shows variability, particularly with a much lower reliability for full irrigation demands. All reservoirs except Ravishankar show full reliability for critical municipal and industrial demands as per monthly analysis.

Ten-daily assessment of the results shows that Ravishankar shows high reliability, particularly in meeting critical water supply and municipal demands. This is consistent with its performance in the annual and monthly assessments. However, its reliability for full irrigation demands is higher than in the annual and monthly assessments but still varies compared to other reservoirs. Sondhur, Dudhawa, and Murumsilli often demonstrate full reliability across many categories, though Dudhawa shows lower performance in meeting full irrigation demands.

Finally, in terms of volume reliability, Ravishankar performs well in meeting

irrigation and municipal demands. Sondhur, on the other hand, shows full reliability for all the demands. Overall, while Ravishankar acquire higher values for critical and volume reliability, it falls short in full demands compared to other reservoirs, particularly for irrigation and power. Sondhur and Dudhawa generally exhibit higher reliability in meeting full demands, though variability exists in specific categories. The trend indicates that reliability is often higher over shorter periods compared to annual assessments, reflecting a better management of demands in the short term.

Table 5.21 Average annual reliability in meeting demands of the projects with SLOP.

Demands	Annual Reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
Full WS demands	-	-	-	62.069
Full MF demands	100	100	100	68.966
Full Irr demands	100	100	100	31.034
Full Lnk demands	100	-	-	-
Full Power demands	-	-	-	13.793
Critical WS demands	-	-	-	86.207
Critical MF demands	100	100	100	100
Critical Irr demands	100	100	100	93.103
Critical Lnk demands	100	-	-	-
Critical Power demands	-	-	-	82.759

Table 5.22 Average Monthly reliability in meeting demands of the projects with SLOP.

Demands	Monthly Reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
Full WS demands	-	-	-	92.241
Full MF demands	100	100	100	93.678
Full Irr demands	100	46.552	100	82.184
Full Link demands	100	-	-	-
Full Power demands	-	-	-	42.816
Critical WS demands	-	-	-	93.103

Critical MF demands	100	100	100	95.977
Critical Irr demands	100	100	100	86.782
Critical Lnk demands	100	-	-	-
Critical Power demands	-	-	-	77.874

Table 5.23 Average ten daily reliability in meeting demands of the projects with SLOP.

Demands	Ten Daily Reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
Full WS demands	-	-	-	95.498
Full MF demands	100	100	100	96.36
Full Irr demands	100	55.556	100	87.739
Full Link demands	100	-	-	-
Full Power demands	-	-	-	49.138
Critical WS demands	-	-	-	95.69
Critical MF demands	100	100	100	96.36
Critical Irr demands	100	100	100	89.368
Critical Lnk demands	100	-	-	-
Critical Power demands	-	-	-	78.736

Table 5.24 Volume reliability in meeting demands of the projects with SLOP.

Demands	Volume reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
WS demands	100	-	-	95.321
MF demands	100	100	100	99.904
Irr demands	100	98.325	100	92.968
Link demands	100	-	-	-
Power demands	-	-	-	58.88

Figure 5.47 represents the storage and spill behavior of the reservoirs during the integrated operation of the system under the standard operation policy. **Figures 5.48-5.51** show the demand-supply plots for each demand of the reservoir for each of the projects.

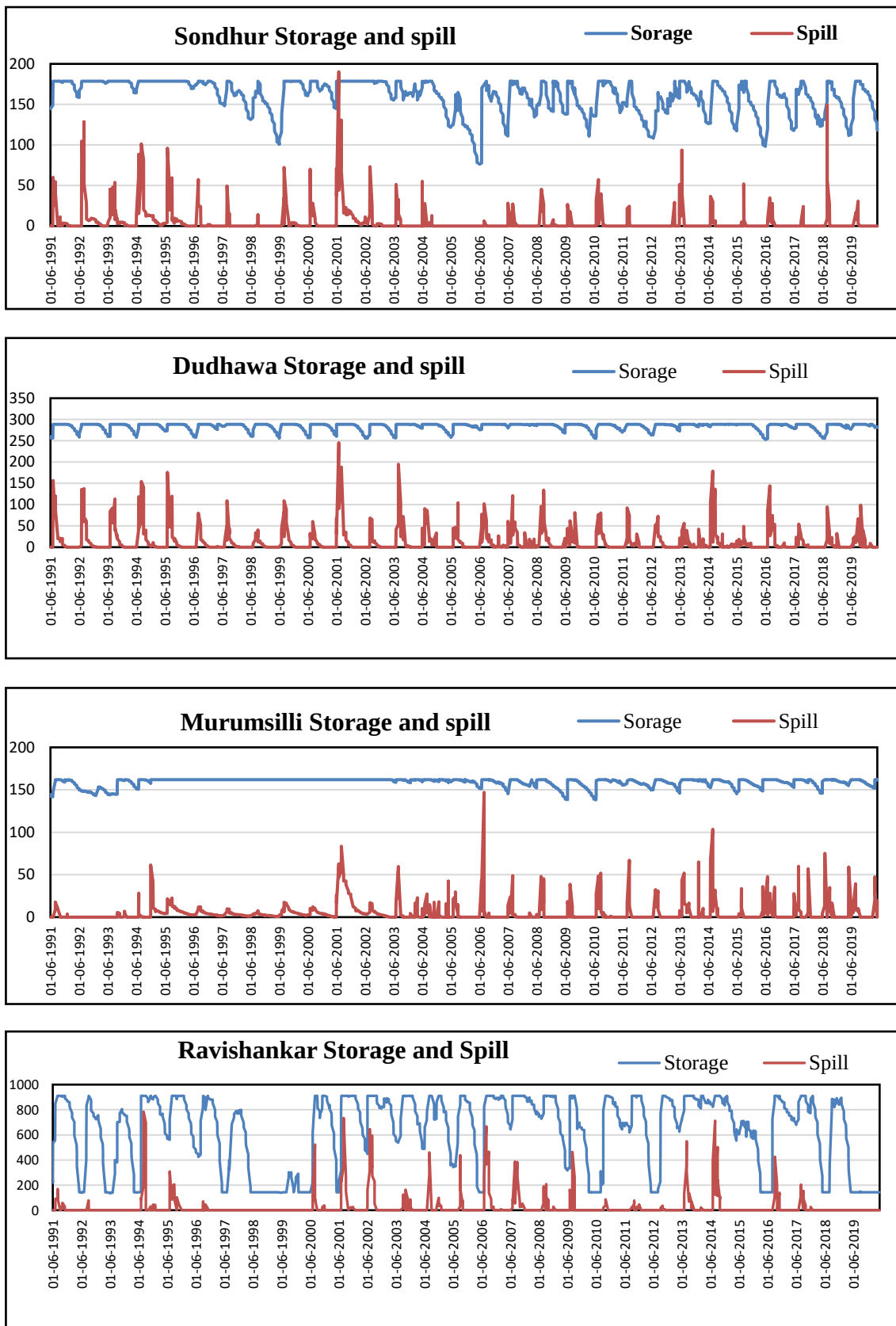


Figure 5.47 Storage and spill behaviors of the reservoirs during integrated operation using SLOP (All values in MCM).

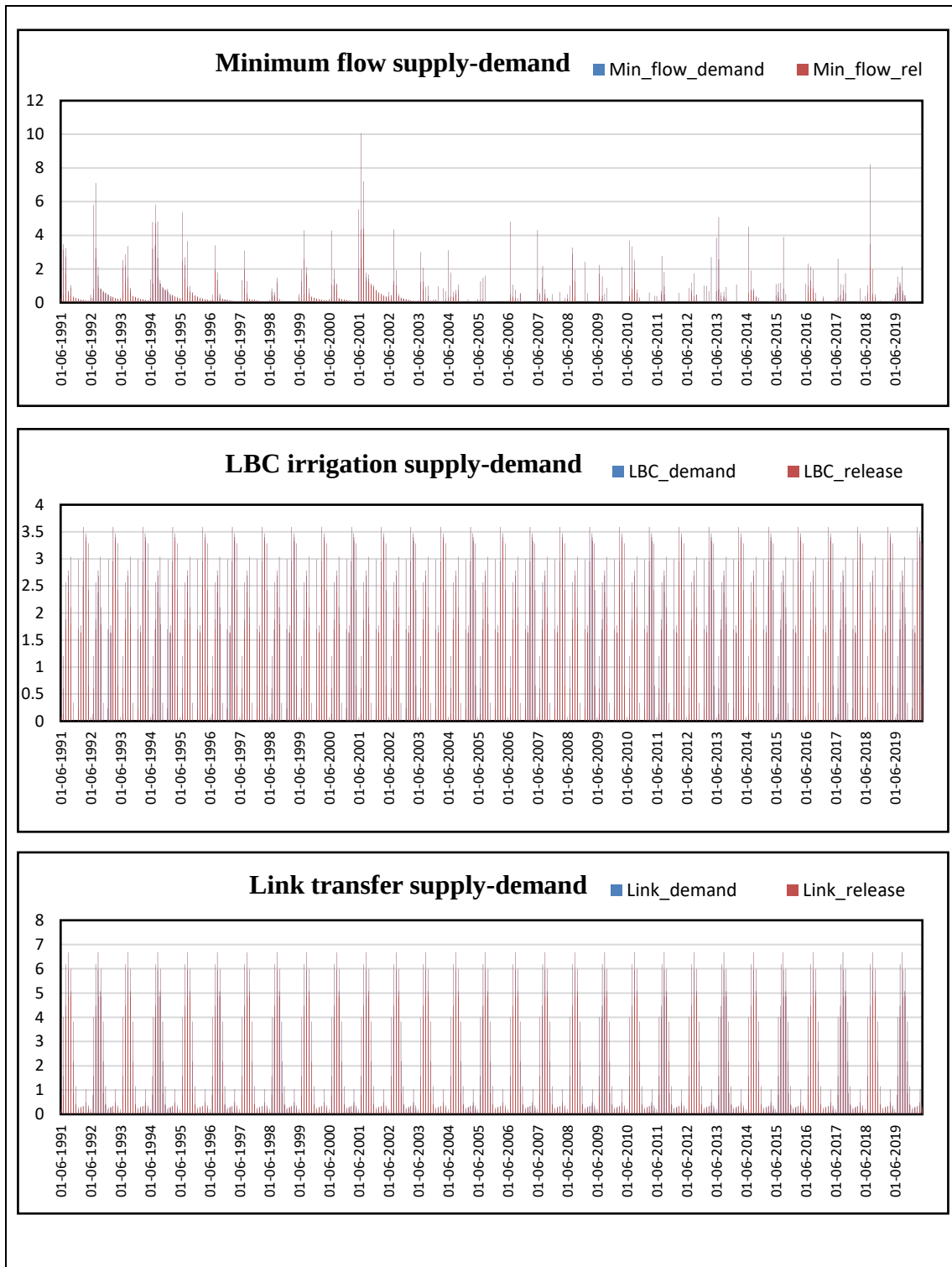


Figure 5.48 Plots for Sondhur reservoir operation results with SLOP (All values in MCM).

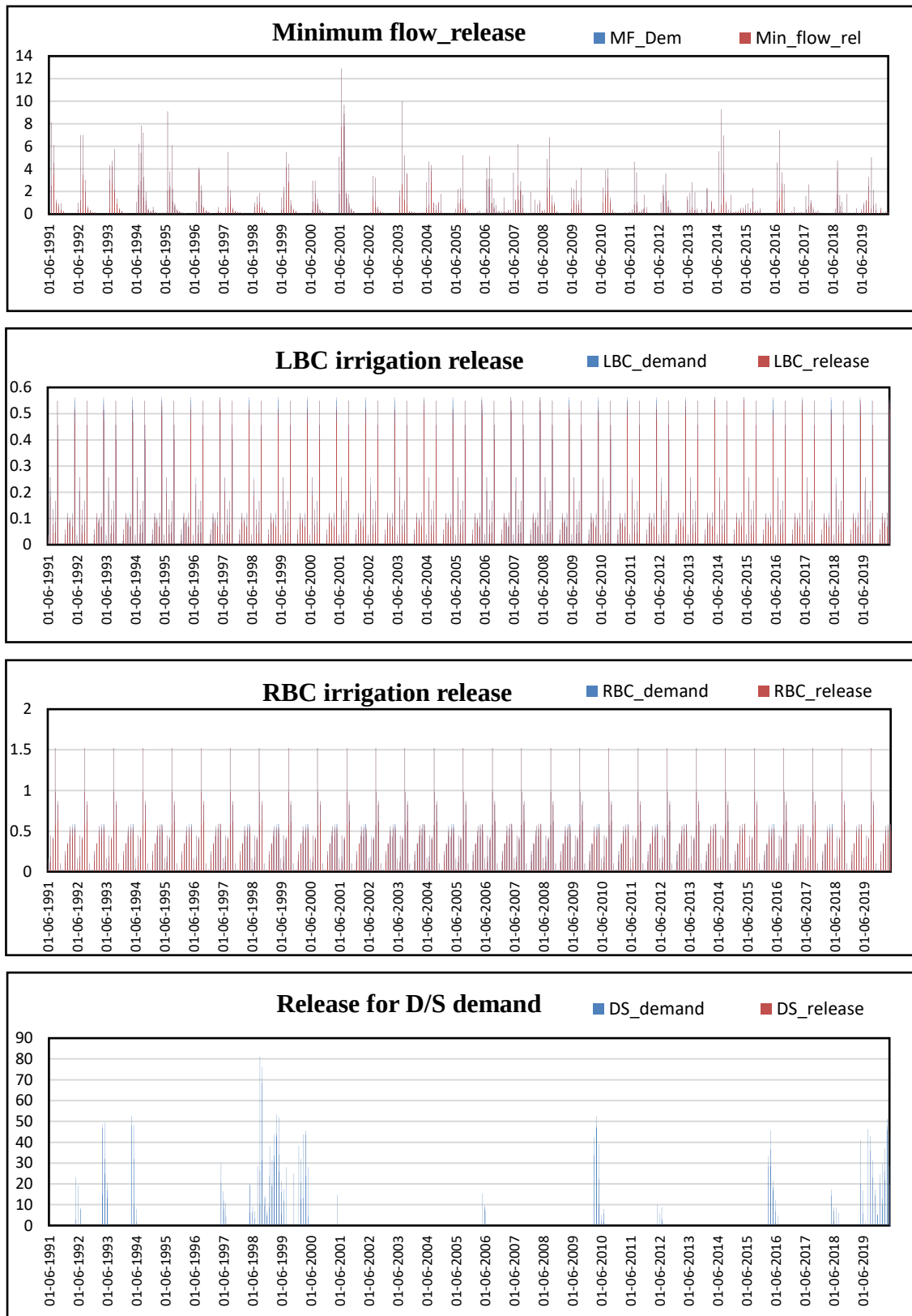


Figure 5.49 Plots for Dudhawa reservoir operation results with SLOP (All values in MCM).

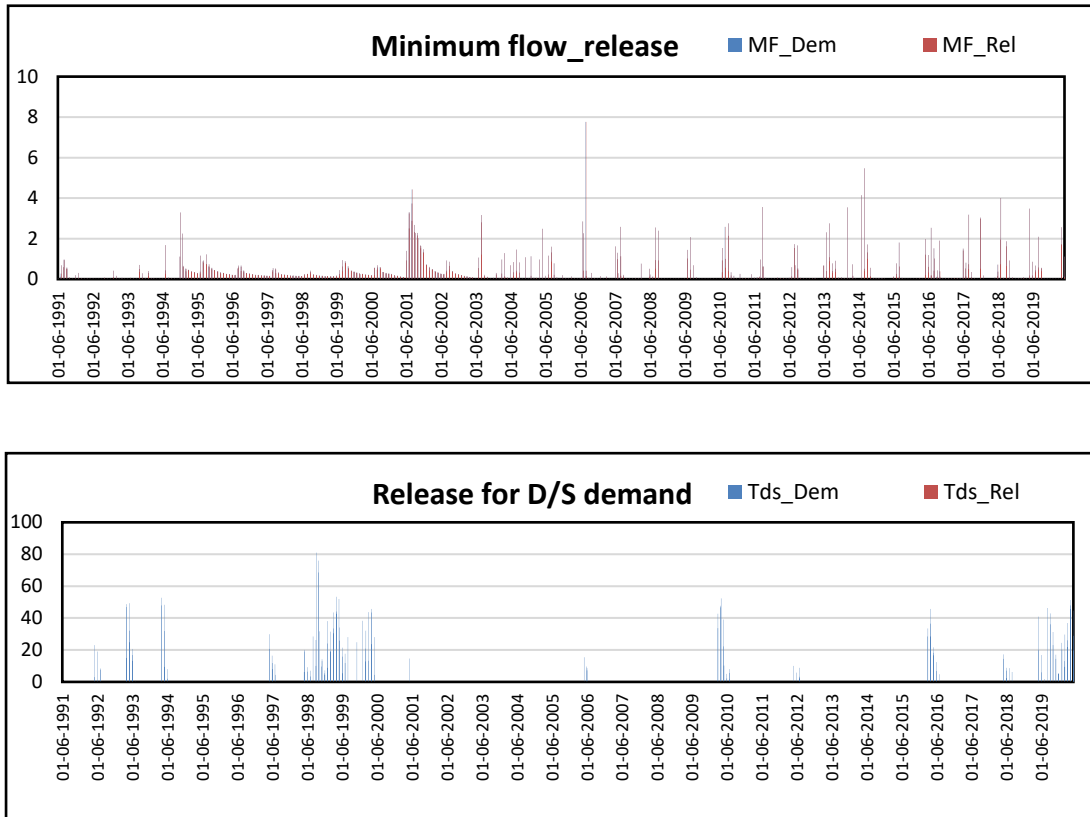


Figure 5.50 Plots for Murumsilli reservoir operation results with SLOP (All values in MCM).

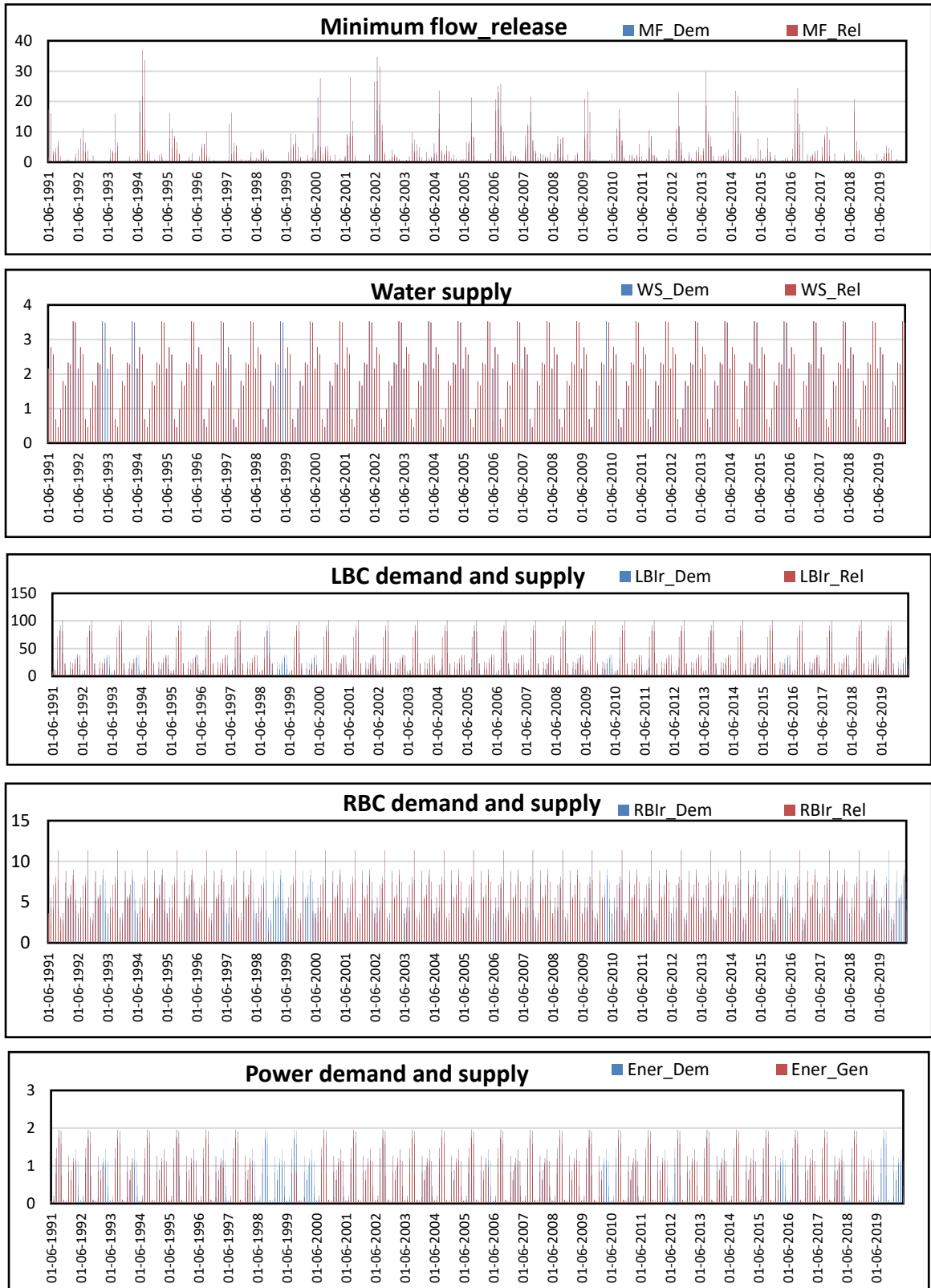


Figure 5.51 Plots for Ravishankar Sagar reservoir operation results with SLOP (All values in MCM).

5.7 Integrated Operation of the System with Initial Rule Curve

After simulating the system for integrated operation of the MRP with SLOP, the ReSyP model was with the derived initial rule curve levels for various reservoirs. These rule curves have been derived for some dependable water availability conditions and the water is spilled in the downstream as soon as the rule curve level is exceeded during the operation of reservoirs. **Tables 5.25, Table 5.26 and Table 5.27** show the average annual reliability of the projects, average monthly reliability and average ten-daily reliability of the projects. Average volume reliability of various projects is given in **Table 5.28**.

Results show that as per annual reliability, all reservoirs except Ravishankar meet full minimum flow requirement 100% of the time annually. Ravishankar has a slightly lower reliability of 89.655%. However, all reservoirs meet critical minimum flow requirement 100% of the time. Ravishankar Reservoir meets full water supply demands. Ravishankar Reservoir is unable in meeting full irrigation and power demands annually, but performs well for critical demands. The other reservoirs (Sondhur, Dudhawa, and Murumsilli) show high reliability across all demands they serve. Monthly reliability analysis shows that Monthly reliability is generally high for most demands. Ravishankar Reservoir shows improvement in reliability for irrigation and power demands on a monthly scale compared to annual results. Ten daily reliability remains consistent with monthly reliability trends. Ravishankar continues to be unsuccessful in meeting full irrigation and power demands, though critical demands are generally met.

Volume reliability is high across most demands. Ravishankar shows a marked improvement in irrigation reliability on a volumetric basis, though it still struggles with power demand reliability. Ravishankar Reservoir is the most variable in terms of reliability. It performs well in meeting water supply and municipal demands, but struggles significantly with irrigation and power demands, especially when considering full demands. Sondhur, Dudhawa, and Murumsilli Reservoirs generally exhibit high reliability across all demands they are tasked with meeting. Reliability tends to improve when moving from annual to ten daily scales, particularly for Ravishankar Reservoir. Volume Reliability Shows a stronger ability to meet demands, particularly for irrigation, where Ravishankar improves significantly. Rule curves aim to optimize the use of water

resources, ensuring that water is available for different purposes at the right time. They help in making decisions about releasing or storing water based on current and anticipated future conditions. The reliability metrics in the tables indicate the reservoirs are able to meet demands while following these rule curves. High reliability values suggest that the rule curves are effective. While still getting low reliability suggests that the rule curves may further be refined.

Table 5.25 Average annual reliability in meeting demands of the projects with Rule Curve.

Demands	Annual Reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
Full WS demands	-	-	-	100
Full MF demands	100	100	100	89.655
Full Irr demands	100	100	100	0
Full Lnk demands	100	-	-	-
Full Power demands	-	-	-	3.448
Critical WS demands	-	-	-	100
Critical MF demands	100	100	100	100
Critical Irri demands	100	100	100	96.552
Critical Link demands	100	-	-	-
Critical Power demands	-	-	-	82.759

Table 5.26 Average Monthly reliability in meeting demands of the projects with Rule Curve.

Demands	Monthly Reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
Full WS demands	-	-	-	100
Full MF demands	100	100	100	98.851
Full Irr demands	100	100	100	64.08
Full Link demands	100	-	-	-
Full Power demands	-	-	-	30.747
Critical WS demands	-	-	-	100
Critical MF demands	100	100	100	100

Critical Irr demands	100	100	100	97.126
Critical Link demands	100	-	-	-
Critical Power demands	-	-	-	69.54

Table 5.27 Average ten daily reliability in meeting demands of the projects with Rule Curve.

Demands	Ten Daily Reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
Full WS demands	-	-	-	100
Full MF demands	100	100	100	99.425
Full Irr demands	100	100	100	69.253
Full Link demands	100	-	-	-
Full Power demands	-	-	-	35.153
Critical WS demands	-	-	-	100
Critical MF demands	100	100	100	100
Critical Irr demands	100	100	100	98.084
Critical Lnk demands	100	-	-	-
Critical Power demands	-	-	-	71.073

Table 5.28 Volume reliability in meeting demands of the projects with Rule Curve.

Demands	Volume reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
WS demands	100	-	-	100
MF demands	100	100	100	99.997
Irr demands	100	100	100	95.379
Link demands	100	-	-	-
Power demands	-	-	-	68.31

Figure 5.52 represents the storage and spill behavior of the reservoirs during the integrated operation of the system under the standard operation policy. **Figures 5.53-5.56** show the demand-supply plots for each demand of the reservoir for each of the projects.

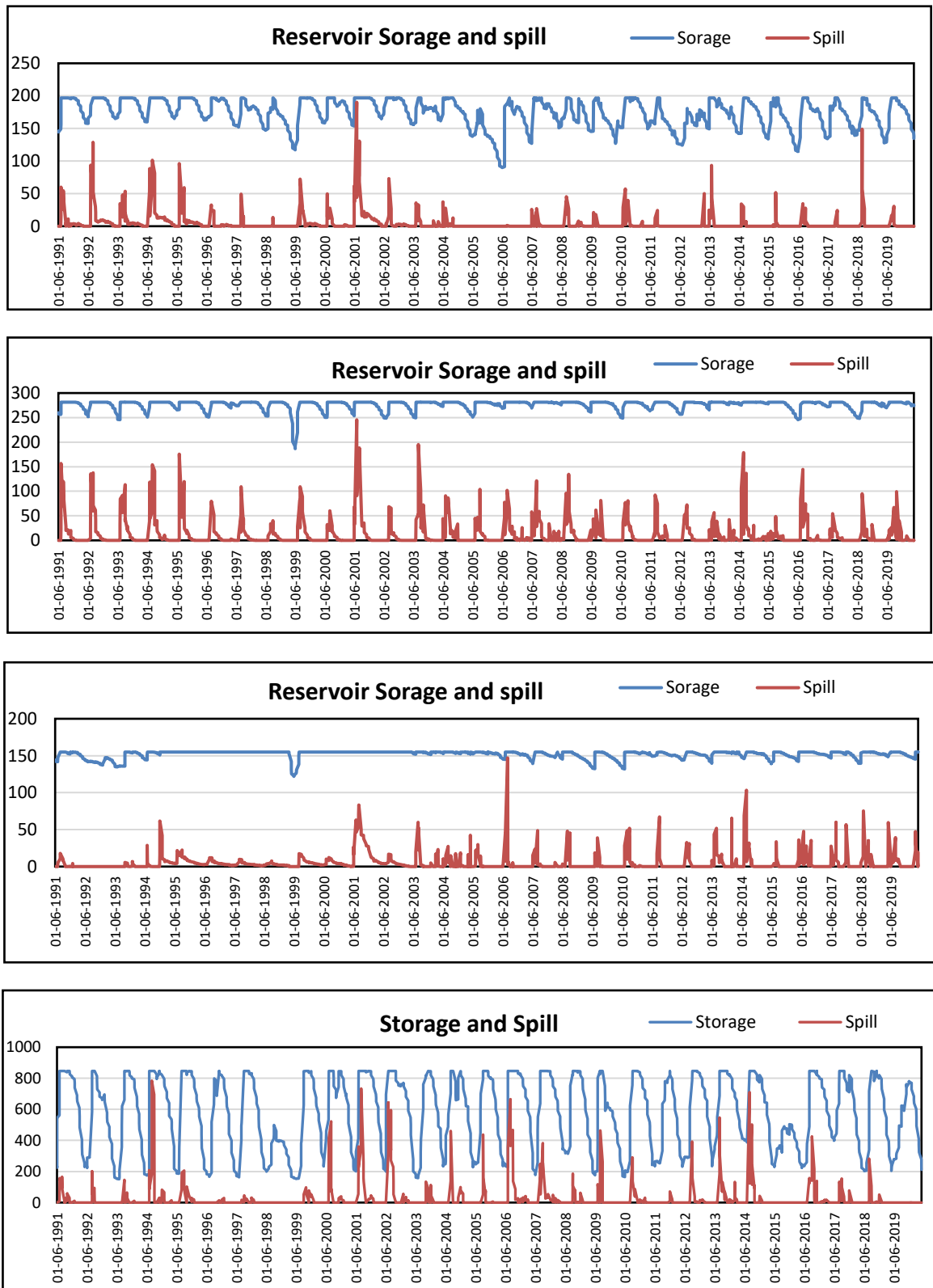


Figure 5.52 Storage and spill behaviors of the reservoirs during integrated operation using Rule Curves (All values in MCM).

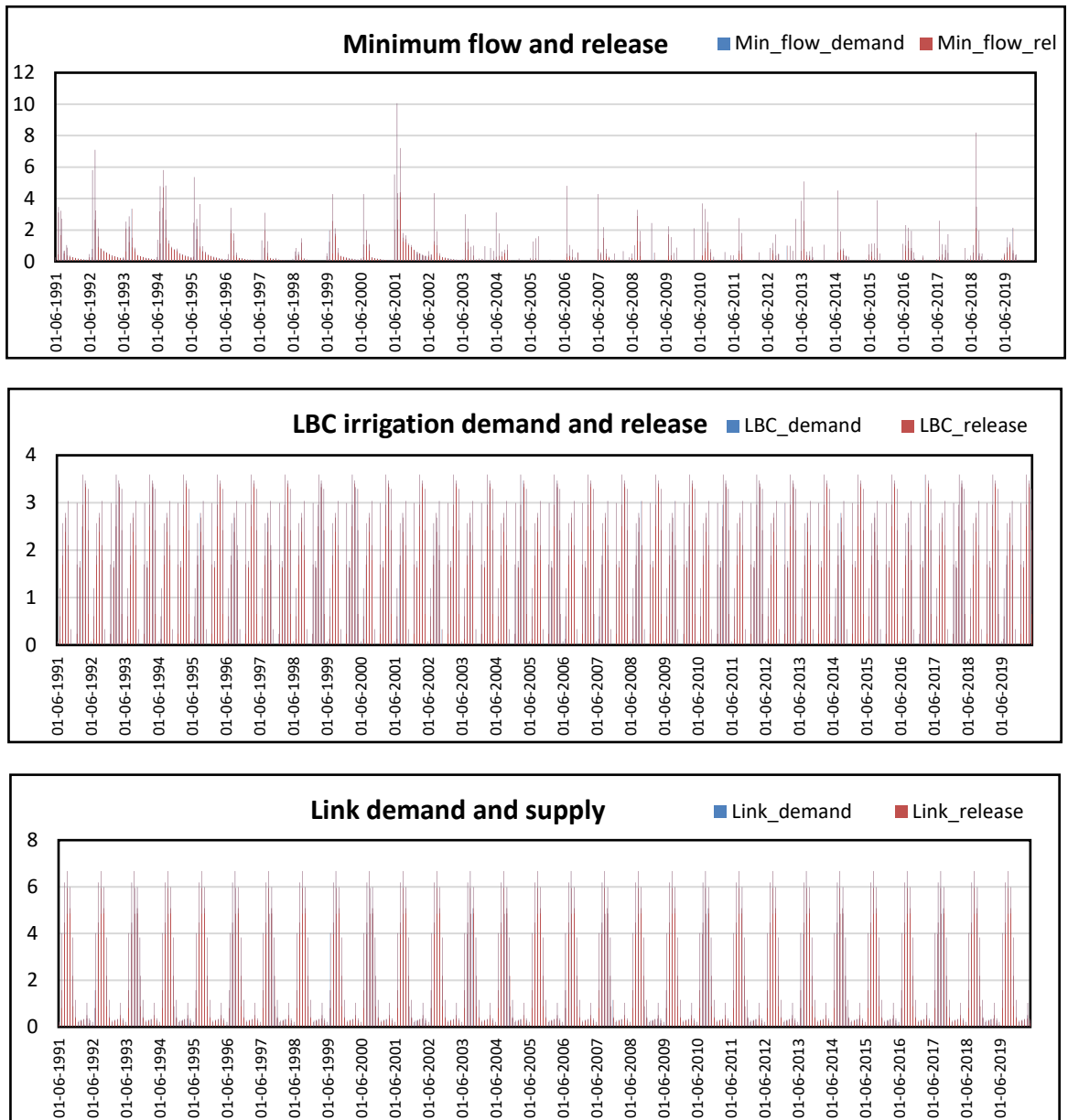


Figure 5.53 Plots for Sondhur reservoir operation results with rule curves(All values in MCM).

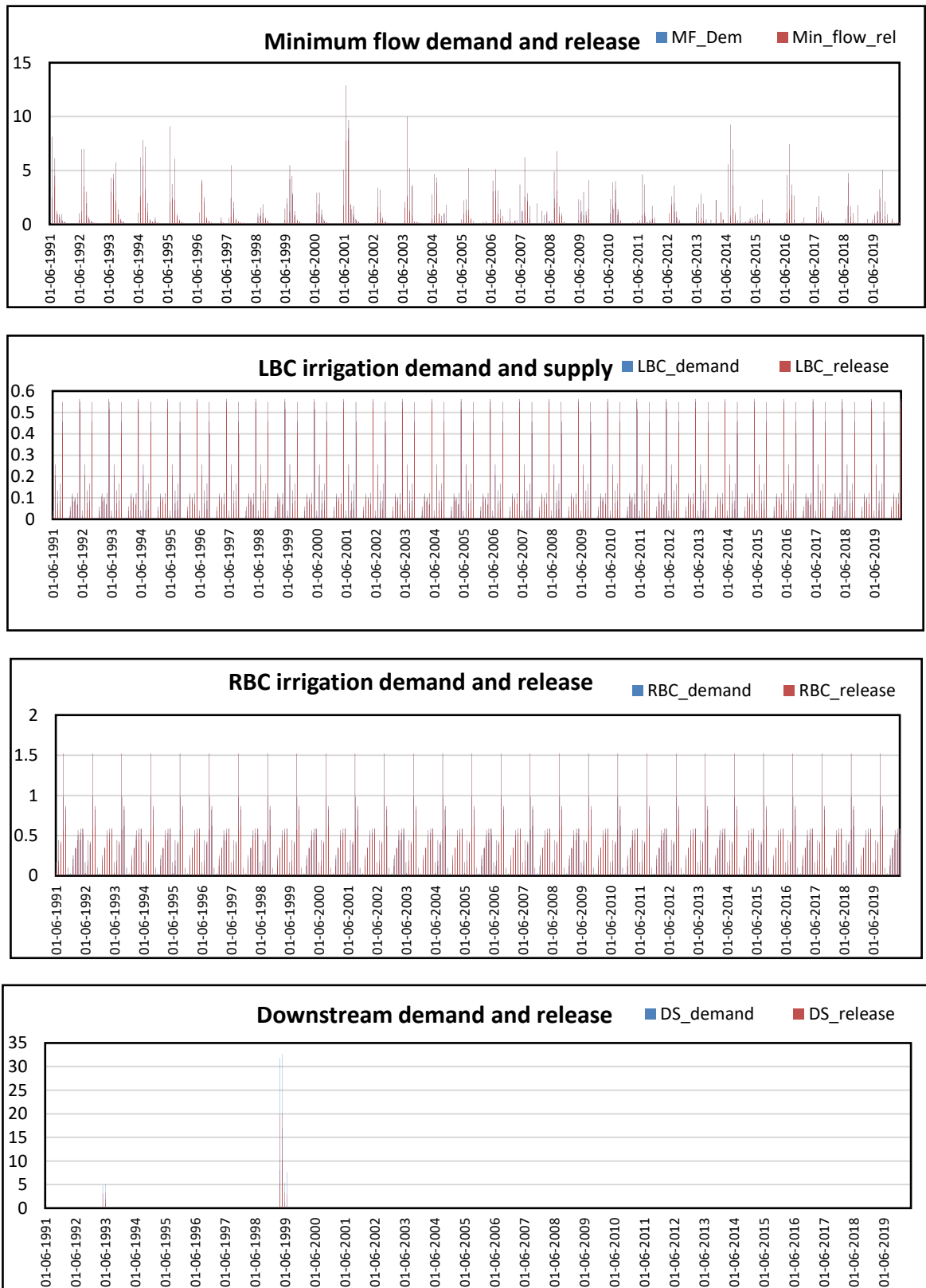


Figure 5.54 Plots for Dudhawa reservoir operation results with rule curves (All values in MCM).

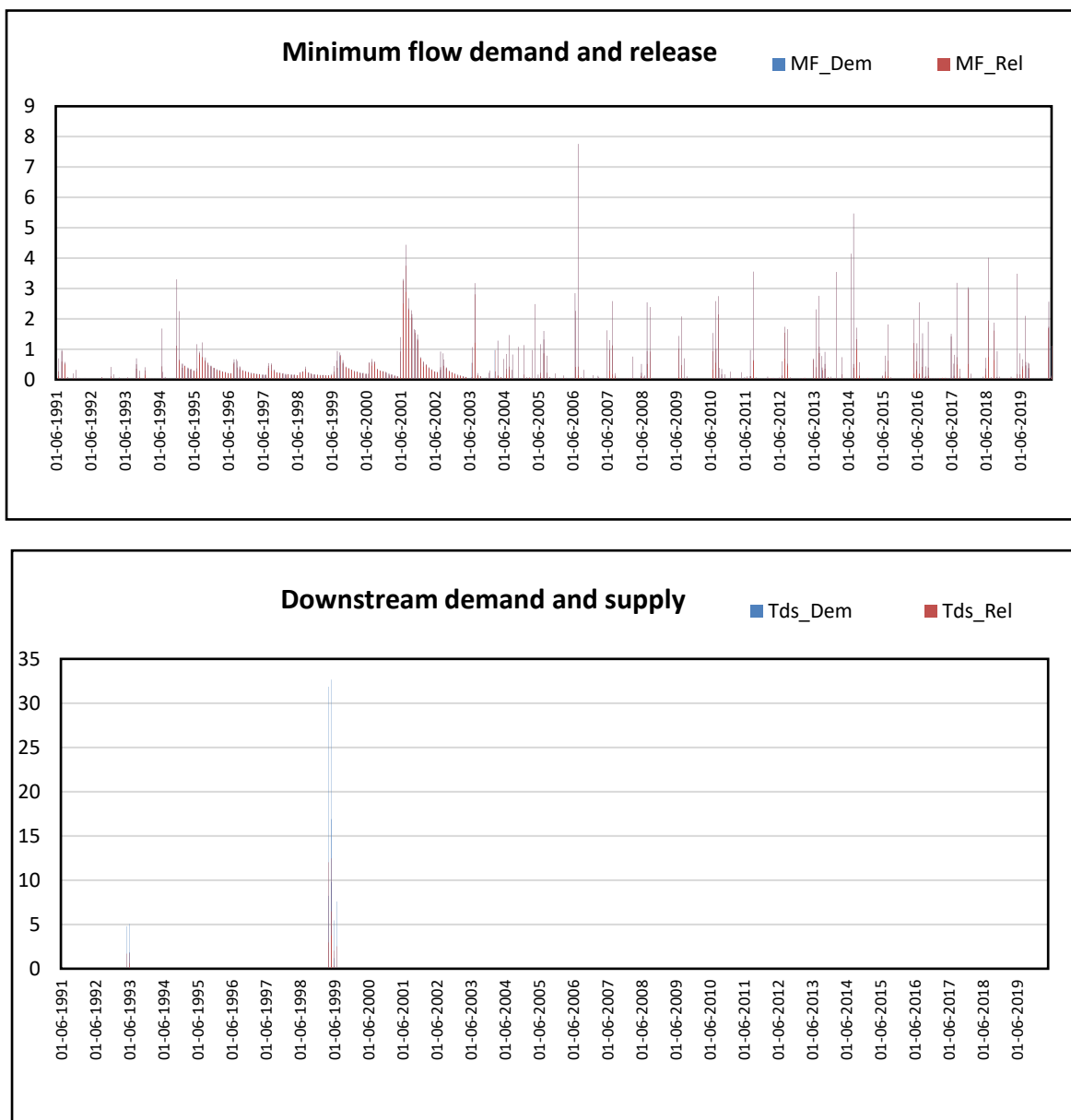


Figure 5.55 Plots for Murumsilli reservoir operation results with rule curves (All values in MCM).

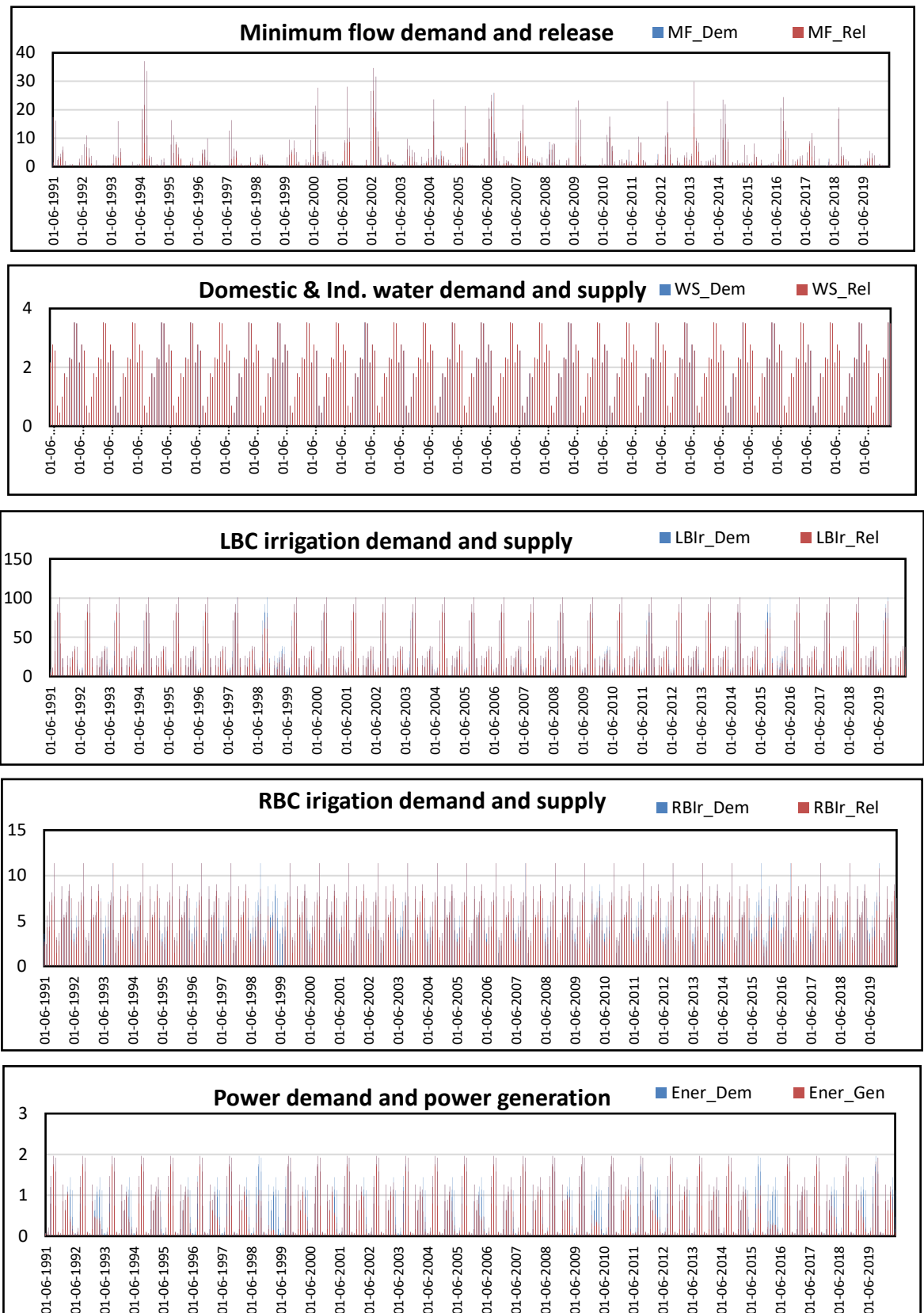


Figure 5.56 Plots for Ravi Shankar Sagar reservoir operation results with rule curves (All values in MCM).

Further month wise reliability analysis shows the ability of reservoirs in meeting demands of each month. Results suggest that Sondhur, Dudhawa and Murumsilli reservoirs maintain perfect reliability for each month for all relevant demands using both SLOP and rule curves. Dudhawa can also supply water to Ravishankar when demanded. Applying rule curves therefore does not seem to give much advantage in case of Sondhur and Dudhawa reservoirs (See in **Figures 5.57 & 5.58**).

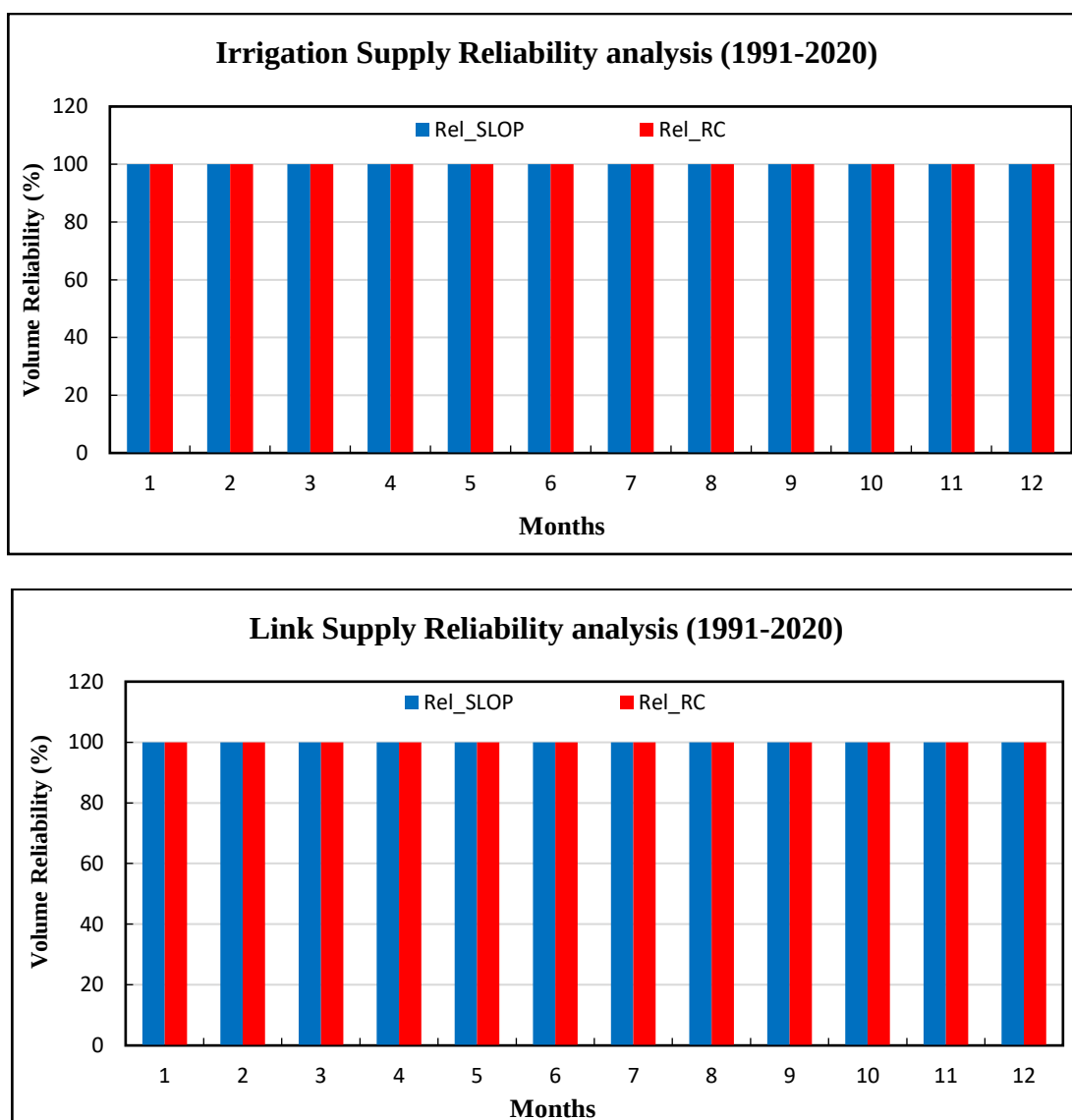


Figure 5.57 Supply reliability Sondhur reservoir.

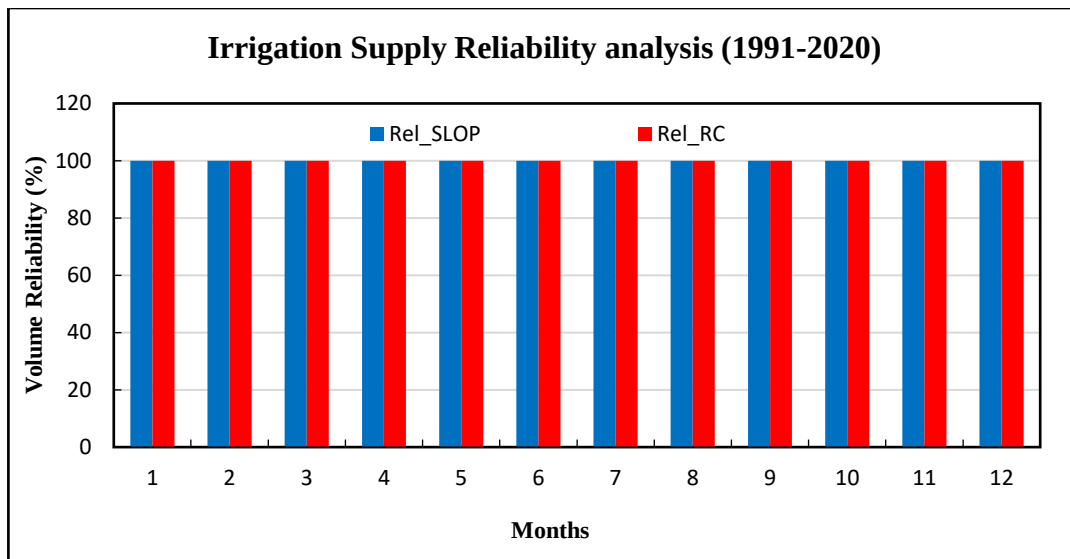
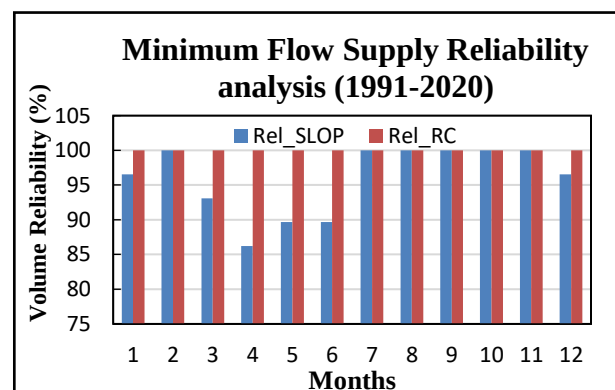
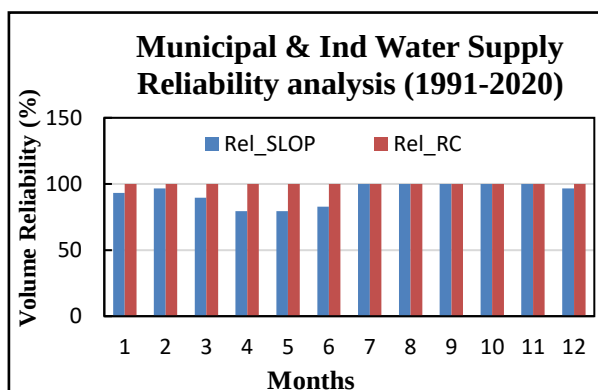


Figure 5.58 Supply reliability Dudhawa reservoir.

There is a significant improvement in meeting irrigation demands under rule curves compared to SLOP, especially during non-monsoon months. The reliability analysis suggests that irrigation supply can be considerably enhanced using rule curves, making them a more promising option for agricultural needs in drier periods. The reliability for meeting power demands drops under rule curves during non-monsoon months compared to SLOP, likely due to the prioritization of other demands. However, there is an improvement in reliability during monsoon months, when water availability is higher, and the rule curves can better accommodate power generation. The monthly supply reliability analysis of Ravishankar Sagar Reservoir is shown in **Figure 5.59**



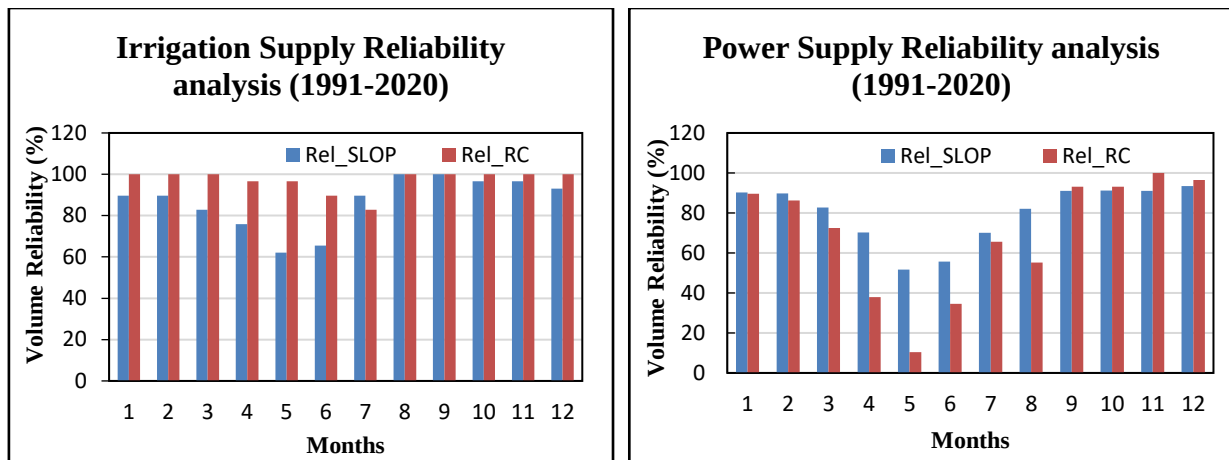


Figure 5.59 Month-wise supply reliability analysis of Ravishankar Sagar reservoir.

The use of rule curves for the integrated operation of the Ravishankar Sagar reservoir generally leads to better outcomes for minimum flow, domestic, industrial, and irrigation demands, particularly in non-monsoon months. However, this improvement comes at the expense of reduced reliability in meeting power demands during the same period, although power reliability improves during the monsoon months. These results suggest that while rule curves provide a more balanced and flexible approach overall, specific adjustments might be needed to better manage power generation, especially during non-monsoon months.

5.8 Climate Change Scenario

Climate change is likely to affect almost all sectors of life and society and it is imperative to address the issue of climate change in a comprehensive manner considering present trends, future possibilities, harmful effects, uncertainties, complexity, response and preparedness. The possible climate change may increase the concentration of carbon dioxide, population, urbanization, etc. leading to changes in precipitation and temperature regime will further affect evapotranspiration, crop water requirement, crop yield and the overall economy of many regions especially agrarian countries. Climate change can significantly affect the demand for irrigation command and the availability of water in reservoirs and other sources. It is desirable to carry out assessment studies where irrigation demand is computed using projected GCM data. The selection of the GCM

climate model plays a vital role in the assessment of crop water requirement, demand, deficit, water availability etc.

5.8.1 Performance Evaluation of GCM

The selection of climatic models from the CMIP6 dataset and the subsequent choice of a specific model for the Sondhur, Dudhawa, Murumsilli and Ravishankar Sagar catchments. The catchment's unique hydrological characteristics and sensitivity to climatic variables make the selection of appropriate models crucial for accurate hydrological simulations and water resource management.

The selection process involved an evaluation of multiple climate models available in the CMIP6 dataset. Various criteria have been considered, including the models' ability to replicate historical climatic patterns, capture regional variability, and provide reliable projections for future climate scenarios. To choose an appropriate climate model, use the Indian Meteorological Department rainfall, maximum temperature and minimum temperature data and historical rainfall, maximum temperature, and minimum temperature data of CMIP6 13 models of the historical period 1991 to 2014 (about 24 years). There are some Statistical Evaluation criteria by which we select the climatic models. These methods such as Coefficient of Determination (R^2), Nash Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), and Percentage of Bias (PBIAS) have been utilized to assess model performance. **Table 5.29 (a) to 5.29 (d)** Performance metrics of precipitation, Tmax and Tmin GCMs for Ravishankar Sagar, Sondhur, Murumsilli and Dudhawa reservoir catchments.

From the **Table 5.29(a) to 5.29(d)**, The selection of one model from the overall model which is the BCC-CSM2-MR model for future climate scenarios based on evaluation criteria, including Coefficient of Determination (R^2), Nash Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), and Percentage of bias (PBIAS) values of rainfall, maximum and minimum temperature. The BCC-CSM2-MR model demonstrated superior performance across these methods compared to the other 13 models in the CMIP6, thus making it the preferred choice for future climate projections in the study area.

Overall, based on these evaluation criteria, the BCC-CSM2-MR model emerged

as the most suitable choice for the assessment of future climate projections, giving accurate information on prospective climate change impacts on the catchment of Ravishankar Sagar, Sondhur, Murumsilii and Dudhawa catchments as well as on command.

Table 5.29 (a) Performance metrics of precipitation, Tmax, and Tmin GCMs for Ravishankar Sagar catchment.

GCMs	Rainfall				Max. Temperature				Min. Temperature			
	NSE	RMSE	Pbias	R ²	NSE	RMSE	Pbias	R ²	NSE	RMSE	Pbias	R ²
NorESM2-MM	0.38	115.93	-14.60	0.57	0.78	0.75	65.94	0.99	0.88	-3.28	56.92	0.99
NorESM2-LM	0.16	135.63	-16.64	0.49	0.81	1.24	60.25	1.00	0.91	-1.90	48.37	0.99
MRI-ESM2-0	0.13	137.89	-0.12	0.34	0.68	0.89	80.85	0.99	0.92	-2.84	46.61	0.99
MPI-ESM1-2-LR	0.34	119.56	-3.83	0.49	0.84	1.73	56.56	1.00	0.91	-1.83	47.35	0.99
MPI-ESM1-2-HR	0.33	121.22	-11.34	0.60	0.86	0.97	52.80	1.00	0.94	-2.58	39.27	0.99
INM-CM5-0	-0.75	195.45	-16.95	0.34	0.78	0.49	66.26	0.99	0.91	-3.39	50.26	0.99
INM-CM4-8	0.11	139.54	1.34	0.46	0.83	-0.50	56.79	1.00	0.89	-3.29	55.79	0.99
EC-Earth3-Veg	0.38	116.59	-2.13	0.55	0.84	1.13	56.22	1.00	0.94	-2.97	40.84	0.99
EC-Earth3	0.43	111.13	-7.50	0.58	0.82	0.82	57.65	1.00	0.92	-4.06	49.69	0.99
CanESM5	-0.32	169.70	1.28	0.16	0.58	-0.64	94.20	0.99	0.83	-4.56	68.93	0.98
BCC-CSM2-MR	0.45	109.39	-6.48	0.52	0.84	0.39	53.77	1.00	0.94	-3.80	44.59	0.99
ACCESS-ESM1-5	-0.43	176.84	-9.50	0.08	0.68	0.07	80.45	0.99	0.87	-4.74	62.44	0.99
ACCESS-CM2	-0.38	173.13	-20.35	0.31	0.65	0.34	87.00	0.99	0.87	-2.27	57.18	0.99

Table 5.29 (b) Performance metrics of precipitation, Tmax, and Tmin GCMs for the Sondhur catchment.

GCMs	Rainfall				Max. Temperature				Min. Temperature			
	NSE	RMSE	Pbias	R ²	NSE	RMSE	Pbias	R ²	NSE	RMSE	Pbias	R ²
NorESM2-MM	0.45	108.87	-10.36	0.55	0.99	64.45	-1.15	0.78	0.98	68.75	-7.60	0.88
NorESM2-LM	0.29	124.08	-10.92	0.48	1.00	59.78	-0.61	0.80	0.99	60.33	-6.42	0.91
MRI-ESM2-0	0.21	130.73	3.84	0.30	0.99	78.91	-1.03	0.68	0.99	60.76	-7.18	0.92
MPI-ESM1-2-LR	0.37	116.75	-3.24	0.47	1.00	53.17	-0.17	0.68	0.99	57.93	-6.13	0.91
MPI-ESM1-2-HR	0.40	114.06	-7.61	0.59	1.00	51.35	-0.86	0.86	0.99	54.10	-6.81	0.94
INM-CM5-0	-0.37	172.70	-10.17	0.33	0.99	65.24	-1.40	0.68	0.98	63.81	-7.74	0.92
INM-CM4-8	0.26	126.53	4.52	0.45	1.00	59.54	-2.23	0.68	0.98	68.22	-7.69	0.89
EC-Earth3-Veg	0.44	110.12	0.90	0.54	1.00	54.70	-0.74	0.68	0.99	56.52	-7.27	0.94
EC-Earth3	0.49	104.97	-3.75	0.58	1.00	56.59	-1.00	0.68	0.98	64.83	-8.23	0.92
CanESM5	-0.22	162.95	5.63	0.08	0.99	99.31	-2.44	0.68	0.98	80.17	-8.80	0.84
BCC-CSM2-MR	0.50	104.66	-2.96	0.46	1.00	54.36	-1.42	0.85	0.99	61.60	-8.00	0.94
ACCESS-ESM1-5	-0.30	167.73	-4.45	-0.12	0.99	84.43	-1.74	0.65	0.98	74.86	-8.75	0.87
ACCESS-CM2	-0.17	159.57	-14.08	0.29	0.99	87.69	-1.49	0.63	0.98	67.73	-6.76	0.87

Table 5.29 (c) Performance metrics and ranking of precipitation, Tmax, and Tmin GCMs for Murumsilli catchment.

GCMs	Rainfall				Max. Temperature				Min. Temperature			
	NSE	RMS E	Pbias	R ²	NSE	RMS E	Pbias	R ²	NSE	RMS E	Pbias	R ²
NorESM2-MM	0.35	118.9	-16.4	0.55	0.99	66.09	-1.19	0.78	0.98	65.60	-6.54	0.88
NorESM2-LM	0.13	137.5	-18.12	0.48	1.00	60.10	60.10	0.80	0.99	56.58	-5.28	0.91
MRI-ESM2-0	0.10	139.5	-1.61	0.30	0.99	81.18	-1.05	0.67	0.99	56.50	-6.11	0.92
MPI-ESM1-2-LR	0.28	125.1	-8.31	0.47	1.00	54.06	-0.21	0.68	0.99	54.99	-5.10	0.91
MPI-ESM1-2-HR	0.28	125.2	-13.2	0.59	1.00	52.32	1.32	0.86	0.99	49.97	-5.82	0.94
INM-CM5-0	-0.81	198.1	-17.6	0.33	0.99	66.82	-1.45	0.68	0.99	60.31	-6.70	0.91
INM-CM4-8	0.07	142.3	0.31	0.45	1.00	60.70	-2.36	0.68	0.98	64.84	-6.58	0.89
EC-Earth3-Veg	0.37	116.8	-3.21	0.54	1.00	54.70	-0.74	0.68	0.99	51.99	-6.25	0.94
EC-Earth3	0.43	111.0	-8.24	0.58	1.00	57.47	-1.10	0.68	0.99	61.11	-7.33	0.92
CanESM5	-0.30	171.8	0.48	0.08	0.99	98.72	-2.56	0.68	0.98	77.76	-7.82	0.83
BCC-CSM2-MR	0.44	112.6	-9.22	0.46	1.00	54.99	-1.51	0.84	0.99	56.64	-7.03	0.94
ACCESS-ESM1-5	-0.45	177.2	-10.7	-0.12	0.99	83.77	-1.85	0.67	0.98	71.84	-7.86	0.87
ACCESS-CM2	-0.41	175.1	-21.4	0.29	0.99	87.69	-1.49	0.63	0.98	64.47	-5.64	0.87

Table 5.29 (d) Performance metrics and ranking of precipitation, Tmax, and Tmin GCMs for Dudhawa catchment.

GCMs	Rainfall				Max. Temperature				Min. Temperature			
	NSE	RMSE	Pbias	R2	NSE	RMSE	Pbias	R2	NSE	RMSE	Pbias	R2
NorESM2-MM	0.43	111.28	-14.55	0.56	0.99	64.64	1.08	0.78	0.99	56.72	-3.75	0.88
NorESM2-LM	0.24	128.18	-15.84	0.48	1.00	60.87	1.59	0.81	0.99	48.65	-2.49	0.91
MRI-ESM2-0	0.16	135.46	-0.48	0.29	0.99	79.25	1.20	0.68	0.99	47.59	-3.32	0.92
MPI-ESM1-2-LR	0.35	118.75	-7.20	0.47	1.00	56.84	2.05	0.84	0.99	47.04	-2.27	0.91
MPI-ESM1-2-HR	0.38	116.31	-11.48	0.61	1.00	52.32	205.37	0.86	0.99	40.06	-3.00	0.94
INM-CM5-0	-0.49	180.18	-15.78	0.35	0.00	7.23	20537.39	0.78	0.99	50.26	-3.39	0.91
INM-CM4-8	0.22	130.20	0.07	0.47	1.00	2.69	-0.05	0.83	0.99	55.53	-3.80	0.89
EC-Earth3-Veg	0.41	113.03	-3.10	0.54	1.00	55.86	55.86	0.84	0.99	41.70	-3.42	0.94
EC-Earth3	0.46	108.07	-8.38	0.57	1.00	57.56	55.86	0.82	0.99	50.02	-4.38	0.92
CanESM5	-0.26	165.31	1.09	0.07	0.99	95.01	55.86	0.56	0.98	68.18	-4.94	0.83
BCC-CSM2-MR	0.49	105.39	-6.96	0.48	1.00	53.51	55.86	0.84	0.99	46.21	-4.17	0.94
ACCESS-ESM1-5	-0.35	170.96	-8.81	-0.16	0.99	81.51	55.86	0.66	0.99	62.14	-5.01	0.87
ACCESS-CM2	-0.24	164.31	-19.12	0.28	0.99	86.48	55.86	0.64	0.99	57.34	-2.83	0.87

5.9 Impact of climate change on Dudhawa catchment

Runoff may be indirectly influenced by temperature by changing surface evaporation losses. In response to a 1°C increase in temperature evaporation increases by 1-3%. In the present study the future projection Tmax, Tmin, and Precipitation during the near century (2025-2055) under different emission scenarios SSPs i.e. SSP126, SSP245, SSP370 & SSP585 are obtained from the best climate model of CMIP6 shown in the **Table 5.29(d)**.

The projections are compared against the base period (1991-2020). The average Tmax and Tmin during the base period are estimated at 32.64 °C and 19.70 °C respectively. The future projection indicated an increase in Tmax by +1.71%, +1.61%, +1.77% & +1.03% in different SSP scenarios similarly Tmin may be increased by +5.98%, +5.54%, +6.66% & +7.66% during the near century in SSP scenarios (SSP1, SSP2, SSP3 & SSP5). The overall high increase has been shown in minimum temperature (Tmin) compared to maximum temperature (Tmax). The monthly analysis of temperature shows that the rise in Tmax is highest in December (1.57°C) under SSP3-7.0, while the highest Tmax drop is observed in July (-1.31°C) under SSP5-8.5. **Figure 5.60** represents the variation between observed and projected average monthly maximum temperature for all scenarios. Similarly, the rise and drop in Tmin are found highest in December (2.78°C) under SSP370 and drop in September (0.29°C) under SSP1, respectively. **Figure 5.61** represents the variation between observed and projected average monthly minimum temperature for all scenarios. The variability in rainfall is one of the indicators of climate change, and it directly affects runoff and the hydrological cycle. The average annual rainfall during the base period is estimated at 1219.01 mm. Future projections showed an increase in rainfall within the range of +0.02-7.47% under different SSP scenarios. The highest percentage increase in annual rainfall is found under SSP1-2.6. The monthly analysis showed an overall increase in rainfall from November to February. **Figure 5.62** shows the monthly variation in precipitation between the baseline period and the projected average monthly precipitation for all scenarios.

The calibrated MIKE11 NAM model is interfaced with future climate projections to predict the future inflow in the Dudhawa catchment. The average annual inflow during the base period is estimated at 350.37 MCM. The future projection showed a decrease in the average annual inflow to -6.38% to -10.24% under SSP126, SSP245, and SSP585

respectively. The maximum decrease in average inflow is found -10.24% under SSP5-8.5 in the near century. The increasing inflow is showing in only the SSP245 scenario. The annual variation of these hydro-climatic variables is shown in **Table 5.30**. **Figure 5.63** shows the monthly variation in future inflow against the MIKE11 NAM simulated baseline period (1991-2020).

Table 5.30 Annual variation of max-min temperature, precipitation, and average inflow of Dudhawa catchment under SSP1, SSP2, SSP3 & SSP585 from the base period.

Parameters	Base period (1991-2020)	SSP126	SSP245	SSP370	SSP585
Tmax (°C)	32.64	+1.72	+1.65	+1.77	+1.03
Tmin (°C)	19.70	+5.98	+5.48	+6.66	+7.66
Rainfall(mm)	1219.01	+7.47	+4.71	+3.56	+0.02
Inflow (MCM)	350.37	-8.35	1.33	-6.38	-10.24

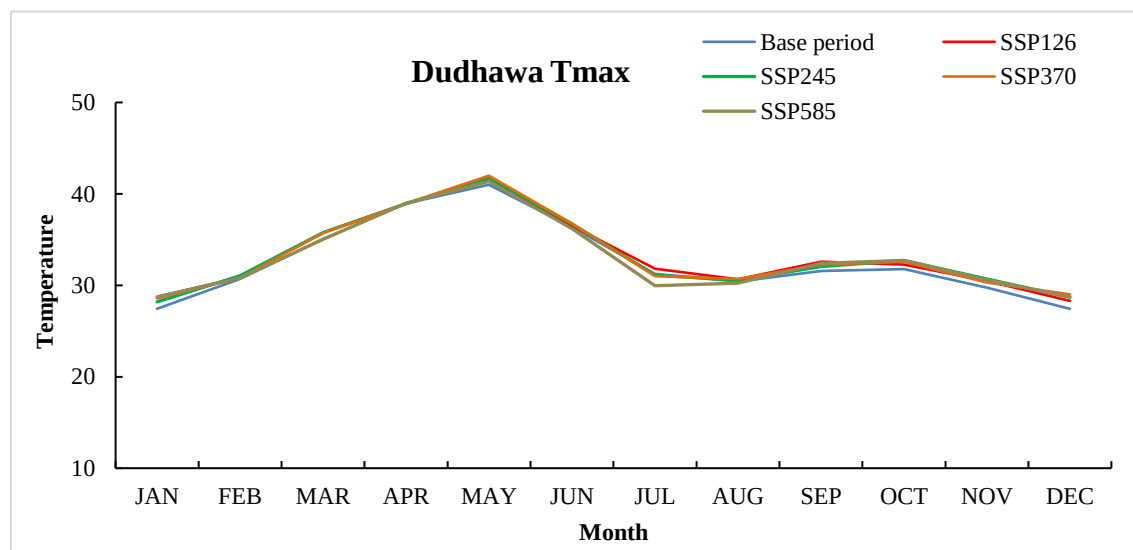


Figure 5.60 Monthly average max temperature for near century of SSP126, SSP245, SSP370 & SSP585 scenario for the Dudhawa catchment.

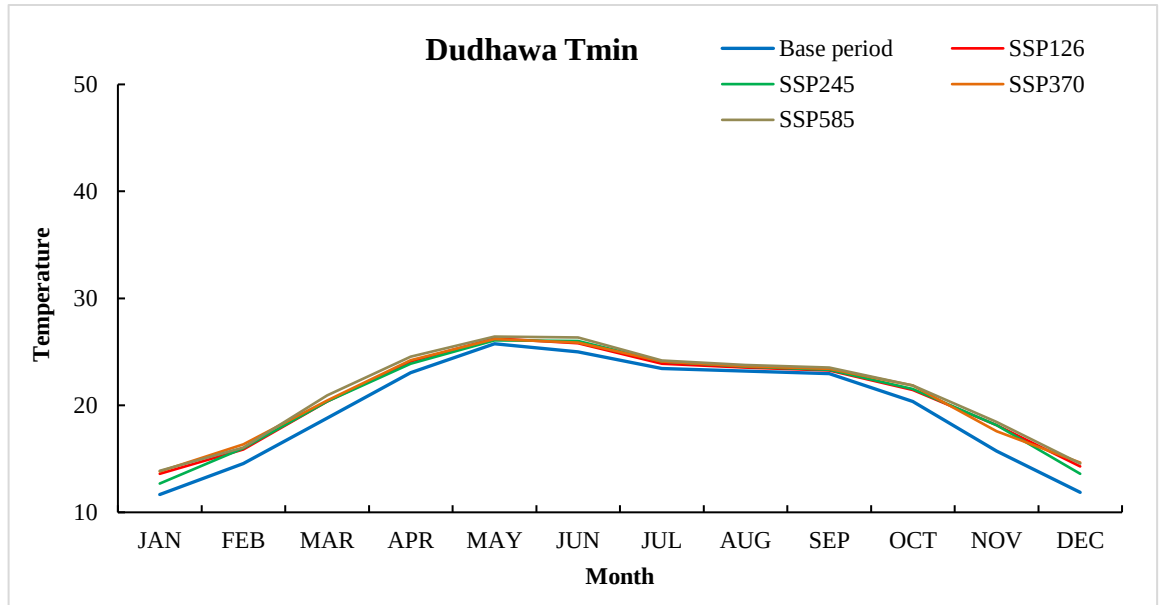


Figure 5.61 Monthly average min temperature for the near century of SSP126, SSP245, SSP370 & SSP585 scenario for the Dudhawa catchment.

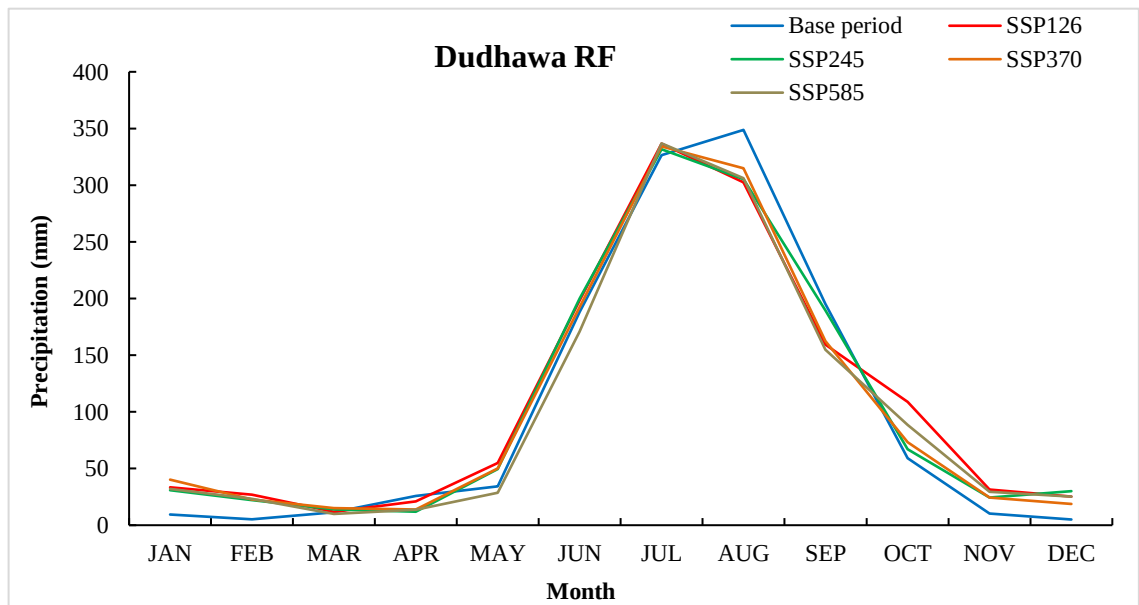


Figure 5.62 Monthly average precipitation for the near century of SSP126, SSP245, SSP370 & SSP585 scenario for the Dudhawa catchment.

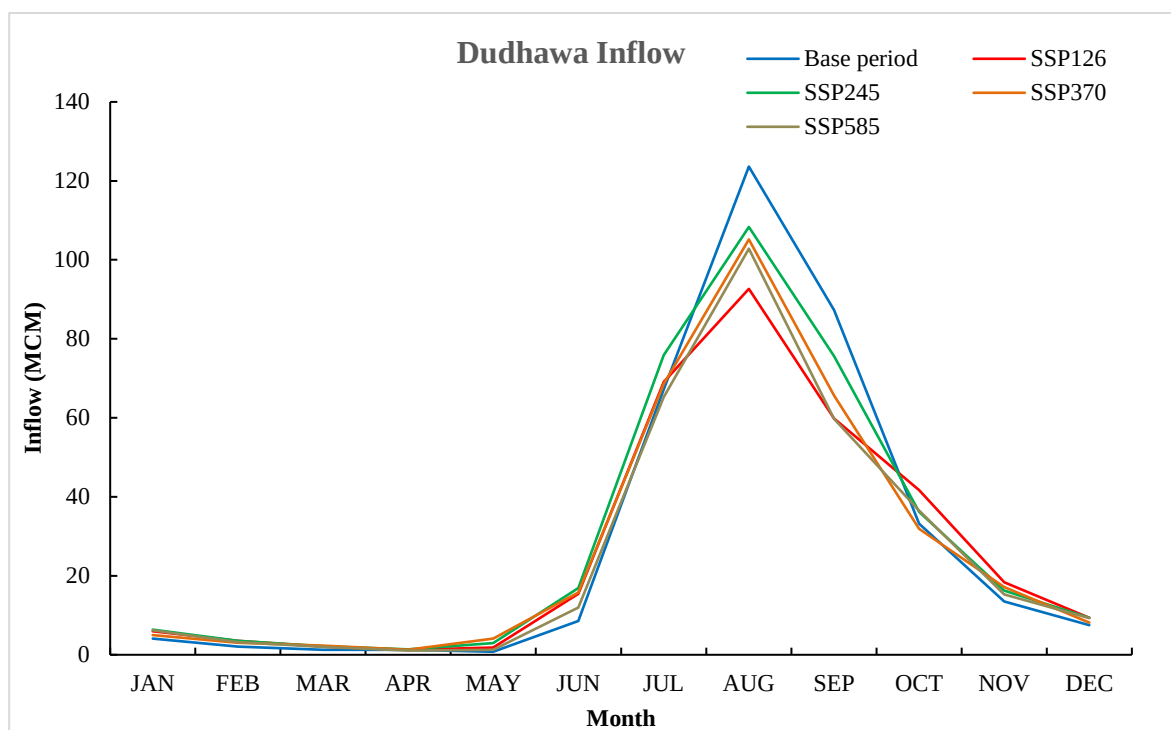


Figure 5.63 Monthly average inflow for the near century (2025-2055) of SPP126, SSP245, SSP370 & SSP585 scenarios for the Dudhawa catchment.

5.10 Impact of climate change on Murumsilli catchment

Runoff may be indirectly influenced by temperature by changing surface evaporation losses. In response to a 1°C increase in temperature evaporation increases by 1-3%. In the present study the future projection Tmax, Tmin, and Precipitation during the near century (2025-2055) under different emission scenarios SSPs i.e. SSP126, SSP245, SSP370 & SSP585 are obtained from the best climate model of CMIP6 shown in **Table 5.29(C)**.

The projections are compared against the base period (1991-2020). The average Tmax and Tmin during the base period are estimated at 32.64 °C and 19.70 °C respectively. The future projection indicated an increase in Tmax by +2.10%, +2.44%, +2.266% & +2.95% in different SSP scenarios similarly Tmin may be increased by +8.97%, +8.39%, +9.61% & +10.58% during the near century in SSP scenarios (SSP1, SSP2, SSP3 & SSP5). The overall high increase has been shown in minimum temperature (Tmin) compared to maximum temperature (Tmax). **Figure 5.64** represents the variation between observed and projected average

monthly maximum temperature for all scenarios. **Figure 5.65** represents the variation between observed and projected average monthly minimum temperature for all scenarios. The variability in rainfall is one of the indicators of climate change, and it directly affects runoff and the hydrological cycle. The average annual rainfall during the base period is estimated at 1125.53 mm. Future projections showed an increase in rainfall within the range of +9.13-17.69% under different SSP scenarios. The highest percentage increase in annual rainfall is found under SSP126. The monthly analysis showed an overall increase in rainfall from October to February. **Figure 5.66** shows the monthly variation in precipitation between the baseline period and the projected average monthly precipitation for all scenarios.

The calibrated MIKE11 NAM model is interfaced with future climate projections to predict the future inflow in the Murumsilli catchment. The average annual inflow during the base period is estimated at 216.26 MCM. The future projection showed a decrease and increase in the average annual inflow. The inflow indicated decreasing -1.01% to -8.97% in SPP370, SSP126 & SSP585 scenarios respectively. The increasing inflow is showing in only the SSP245 scenario. The maximum decrease in average annual inflow is found -8.97% under SSP5-8.5 in the near century. The annual variation of these hydro-climatic variables is shown in **Table 5.31**. **Figure 5.67** shows the monthly variation in future inflow against the MIKE11 NAM simulated baseline period (1991-2020).

Table 5.31 Annual variation of max-min temperature, precipitation, and average inflow of Murumsilli catchment under SSP1, SSP2, SSP3 & SSP5 from the base period.

Parameters	Base period (1991-2020)	SSP126	SSP245	SSP370	SSP585
Tmax (°C)	32.64	+2.10	+2.44	+2.26	+2.95
Tmin (°C)	19.70	+8.97	+8.39	+9.61	+10.58
Rainfall(mm)	1125.53	+17.69	+14.28	+12.12	+9.13
Inflow(MCM)	216.26	-4.80	+4.25	-1.01	-8.97

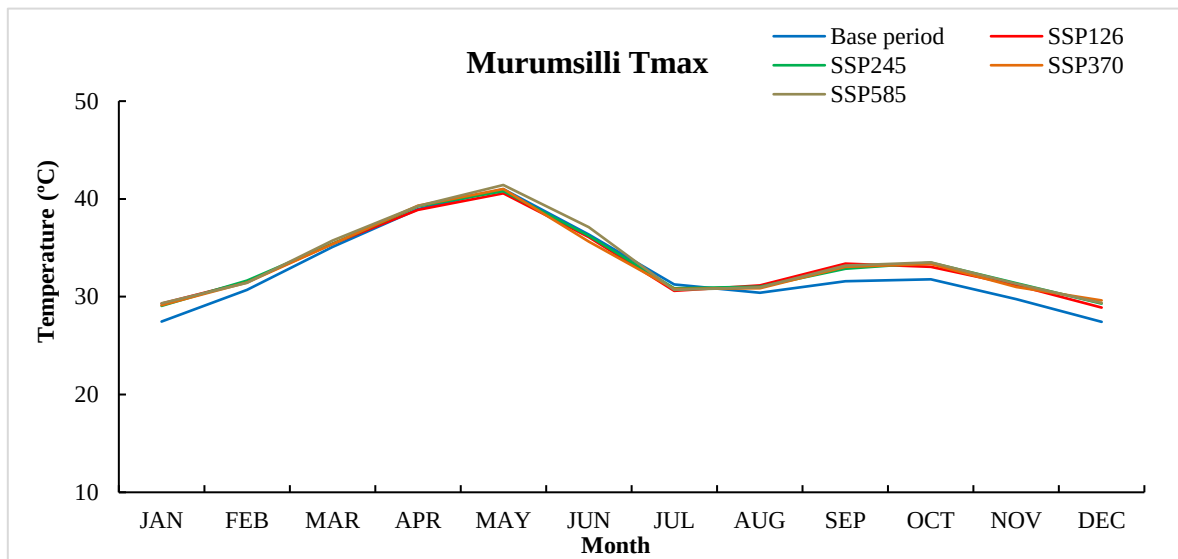


Figure 5.64 Monthly average max temperature for the near century of SSP126, SSP245, SSP370 & SSP585 scenario for the Murumsilli catchment.

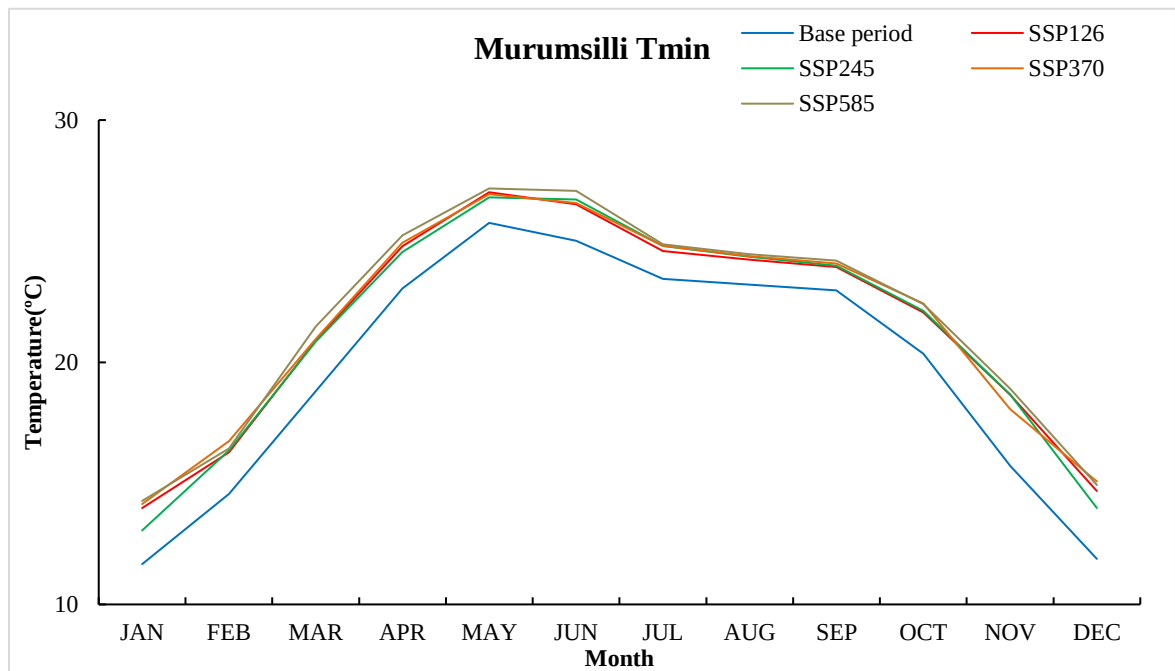


Figure 5.65 Monthly average min temperature for the near century of SSP126, SSP245, SSP370 & SSP585 scenario for the Murumsilli catchment.

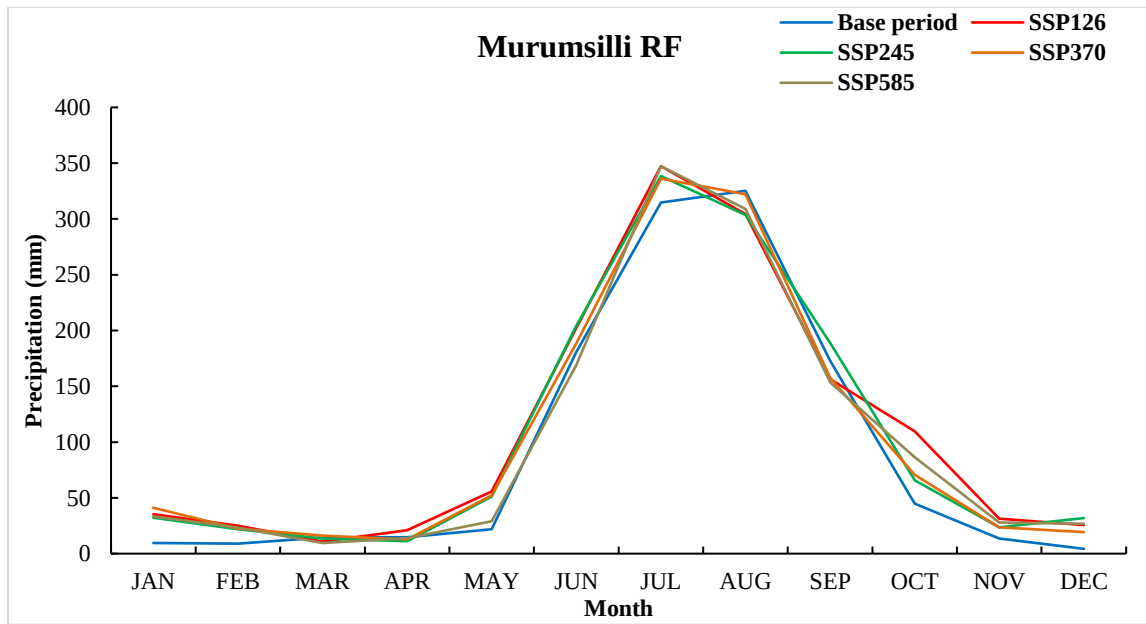


Figure 5.66 Monthly average precipitation for the near century of SSP126, SSP245, SSP370 & SSP585 scenario for the Murumsilli catchment.

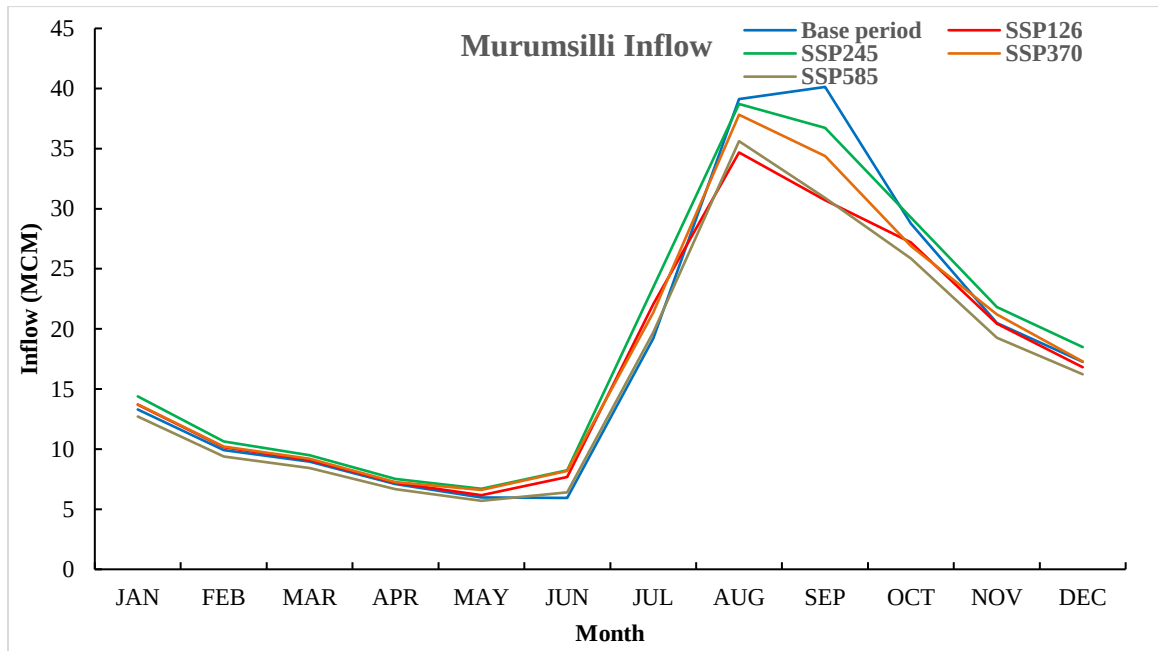


Figure 5.67 Monthly average inflow for the near century (2025-2055) of SPP126, SSP245, SSP370 & SSP585 scenarios for the Murumsilli catchment.

5.11 Impact of climate change on Ravishankar Sagar catchment

Runoff may be indirectly influenced by temperature by changing surface evaporation losses. In response to a 1°C increase in temperature evaporation increases by 1-3%. In the present study the future projection Tmax, Tmin, Precipitation, and inflow during the near century (2025-2055) under different emission scenarios SSPs i.e. SSP126, SSP245, SSP370 & SSP585 are obtained from the best climate model of CMIP6 shown in **Table 5.29(a)**.

The projections are compared against the base period (1991-2020). The average Tmax and Tmin during the base period are estimated at 32.64 °C and 19.70 °C respectively. The future projection indicated an increase in Tmax by +1.15%, +1.32%, +0.58% & +0.63% in different SSP scenarios similarly Tmin may be increased by +3.70%, +3.17%, +4.29% & +5.38% during the near century in SSP scenarios (SSP1, SSP2, SSP3 & SSP5). The overall high increase has been shown in minimum temperature (Tmin) compared to maximum temperature (Tmax). **Figure 5.68** represents the variation between observed and projected average monthly maximum temperature for all scenarios. **Figure 5.69** represents the variation between observed and projected average monthly minimum temperature for all scenarios. The variability in rainfall is one of the indicators of climate change, and it directly affects runoff and the hydrological cycle. The average annual rainfall during the base period is estimated at 1274.64 mm. Future projections showed an increase in rainfall under SSP1&SSP2 scenarios. The increase percentage of rainfall by +3.58% and +1.09% under SSP1 and SSP2 scenarios. The future projection indicated a decrease in rainfall by -0.765% and -3.49% under SSP3 and SSP5 scenarios. The highest percentage increase in annual rainfall is found under SSP1-2.6. The monthly analysis showed an overall increase in rainfall from October to February. **Figure 5.70** shows the monthly variation in precipitation between the baseline period and the projected average monthly precipitation for all scenarios.

The calibrated MIKE11 NAM model is interfaced with future climate projections to predict the future inflow in the Ravishankar Sagar catchment. The average annual inflow during the base period is estimated at 1793.98 MCM. The future projection showed a decrease in the average annual inflow from -7.14% to -14.80% respectively. The maximum decrease in average annual inflow is found -14.80% under SSP1-2.6 in the near century. The annual variation of these hydro-climatic variables is shown in **Table 5.32**. **Figure 5.71** shows the

monthly variation in future inflow against the MIKE11 NAM simulated baseline period (1991-2020).

Table 5.32 Annual variation of max-min temperature, precipitation, and average inflow of Ravishankar Sagar catchment under SSP1, SSP2, SSP3 & SSP585 from the base period.

Parameters	Base period (1991-2020)	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5
Tmax (°C)	32.64	+1.15	+1.32	+0.58	+0.63
Tmin (°C)	19.70	+3.70	+3.17	+4.29	+5.38
Rainfall(mm)	1274.64	+3.85	+1.09	-0.76	-3.94
Inflow (MCM)	1793.98	-14.80	-7.14	-10.35	-13.75

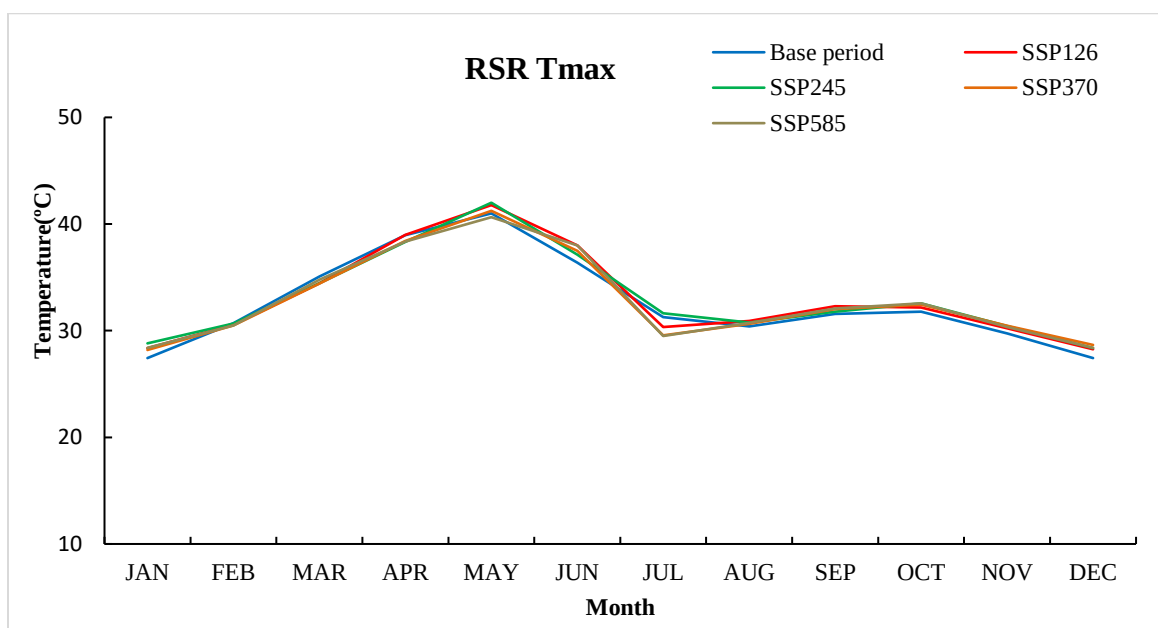


Figure 5.68 Monthly average max temperature for the near century of SSP126, SSP245, SSP370 & SSP585 scenario for the Ravishankar Sagar catchment.

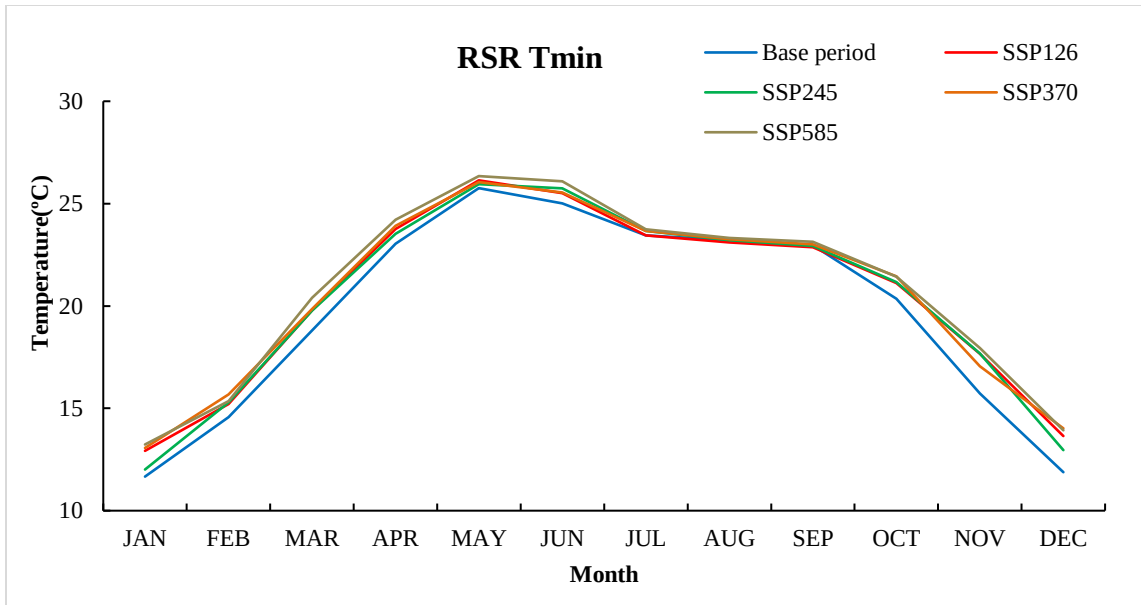


Figure 5.69 Monthly average min temperature for the near century of SSP126, SSP245, SSP370 & SSP585 scenario for the Ravishankar Sagar catchment.

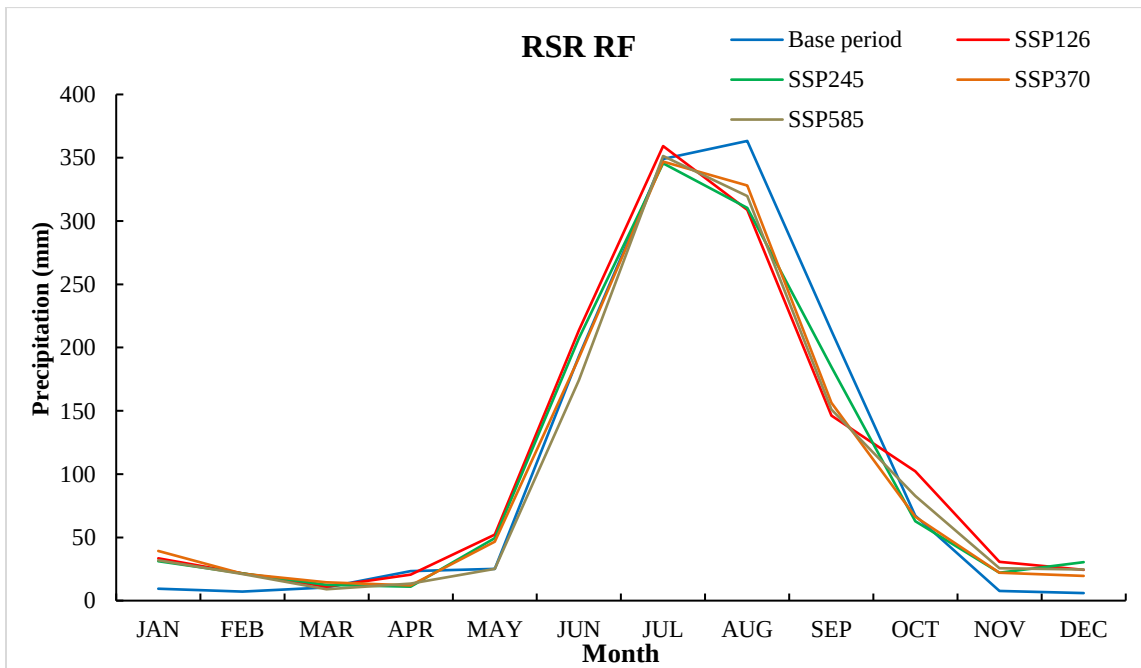


Figure 5.70 Monthly average precipitation for the near century of SSP126, SSP245, SSP370 & SSP585 scenario for the Ravishankar Sagar catchment.

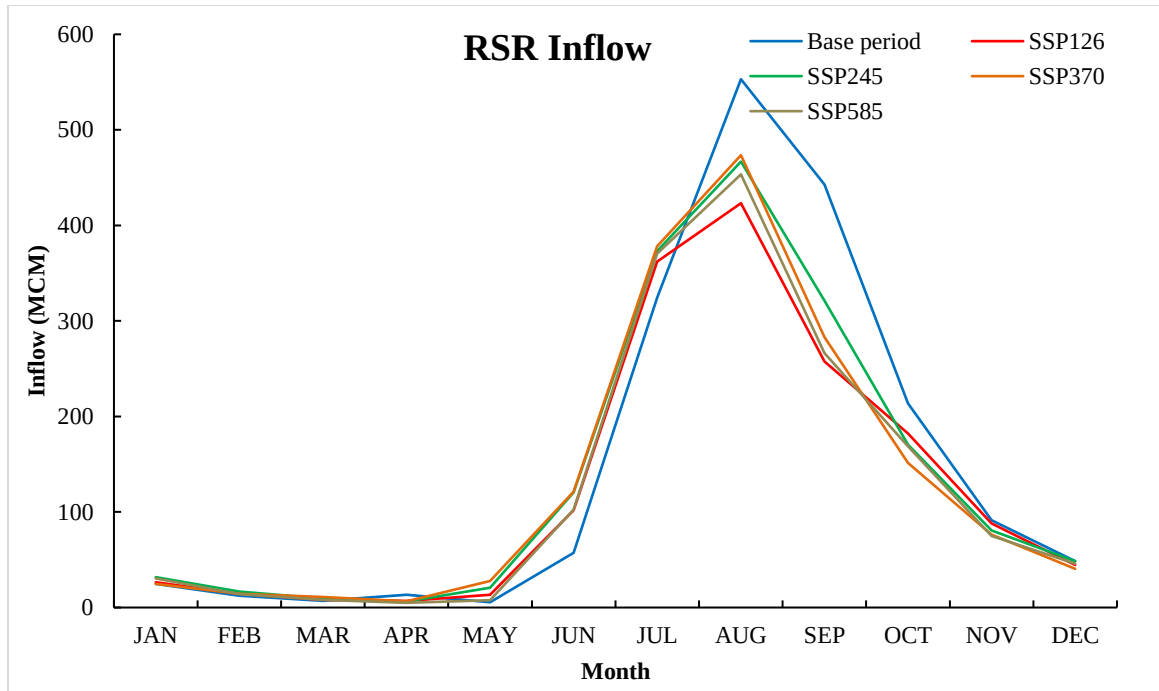


Figure 5.71 Monthly average inflow for the near century (2025-2055) of SPP126, SSP245, SSP370 & SSP585 scenarios for the Ravishankar Sagar catchment.

5.12 Impact of climate change on Sondhur catchment

Runoff may be indirectly influenced by temperature by changing surface evaporation losses. In response to a 1°C increase in temperature, evaporation increased by 1-3% (Agarwal et al.,2024). In the present study the future projection Tmax, Tmin, Precipitation, and inflow during the near century (2025-2055) under different emission scenarios SSPs i.e. SSP1-2.6, SSP2-4.5, SSP3-7.0 & SSP5-8.5 are obtained from best climate model of CMIP6 shown in **Table 5.29(b)**.

The projections are compared against the base period (1991-2020). The average Tmax and Tmin during the base period are estimated at 32.64 °C and 19.70 °C respectively. The future projection indicated an increase in Tmax by +2.21%, +2.49%, +2.06% & +2.73% in different SSP scenarios similarly Tmin may be increased by +9.90%, +9.40%, +10.64% & +11.58% during the near century in SSP scenarios (SSP1, SSP2, SSP3 & SSP5). The overall high increase has been shown in minimum temperature (Tmin) compared to maximum temperature (Tmax). **Figure 5.72** represents the variation between observed and projected average monthly maximum temperature for all scenarios. **Figure 5.73** represents the variation

between observed and projected average monthly minimum temperature for all scenarios. The variability in rainfall is one of the indicators of climate change, and it directly affects runoff and the hydrological cycle. The average annual rainfall during the base period is estimated at 1125.53 mm. Future projections showed an increase in rainfall within the range of +3.81-11.64% under different SSP scenarios. The highest percentage increase in annual rainfall is found under SSP1-2.6. The monthly analysis showed an overall increase in rainfall from October to February. **Figure 5.74** shows the monthly variation in precipitation between the baseline period and the projected average monthly precipitation for all scenarios.

The calibrated MIKE11 NAM model is interfaced with future climate projections to predict the future inflow in the Sondhur catchment. The average annual inflow during the base period is estimated at 261.59 MCM. The future projection showed a decrease in the average annual inflow from -7.99% to -24.90% respectively. The maximum decrease in average annual inflow is found -24.90% under SSP5-8.5 in the near century. The annual variation of these hydro-climatic variables is shown in **Table 5.33**. **Figure 5.75** shows the monthly variation in future inflow against the MIKE11 NAM simulated baseline period (1991-2020).

Table 5.33 Annual variation of max-min temperature, precipitation, and average inflow of Sondhur catchment under SSP1, SSP2, SSP3 & SSP585 from the base period.

Parameters	Base period (1991-2020)	SSP126	SSP245	SSP370	SSP585
Tmax (°C)	32.64	+2.21	+2.49	+2.06	+2.73
Tmin (°C)	19.70	+9.90	+9.40	+10.64	+11.55
Rainfall(mm)	1125.53	+11.64	+8.69	+7.16	+3.81
Inflow (MCM)	261.59	-20.03	-7.99	-12.89	-24.90

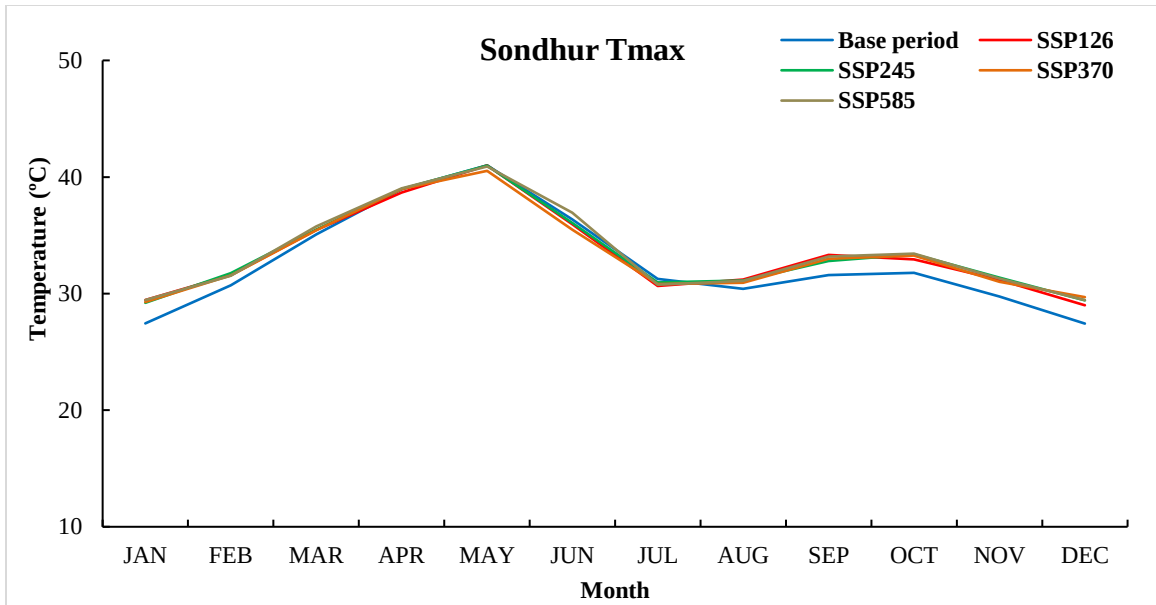


Figure 5.72 Monthly average max temperature for the near century of SSP126, SSP245, SSP370 & SSP585 scenario for the Sondhur catchment.

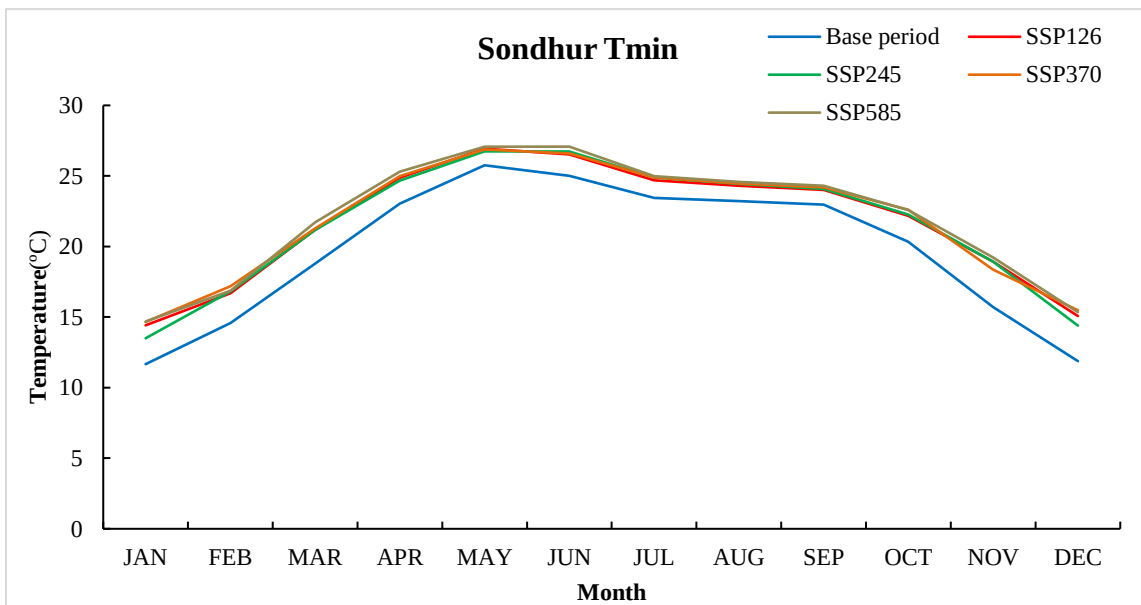


Figure 5.73 Monthly average min temperature for the near century of SSP126, SSP245, SSP370 & SSP585 scenario for the Sondhur catchment.

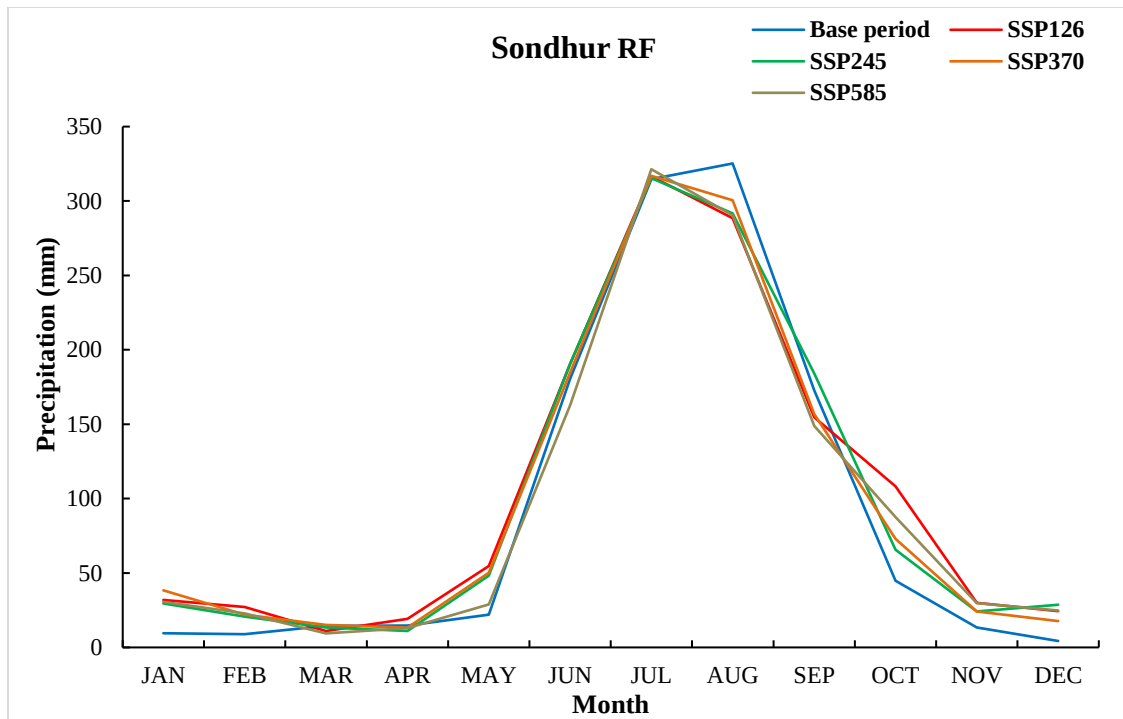


Figure 5.74 Monthly average precipitation for the near century of SSP126, SSP245, SSP370 & SSP585 scenario for the Ravishankar Sagar catchment.

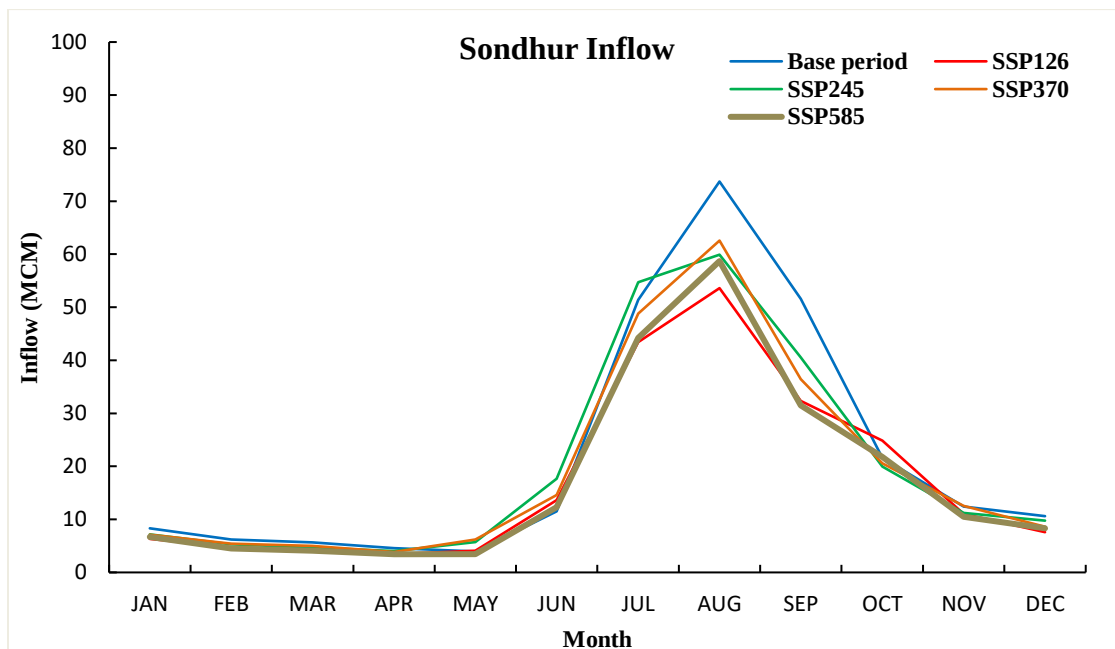


Figure 5.75 Monthly average inflow for the period near century (2025-2055) of SPP126, SSP245, SSP370 & SSP585 scenarios for the Sondhur catchment.

5.13 Assessment of Climate Change Impact on Irrigation Water Requirement in the Command of Ravi Shankar Sagar Reservoir

The Ravishankar Sagar Reservoir Command Area, located in the Indian state of Chhattisgarh, receives the majority of its annual rainfall during the monsoon season, which typically lasts from June to October. The area experiences a tropical monsoon climate with a distinct wet and dry season. The average annual rainfall in the command area is around 1,200 mm, with the majority of the rainfall occurring during the monsoon season. The rainfall is critical for agriculture in the command area, and it has been instrumental in providing irrigation water to the crops during the dry season. The Ravishankar Sagar Reservoir stores water during the monsoon season, which is used for irrigation and power generation during the rest of the year. In recent years, the command area has also experienced fluctuations in rainfall patterns, with occasional droughts and floods. The state government has implemented various measures to mitigate the impacts of climate change and ensure sustainable use of water resources in the region.

Figure 5.76 represents a command area with a grid-based structure. The legend on the map indicates that it comprises grids based on rainfall data from the Indian Meteorological Department (IMD). Each grid has a resolution of 0.25° by 0.25° units, and there are a total of 10 rainfall grids within the command area. Additionally, the map incorporates IMD Temperature grids, which have a resolution of 1° by 1° units. The three temperature grids closest to each location of interest have been selected. To examine future climate projections, the map also includes nine grids of Climate Model Intercomparison Project Phase 6 (CMIP6) grids. These grids represent future rainfall and temperature data and have a resolution of 0.25° by 0.25° units.

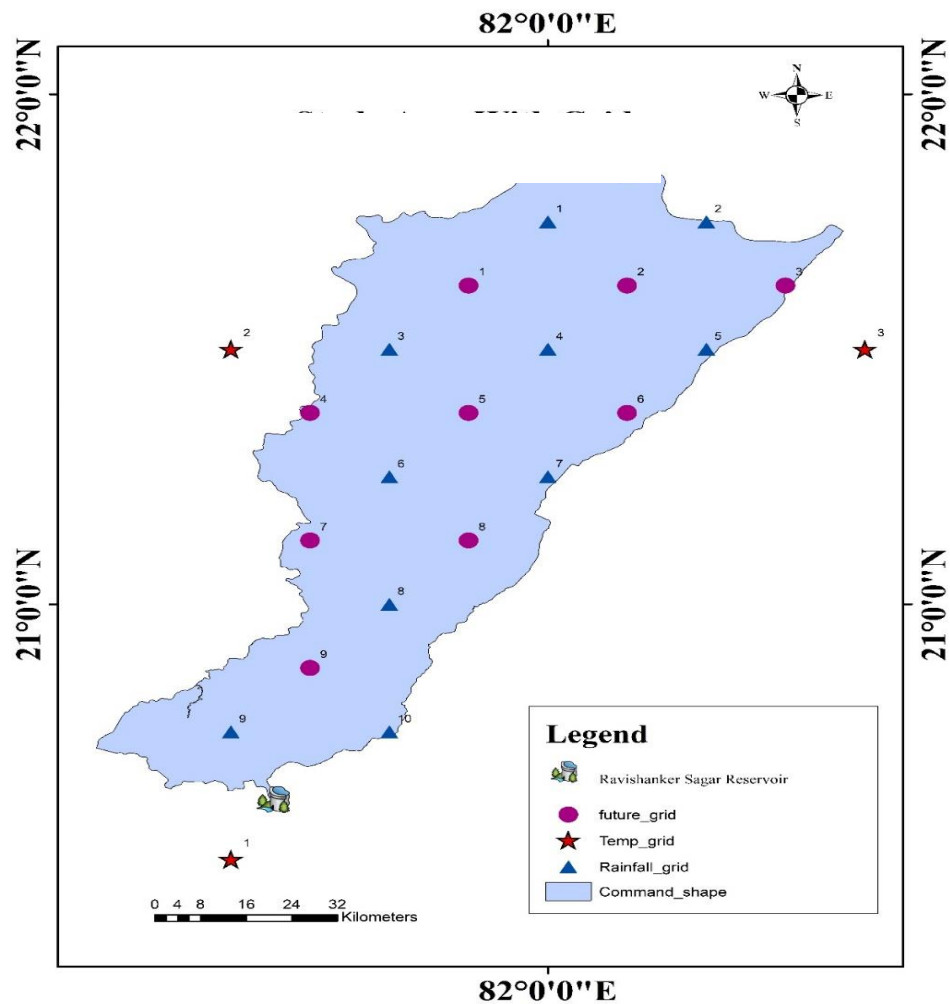


Figure 5.76 Command Area with IMD and SSPs Grids.

5.13.1 Rainfall variation over the command area

The **Figure 5.77** spatial map below illustrates the variation in rainfall period (1991-2020) across the command area, ranging from 951mm to 1120mm. The map consists of 10 IMD rainfall grids, with each grid representing a distinct region with a different amount of rainfall. The upper portion of the map exhibits higher rainfall values, specifically in Baloda Bazar District of Chhattisgarh. This region experiences the highest amount of rainfall within the study area.

As we move further down the map, the depicted rainfall gradually decreases,

encompassing areas such as Raipur (the capital of Chhattisgarh) and Dhamteri District within the command area. The distribution of rainfall within the study area is visible on the map, allowing for a visual understanding of the spatial patterns. The variation in rainfall from grid to grid indicates the localized nature of precipitation in the region. The grid-based representation enables to assess the specific rainfall conditions in each area and identify areas of higher or lower rainfall intensity.

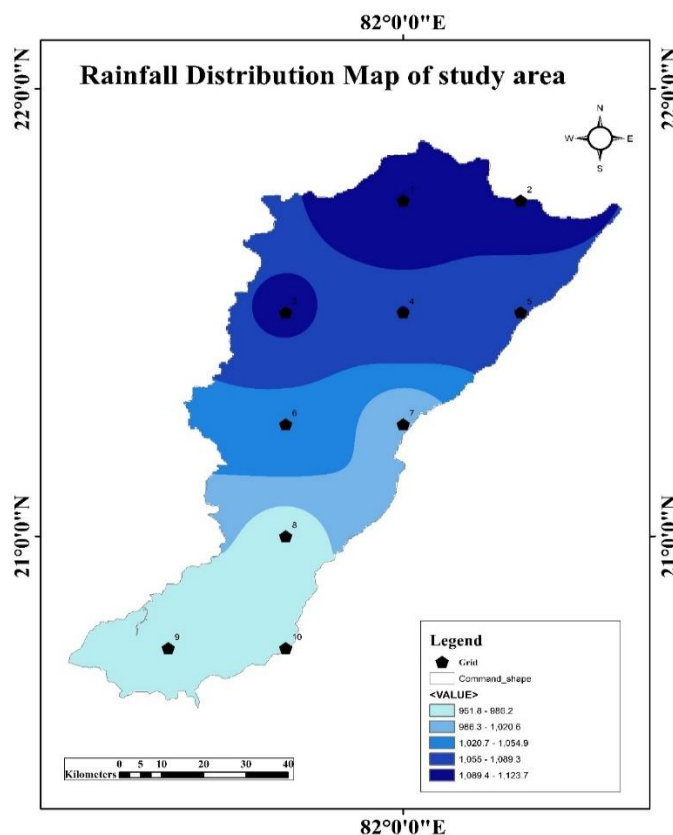


Figure 5.77 Rainfall Spatial Distribution Map of Command Area.

5.13.2 Temperature variation over the command area

The **Figure 5.78** spatial map provided illustrates the variation in maximum temperature across the command area, ranging from 32°C to 34°C. The map comprises three IMD temperature grids, with each grid representing a specific region with a different maximum temperature value.

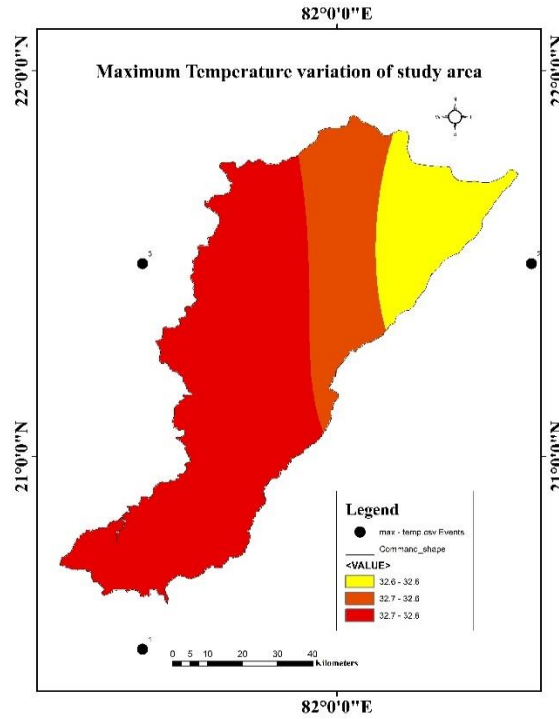


Figure 5.78 Maximum Temperature variation in Command area.

The **Figure 5.79** spatial map illustrates the variation in minimum temperature across the command area, ranging from 19°C to 20°C. The map consists of three IMD temperature grids, with each grid representing a specific region and displaying a different minimum temperature value.

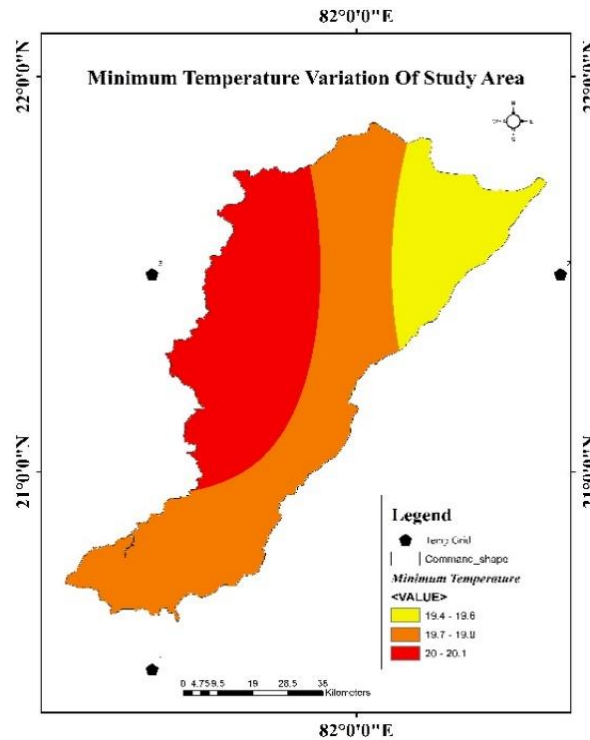


Figure 5.79 Minimum Temperature variation in command Area

5.13.3 Irrigation Water Requirement of the command area during the base period (1991-2020)

Table 5.34 represents the average seasonal rainfall and average irrigation water requirement for ten different grids. Each grid is assigned a number from 1 to 10. The first column indicates the grid number, while the second column represents the average seasonal rainfall in that particular grid. The third column shows the average irrigation water requirement for each grid. From analyzing the data, it can be observed that there is a gradual decrease in both the average seasonal rainfall and the average irrigation water requirement as we move from Grid 1 to Grid 10. This suggests a general trend of decreasing rainfall and irrigation needs from the first grid to the last.

Table 5.34 Irrigation Water Requirement of Ravi Shanker Sagar Reservoir Command for monsoon period crop of all 10 grids.

GRID	Average Seasonal Rainfall (mm)	Average Irrigation Water Requirement (mm)
1	1123.69	282.5
2	1113.03	286.2
3	1098.32	290.25
4	1089.66	291.96
5	1071.31	294.4
6	1054.10	295.88
7	989.519	300.8
8	971.58	301.95
9	961.719	311.9
10	951.791	313.86
Average	1042.47	296.97

Figure 5.80 represents a spatial map of the command area, illustrating the distribution of irrigation water requirements. The graph indicates that grids 1, 2, 3, and 4, which encompass Balodabazar district and certain parts of Raipur in Chhattisgarh, exhibit lower irrigation water requirements. On the other hand, grids 5, 6, 7, and 8, covering Raipur (the capital of Chhattisgarh) and some areas of Baloda Bazar, demonstrate a moderate irrigation water requirement. Finally, grids 9 and 10, encompassing Dhamteri district in Chhattisgarh, exhibit the highest irrigation water requirement. Notably, the map shows an increase in irrigation water requirement as one moves downward on the map.

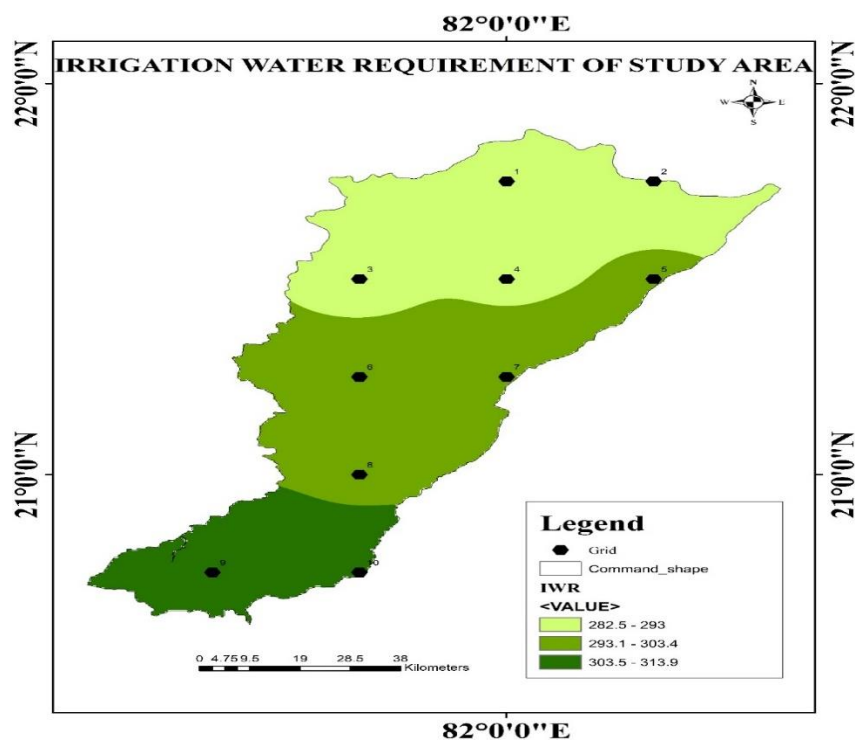


Figure 5.80 Irrigation Water Requirement of Ravi Shankar Sagar Reservoir Command for monsoon period crop of all 10 grids.

5.14 Selection of climatic model for Mahanadi command using goodness of fit criteria

Mishra et al. conducted a study focused on the South Asia region, specifically evaluating 13 different climatic models. Their objective was to determine which of these models were most suitable for the study area based on several goodness-of-fit criteria, including Nash-Sutcliffe Efficiency (NSE), Percent Bias (PBIAS), Coefficient of Determination (R^2), and Root Mean Square Error (RMSE). This selection process based on goodness-of-fit criteria ensured that the chosen climatic model provided the closest approximation to the observed data and demonstrated the highest level of accuracy and reliability in representing the climate patterns and dynamics in the specific region under investigation. The Performance metrics of precipitation, Tmax, and Tmin GCMs for the Mahanadi command are shown in **Table 5**.

Table 5.35 Performance metrics of precipitation, Tmax, and Tmin GCMs for Mahanadi Command.

GCMs	Rainfall				Max. Temperature				Min. Temperature			
	NSE	RMSE	Pbias	R ²	NSE	RMSE	Pbias	R ²	NSE	RMSE	Pbias	R ²
NorESM2-MM	0.48	98.36	-13.58	0.62	0.78	0.75	65.94	0.99	0.88	-3.28	56.92	0.99
NorESM2-LM	0.18	123.56	-16.71	0.52	0.81	1.24	60.25	1.00	0.91	-1.90	48.37	0.99
MRI-ESM2-0	0.16	95.27	-1.67	0.38	0.68	0.89	80.85	0.99	0.92	-2.84	46.61	0.99
MPI-ESM1-2-LR	0.49	97.17	-5.75	0.62	0.84	1.73	56.56	1.00	0.91	-1.83	47.35	0.99
MPI-ESM1-2-HR	0.49	95.27	-7.76	0.66	0.86	0.97	52.80	1.00	0.94	-2.58	39.27	0.99
INM-CM5-0	-0.18	142.28	-9.65	0.42	0.78	0.49	66.26	0.99	0.91	-3.39	50.26	0.99
INM-CM4-8	0.11	128.61	1.18	0.51	0.83	-0.50	56.79	1.00	0.89	-3.29	55.79	0.99
EC-Earth3-Veg	0.49	97.53	-0.92	0.60	0.84	1.13	56.22	1.00	0.94	-2.97	40.84	0.99
EC-Earth3	0.46	100.29	-9.51	0.61	0.82	0.82	57.65	1.00	0.92	-4.06	49.69	0.99
CanESM5	-0.33	158.30	2.97	0.13	0.58	-0.64	94.20	0.99	0.83	-4.56	68.93	0.98
BCC-CSM2-MR	0.52	95.34	-8.06	0.62	0.84	0.39	53.77	1.00	0.94	-3.80	44.59	0.99
ACCESS-ESM1-5	-0.37	160.58	-9.77	0.09	0.68	0.07	80.45	0.99	0.87	-4.74	62.44	0.99
ACCESS-CM2	-0.40	162.06	-20.48	0.31	0.65	0.34	87.00	0.99	0.87	-2.27	57.18	0.99

5.15 Assessment of climate change impact on Irrigation Water Requirement under projected scenarios for the selected climatic model

The assessment aims to evaluate the impact of climate change on irrigation water requirements under projected scenarios (SSP125, SSP245, SSP370, and SSP585) using a selected climatic model. By comparing the irrigation water requirements during a base period with those projected under different scenarios, it can assess the potential changes in water demand due to climate change. The percentage change of irrigation water requirement is shown in **Table 5.36**. **Figure 5.81** depicts the spatial variation of the irrigation water requirement of the command area and provides insights into the Irrigation Water Requirement for both the base period (1991-2022) and four future scenarios based on different socio-economic pathways (SSP-1, SSP-2, SSP-3, and SSP-5). By examining the figure, it can analyze the changes in Irrigation Water Requirements across the command area. In the base period map, certain grids in Balodabazar district and Raipur district demonstrate an increase in Irrigation Water Requirement. This indicates that during the base period, these regions experienced an elevated demand for water resources to support agricultural irrigation. This analysis will provide valuable insights for water resource management and agricultural planning, helping stakeholders understand the challenges and develop adaptation strategies to ensure sustainable irrigation practices in the face of changing climatic conditions.

Table 5.36 The percentage change of irrigation water requirement of Mahanadi command under SSP1, SSP2, SSP3, and SSP5 from the base period (1991-2020).

Parameter	Base period (1991-2020)	SSP126 (%)	SSP245 (%)	SSP370 (%)	SSP585 (%)
Average Irrigation water requirement (mm)	296.97	+20.2	+26.9	+26.6	+26.7

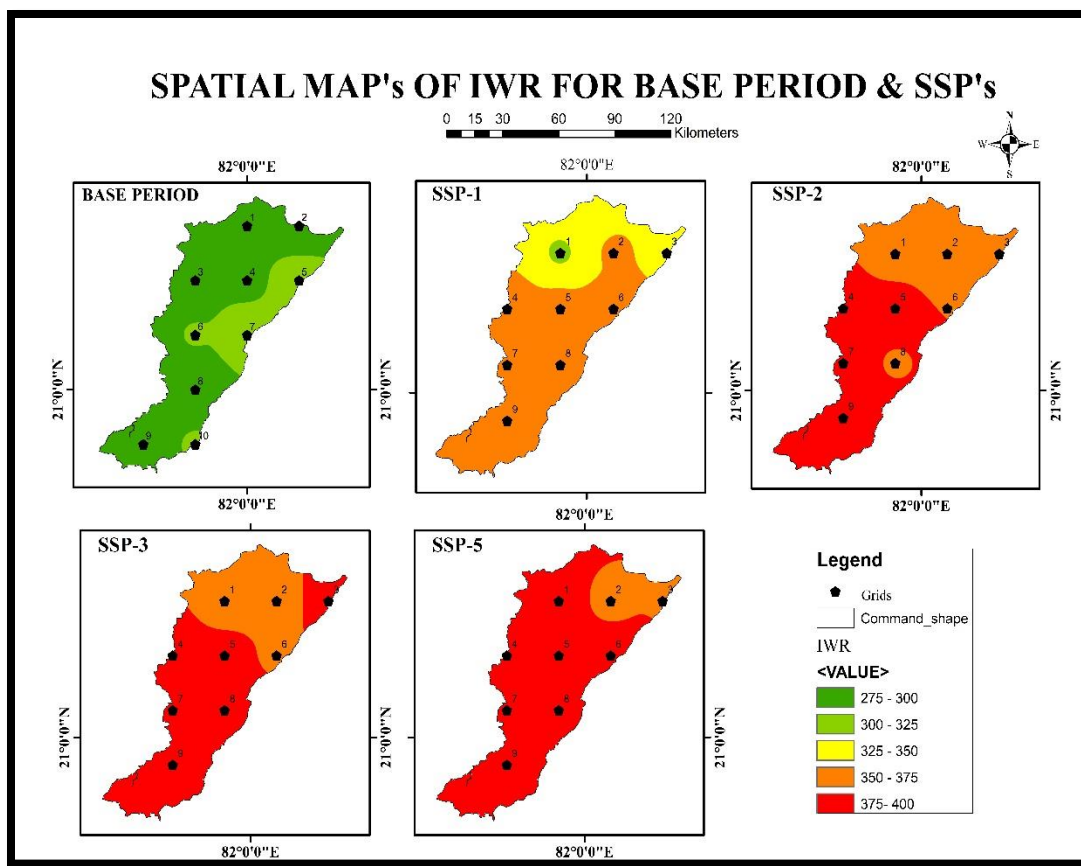


Figure 5.81 Spatial map of IWR for Base Period and SSP's.

The above percentage change of future irrigation demand has been used in NIH_resyP for developing the future rule curve for the Sondhur, Dudhawa, and Ravishankar Sagar reservoirs.

5.16 Prediction of future population in Mahanadi command

The Ravishankar Sagar Reservoir primarily supplies water to three districts in the Indian state of Chhattisgarh Dhamtari, Durg, and Raipur. This reservoir plays a crucial role in meeting the water needs of these districts. Predicting future populations and adjusting the reservoir rule curve accordingly helps ensure that the water supply infrastructure can meet future demands. By forecasting population growth and water needs, it can better plan for reservoir management, ensure sustainability, and meet the domestic water supply requirements effectively. The predicted population is shown in **Table 5.37**. Factor 1.92 has been multiplying in the current domestic supply for future domestic water demand estimation and developing a rule curve.

Table 5.37 Predicted population of Mahanadi domestic users for 2055.

S.N.	Year	Population			Total Population	Increment	Rate of Growth
		Dhamtari	Durg	Raipur			
1	1901	164530	564794	579370	1308694.00		
2	1911	197779	672847	696452	1567078.00	258384.00	0.20
3	1921	209792	683421	738757	1631970.00	64892.00	0.04
4	1931	230637	692559	812156	1735352.00	103382.00	0.06
5	1941	255951	799772	901297	1957020.00	221668.00	0.13
6	1951	276762	826050	974581	2077393.00	120373.00	0.06
7	1961	328920	1107721	1216875	2653516.00	576123.00	0.28
8	1971	410189	1469127	1640498	3519814.00	866298.00	0.33
9	1981	473361	1890467	1943361	4307189.00	787375.00	0.22
10	1991	587679	2397134	2529166	5513979.00	1206790.00	0.28
11	2001	706591	2810436	3016930	6533957.00	1019978.00	0.18
12	2011	799781	3343872	4063872	8207525.00	1673568.00	0.26
Geometrical mean							0.16
	P-2021				9489047		
	P-2031				10970667		
	P-2041				12683626		
	P-2051				14664047		
	P-2055				15767362		
Factor							1.92

5.17 Estimation of Reservoir Rule Curves for Climate Change Scenarios

From the calibrated MIKE NAM model for all catchments, the inflow series of all SSP scenarios at different dependability levels (50%, 60%, 75% 80%, and 90%) are estimated. The estimated percentage dependable flow of Sondhur, Dudhawa, Murumsilli and Ravishankar Sagar reservoirs for all SSPs scenarios (SSP126, SSP245 & SSP585) have been presented in **Table 5.38(a)-5.38(d) for SSP126, 5.39(a)-5.39(d) for SSP245 and 5.40(a) to 5.40(d) for SSP585**. Knowing the dependable inflows, water demands, evaporation depths, and reservoir features (FRL, MDDL, and EAC table), initial trial rule curves have been derived for all reservoirs using an NIH_ReSyP.

Table 5.38 (a) Percentage dependable flow of Sondhur Reservoir for SSP126.

Month	50%	60%	75%	80%	90%
Jan	5.83	4.79	3.26	2.72	1.52
Feb	4.62	3.86	2.68	2.25	1.23
Mar	3.88	3.18	2.16	1.80	0.97
Apr	3.22	2.67	1.84	1.54	0.87
May	3.32	2.66	1.78	1.50	0.91
Jun	6.51	5.14	3.59	3.15	2.29
Jul	40.12	33.57	24.18	20.96	13.75
Aug	49.19	42.87	33.52	30.19	22.43
Sep	28.94	24.22	17.49	15.18	10.05
Oct	19.45	15.25	9.78	8.06	4.60
Nov	8.71	6.95	4.67	3.95	2.49
Dec	7.10	5.85	3.97	3.31	1.79

Table 5.38 (b) Percentage dependable flow of Dudhawa Reservoir for SSP126.

Month	50%	60%	75%	80%	90%
Jan	5.11	4.43	3.49	3.18	2.48
Feb	2.79	2.39	1.86	1.69	1.32
Mar	1.75	1.50	1.16	1.05	0.82
Apr	1.13	0.98	0.77	0.69	0.54
May	0.86	0.70	0.51	0.45	0.34
Jun	3.49	2.24	1.12	0.86	0.44
Jul	59.86	49.04	34.11	29.16	18.51

Aug	85.97	75.19	59.57	54.11	41.58
Sep	53.87	46.93	37.20	33.89	26.43
Oct	30.18	25.38	19.35	17.47	13.52
Nov	13.99	12.12	9.70	8.92	7.25
Dec	8.47	7.46	6.03	5.53	4.41

Table 5.38 (c) Percentage dependable flow of Murumsilli Reservoir for SSP126.

Month	50%	60%	75%	80%	90%
Jan	12.95	11.22	8.66	7.76	5.66
Feb	9.66	8.38	6.48	5.80	4.22
Mar	8.47	7.33	5.68	5.10	3.78
Apr	6.81	5.89	4.54	4.07	2.96
May	5.81	5.03	3.89	3.49	2.56
Jun	6.11	5.15	3.93	3.55	2.73
Jul	19.56	16.28	11.77	10.28	7.04
Aug	31.66	27.23	20.87	18.67	13.69
Sep	29.21	25.30	19.47	17.38	12.50
Oct	25.19	21.85	17.06	15.39	11.61
Nov	19.90	17.25	13.20	11.72	8.19
Dec	16.10	13.99	10.83	9.69	7.04

Table 5.38 (d) Percentage dependable flow of Ravishankar Sagar Reservoir for SSP126.

Month	50%	60%	75%	80%	90%
Jan	22.80	19.78	15.72	14.38	11.43
Feb	11.68	10.05	7.93	7.24	5.76
Mar	6.94	6.00	4.74	4.32	3.41
Apr	4.23	3.58	2.79	2.55	2.04
May	3.40	2.71	1.96	1.76	1.35
Jun	63.40	42.56	19.02	12.89	3.34
Jul	331.20	283.50	216.04	193.01	141.40
Aug	389.27	342.76	275.23	251.58	197.00
Sep	232.15	205.17	167.22	154.24	124.83
Oct	146.32	125.09	97.44	88.56	69.49
Nov	70.06	60.66	48.44	44.50	36.00
Dec	40.15	35.27	28.48	26.18	21.02

Table 5.39 (a) Percentage dependable flow of Sondhur Reservoir for SSP245.

Month	50%	60%	75%	80%	90%
Jan	7.67	6.82	5.34	4.72	2.97
Feb	5.62	4.96	3.82	3.35	2.04
Mar	4.90	4.31	3.31	2.90	1.81
Apr	3.60	3.07	2.33	2.08	1.53
May	3.18	2.66	2.03	1.84	1.44
Jun	11.94	9.16	5.75	4.74	2.77
Jul	49.29	43.00	33.56	30.16	22.17
Aug	50.95	45.80	38.88	36.59	31.49
Sep	35.00	29.42	21.35	18.55	12.24
Oct	16.02	13.30	9.61	8.40	5.81
Nov	9.62	8.19	6.18	5.51	4.01
Dec	9.90	8.87	7.08	6.34	4.26

Table 5.39 (b) Percentage dependable flow of Dudhawa Reservoir for SSP245.

Month	50%	60%	75%	80%	90%
Jan	4.97	4.23	3.27	2.97	2.33
Feb	2.84	2.40	1.83	1.65	1.26
Mar	1.80	1.52	1.15	1.03	0.78
Apr	0.93	0.77	0.58	0.52	0.40
May	0.77	0.59	0.40	0.35	0.25
Jun	8.41	5.49	2.39	1.62	0.46
Jul	59.15	50.66	39.34	35.64	27.61
Aug	96.68	86.98	73.33	68.64	57.95
Sep	69.75	60.64	46.58	41.40	28.90
Oct	27.61	23.47	18.11	16.40	12.74
Nov	12.90	11.24	9.06	8.36	6.81
Dec	7.83	6.82	5.46	5.02	4.04

Table 5.39 (c) Percentage dependable flow of Murumsilli Reservoir for SSP245.

Month	50%	60%	75%	80%	90%
Jan	5.23	5.07	4.95	4.86	4.71
Feb	3.84	3.76	3.65	3.60	3.53
Mar	10.12	9.12	7.38	6.66	4.64
Apr	8.01	7.22	5.85	5.27	3.67
May	6.52	5.73	4.55	4.13	3.13
Jun	6.76	5.87	4.68	4.29	3.45
Jul	19.67	16.72	12.61	11.24	8.19
Aug	37.46	33.53	27.29	24.93	19.04
Sep	35.06	31.21	25.01	22.63	16.61
Oct	28.64	25.54	20.37	18.31	12.85
Nov	21.66	19.35	15.43	13.84	9.55
Dec	18.48	16.63	13.45	12.15	8.55

Table 5.39 (d) Percentage dependable flow of Ravishankar Sagar Reservoir for SSP245.

Month	50%	60%	75%	80%	90%
Jan	23.97	19.95	14.86	13.27	9.93
Feb	12.79	10.59	7.79	6.91	5.07
Mar	7.83	6.51	4.77	4.21	3.02
Apr	3.87	3.16	2.30	2.04	1.51
May	3.46	2.52	1.58	1.34	0.89
Jun	82.95	59.58	29.87	21.11	5.73
Jul	315.21	276.24	221.88	203.44	162.01
Aug	429.14	388.70	330.09	309.49	261.54
Sep	298.46	261.81	204.40	182.94	130.39
Oct	139.10	118.67	91.08	81.99	62.19
Nov	65.97	56.76	44.41	40.35	31.49
Dec	41.87	35.94	27.64	24.83	18.54

Table 5.40 (a) Percentage dependable flow of Sondhur Reservoir for SSP585.

Month	50%	60%	75%	80%	90%
Jan	5.99	5.08	3.82	3.40	2.46
Feb	4.09	3.43	2.49	2.17	1.44
Mar	3.71	3.10	2.23	1.92	1.25
Apr	3.13	2.60	1.84	1.58	1.00
May	2.74	2.21	1.51	1.29	0.84
Jun	4.74	3.41	1.98	1.59	0.90
Jul	40.41	34.33	24.99	21.57	13.43
Aug	53.78	47.56	38.48	35.27	27.84
Sep	29.40	24.98	18.27	15.84	10.13
Oct	13.62	10.78	7.39	6.38	4.39
Nov	8.74	7.27	5.25	4.58	3.11
Dec	7.43	6.32	4.70	4.13	2.83

Table 5.40 (b) Percentage dependable flow of Dudhawa Reservoir for SSP585.

Month	50%	60%	75%	80%	90%
Jan	4.58	4.05	3.38	3.17	2.72
Feb	2.55	2.23	1.82	1.69	1.41
Mar	1.61	1.41	1.16	1.08	0.90
Apr	0.87	0.76	0.62	0.58	0.48
May	0.53	0.45	0.36	0.34	0.28
Jun	1.79	1.16	0.59	0.46	0.25
Jul	57.36	47.98	34.16	29.30	18.25
Aug	93.81	83.93	69.82	64.93	53.70
Sep	56.83	49.84	39.09	35.13	25.61
Oct	23.91	20.81	16.89	15.66	13.02
Nov	11.80	10.62	9.08	8.58	7.49
Dec	6.88	6.26	5.46	5.20	4.64

Table 5.40 (c) Percentage dependable flow of Murumsilli Reservoir for SSP585.

Month	50%	60%	75%	80%	90%
Jan	11.64	10.23	8.22	7.52	5.93
Feb	8.50	7.40	5.84	5.30	4.08
Mar	7.71	6.69	5.23	4.72	3.56
Apr	6.10	5.29	4.14	3.73	2.82
May	5.27	4.57	3.56	3.21	2.39
Jun	4.72	3.98	3.02	2.71	2.04
Jul	15.68	13.06	9.52	8.35	5.85
Aug	32.61	29.05	23.91	22.12	17.97
Sep	30.38	27.00	21.53	19.41	14.00
Oct	23.30	19.97	15.14	13.45	9.62
Nov	17.37	14.95	11.47	10.26	7.50
Dec	14.85	12.92	10.11	9.12	6.85

Table 5.40 (d) Percentage dependable flow of Ravishankar Sagar Reservoir for SSP585.

Month	50%	60%	75%	80%	90%
Jan	21.97	19.00	15.26	14.09	11.59
Feb	10.99	9.55	7.72	7.14	5.89
Mar	6.47	5.68	4.66	4.34	3.64
Apr	3.49	3.04	2.48	2.31	1.93
May	2.08	1.78	1.42	1.31	1.09
Jun	42.79	26.52	10.28	6.58	1.49
Jul	332.39	293.03	235.82	215.75	169.38
Aug	423.69	381.64	320.03	298.22	247.19
Sep	260.16	230.67	182.76	164.21	116.87
Oct	120.04	103.43	82.27	75.57	61.26
Nov	61.74	53.94	43.49	40.06	32.52
Dec	35.60	31.32	25.79	24.01	20.14

For a reservoir, different rule curves can be specified for different water availability and water demand conditions. Monthly demands of all SSP scenarios (SSP126, SPP245 & SSP585) for each reservoir are given in **Tables 5.41 to 5.43**. The position of rule curves for various demands depends on the relative availability of water. Starting upwards from the dead storage level, first lies the rule curve for 75% dependable flow condition. This rule curve is calculated for the case when water is scarce and it is possible to meet only the 75% dependable scenario demands. When the reservoir level falls below this rule level, it is suggested to meet full/partial 75% dependable scenario demands.

For deriving a rule curve for a water availability condition, the monthly inflow series at the project site is analysed and inflow values corresponding to different probability levels, say 50%, 60%, 75%, 80%, and 90% are worked out for each month using a statistical approach. Using this dependable inflow series, the water availability is assumed to correspond to a particular probability of the inflow series. For deriving critical rule levels for different water availability conditions, the water demands at corresponding conditions are assumed. A reservoir is assumed to be empty at the end of a water year. Then, computations of end-of-month reservoir levels are made after allowing for water demands and evaporation losses from the reservoir surface. Rule curves for different water availability conditions are computed separately. First, computations are made for the least water availability condition. The rule curve for a water availability condition is calculated for the case when water is scarce in the reservoir and it is just possible to meet various demands at that condition in full throughout the year. Rule levels are calculated assuming the following conditions:

- i) Reservoir level reaches to intended lowest level by the end of the water year (May end).
- ii) Inflow at a particular water availability condition (75%, 65%, or average) is entering the reservoir.
- iii) Water demands corresponding to that water availability condition are satisfied.

Backward computations are made starting from the end of May. Evaporation loss is considered at a normal monthly rate over the surface area of the reservoir corresponding to a particular elevation. The following formula is used:

$$\text{Storage}_{\text{begin}} = \text{Storage}_{\text{end}} - \text{Inflow} + \text{Release} + \text{Evaporation} + \text{Spill} \quad \dots(5.1)$$

Effort is made to find such a level at which all the demands can be satisfied in full even at that water availability condition. This way, the initial trial rule curve levels for various water availability conditions are computed. It needs to be mentioned that the rule curve level in any month rises with the water availability condition. Thus, the rule curve level for the 65% condition will be higher than the 75% condition, and so on.

The rule curves obtained from SSPs scenarios for each reservoir (Sondhur, Dudhawa, Murumsilli and Ravishankar Sagar) in the system are shown in **Figure 5.82(a) to Figure 5.82(d) for SSP126, Figure 5.83(a) to Figure 5.83(d) for SSP245 and Figure 5.84(a) to Figure 5.84 (d) for SSP585**. Here domestic supply is considered as priority demand, environmental flow is the second priority, irrigation is third and hydropower is considered as fourth priority demand.

Table 5.41 Monthly demand of all reservoirs (Sondhur, Dudhawa, Murumsilli, and Ravishankar Sagar Reservoir) all value in MCM for SSP126.

Months	Sondhur reservoir			Dudhawa reservoir		Murumsilli reservoir	Ravishankar Sagar reservoir				
	ENV Demand	Irri Demand	Link transfer	ENV Demand	Irri Dudhawa	ENV Demand	WS Demand	ENV Demand	MMC Irri.	MFC Irri.	HP Demand
Jan	0.01	6.65	0.76	0.010	0.95	0.023	23.84	0.04	51.29	25.73	2.73
Feb	0.01	6.81	1.20	0.006	1.88	0.017	23.65	0.02	57.34	19.71	2.58
Mar	0.01	12.21	1.11	0.003	2.43	0.015	15.11	0.01	94.04	22.44	3.96
Apr	0.01	13.77	1.37	0.002	2.45	0.012	28.58	0.01	127.65	30.11	4.24
May	0.01	8.59	0.84	0.003	5.08	0.010	32.63	0.02	86.62	20.09	2.12
Jun	0.02	0.11	0.18	0.025	0.39	0.013	21.09	0.17	19.67	12.32	0.26
Jul	0.07	2.62	5.51	0.113	1.79	0.037	26.93	0.60	33.70	14.78	0.45
Aug	0.09	8.30	17.27	0.157	2.00	0.058	24.77	0.71	143.45	18.47	4.15
Sep	0.05	10.60	19.22	0.101	4.45	0.051	11.91	0.43	307.20	26.56	6.50
Oct	0.04	9.37	16.36	0.069	5.47	0.045	14.22	0.30	269.05	27.70	5.09
Nov	0.02	0.47	8.97	0.030	0.13	0.034	13.72	0.15	69.69	9.09	0.33
Dec	0.01	0.01	2.81	0.016	0.04	0.028	22.27	0.07	2.40	10.49	0.18

Table 5.42 Monthly demand of all reservoirs (Sondhur, Dudhawa, Murumsilli, and Ravishankar Sagar Reservoir) all value in MCM for SSP245.

Months	Sondhur reservoir			Dudhawa reservoir		Murumsilli reservoir	Ravishankar Sagar reservoir				
	ENV Demand	Irri Demand	Link transfer	ENV Demand	Irri Dudhawa	ENV Demand	WS Demand	ENV Demand	MMC Irri.	MFC Irri.	HP Demand
Jan	0.01	7.03	0.8	0.01	1.01	0.02	0.04	23.84	54.28	27.23	2.28
Feb	0.01	7.2	1.27	0.01	1.99	0.02	0.02	23.65	60.69	20.86	2.15
Mar	0.01	12.92	1.18	0.00	2.57	0.02	0.01	15.11	99.53	23.74	3.30
Apr	0.01	14.57	1.45	0.00	2.60	0.01	0.01	28.58	135.09	31.86	3.53
May	0.01	9.09	0.89	0.01	5.37	0.01	0.02	32.63	91.67	21.26	1.77
Jun	0.03	0.11	0.19	0.03	0.42	0.01	0.17	21.09	20.82	13.04	0.22
Jul	0.09	2.77	5.83	0.13	1.90	0.04	0.60	26.93	35.67	15.65	0.37
Aug	0.10	8.78	18.28	0.18	2.12	0.07	0.71	24.77	151.81	19.55	3.46
Sep	0.07	11.22	20.34	0.13	4.71	0.06	0.43	11.91	325.12	28.11	5.42
Oct	0.03	9.91	17.31	0.06	5.79	0.05	0.30	14.22	284.74	29.31	4.24
Nov	0.02	0.49	9.49	0.03	0.14	0.04	0.15	13.72	73.75	9.62	0.28
Dec	0.02	0.01	2.97	0.02	0.04	0.03	0.07	22.27	2.54	11.10	0.15

Table 5.43 Monthly demand of all reservoirs (Sondhur, Dudhawa, Murumsilli, and Ravishankar Sagar Reservoir) all value in MCM for SSP585.

Months	Sondhur reservoir			Dudhawa reservoir		Murumsilli reservoir	Ravishankar Sagar reservoir				
	ENV Demand	Irri Demand	Link transfer	ENV Demand	Irri Dudhawa	ENV Demand	WS Demand	ENV Demand	MMC Irri.	MFC Irri.	HP Demand
Jan	0.01	6.98	0.80	0.01	1.00	0.02	23.84	0.05	53.85	27.01	2.89
Feb	0.01	7.15	1.27	0.01	1.97	0.02	23.65	0.02	60.21	20.70	2.73
Mar	0.01	12.82	1.18	0.00	2.55	0.01	15.11	0.01	98.74	23.56	4.19
Apr	0.01	14.46	1.45	0.00	2.58	0.01	28.58	0.01	134.03	31.61	4.49
May	0.01	9.02	0.89	0.00	5.33	0.01	32.63	0.01	90.95	21.09	2.25
Jun	0.02	0.11	0.19	0.02	0.41	0.01	21.09	0.17	20.65	12.94	0.27
Jul	0.07	2.75	5.83	0.11	1.88	0.03	26.93	0.62	35.39	15.52	0.47
Aug	0.10	8.71	18.28	0.17	2.10	0.06	24.77	0.76	150.62	19.39	4.39
Sep	0.05	11.13	20.34	0.10	4.67	0.05	11.91	0.44	322.56	27.89	6.88
Oct	0.04	9.84	17.31	0.06	5.74	0.04	14.22	0.28	282.50	29.08	5.38
Nov	0.02	0.49	9.49	0.03	0.14	0.03	13.72	0.13	73.17	9.54	0.35
Dec	0.01	0.01	2.97	0.02	0.04	0.03	22.27	0.08	2.52	11.01	0.19

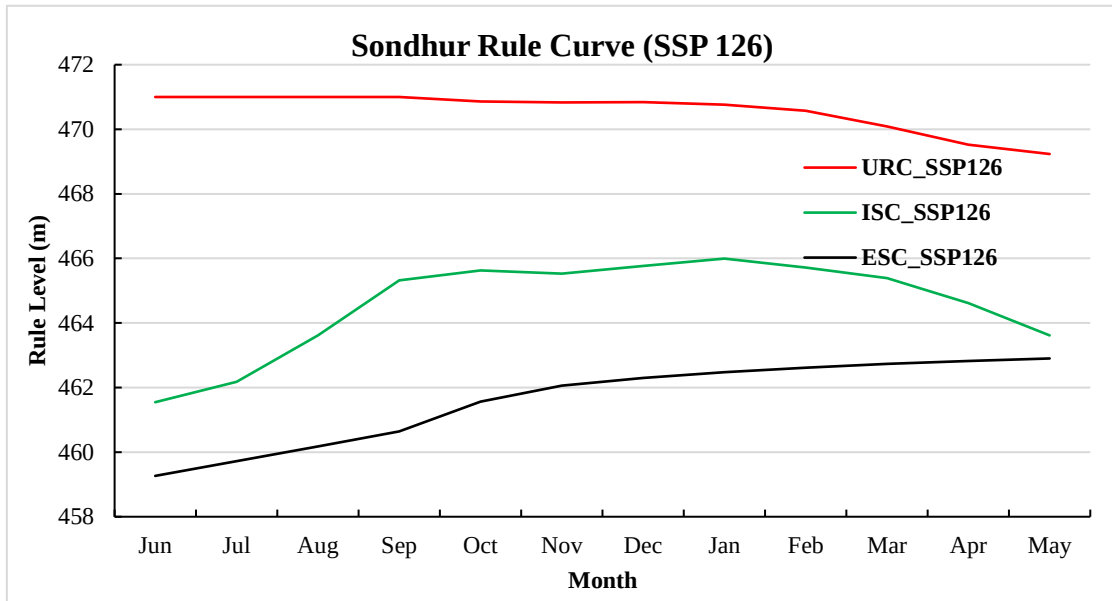


Figure 5.82 (a) Rule curve for Soundur reservoir under SSP126 scenario.

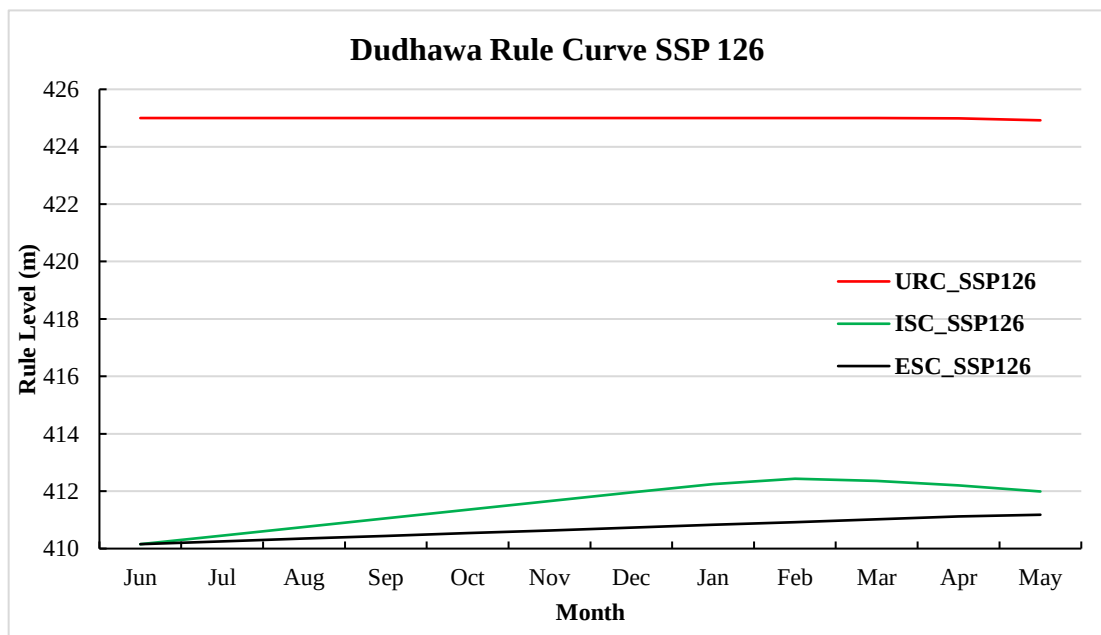


Figure 5.82 (b) Rule curve for Dudhawa reservoir under SSP126 scenario.

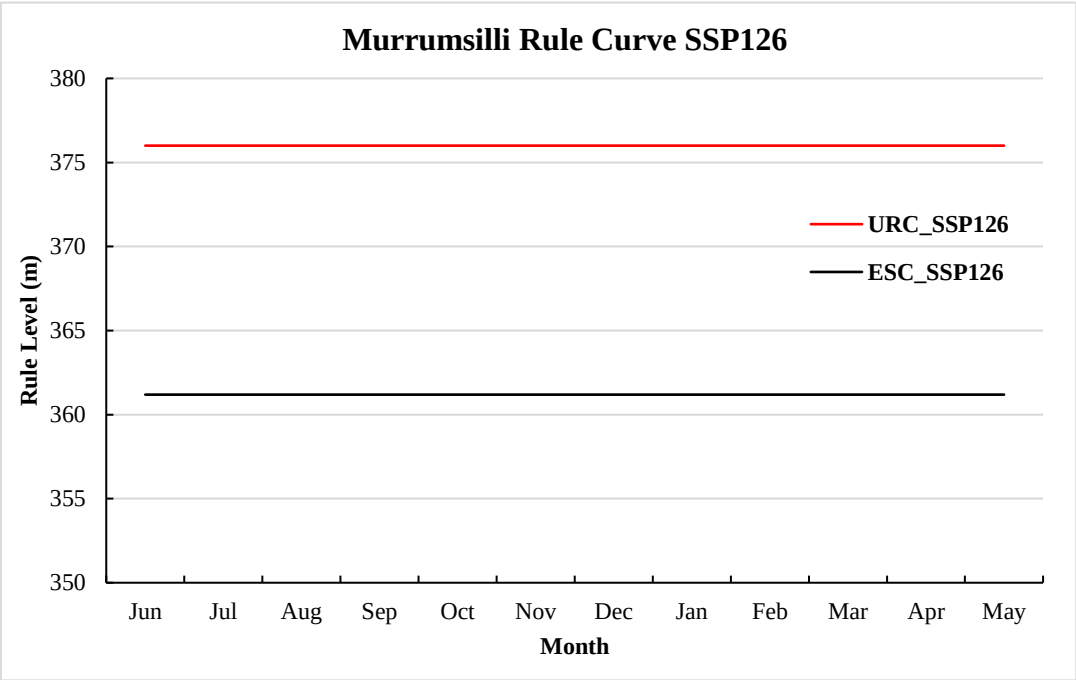


Figure 5.82 (c) Rule curve for Murumsilli reservoir under SSP126 scenario.

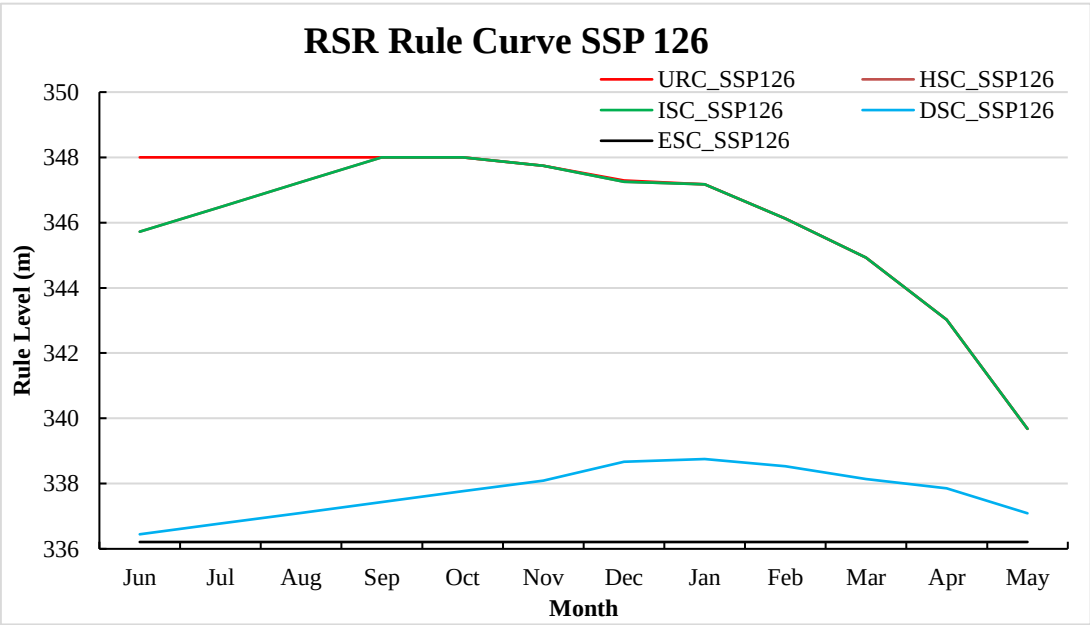


Figure 5.82 (d) Rule curve for Ravishankar Sagar reservoir under SSP126 scenario.

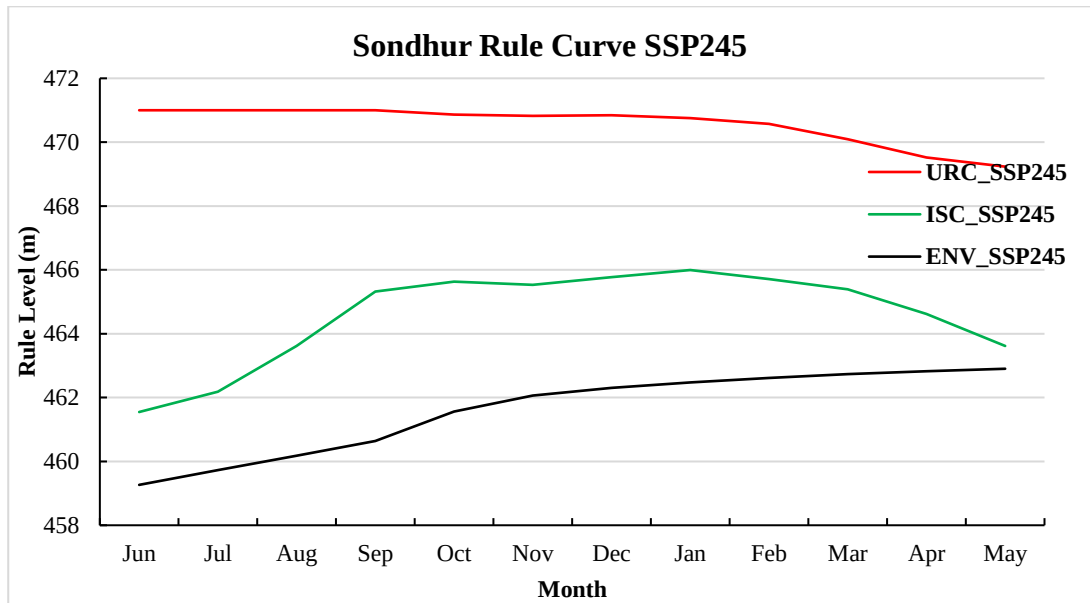


Figure 5.83 (a) Rule curve for Soundhur reservoir under SSP245 scenario.

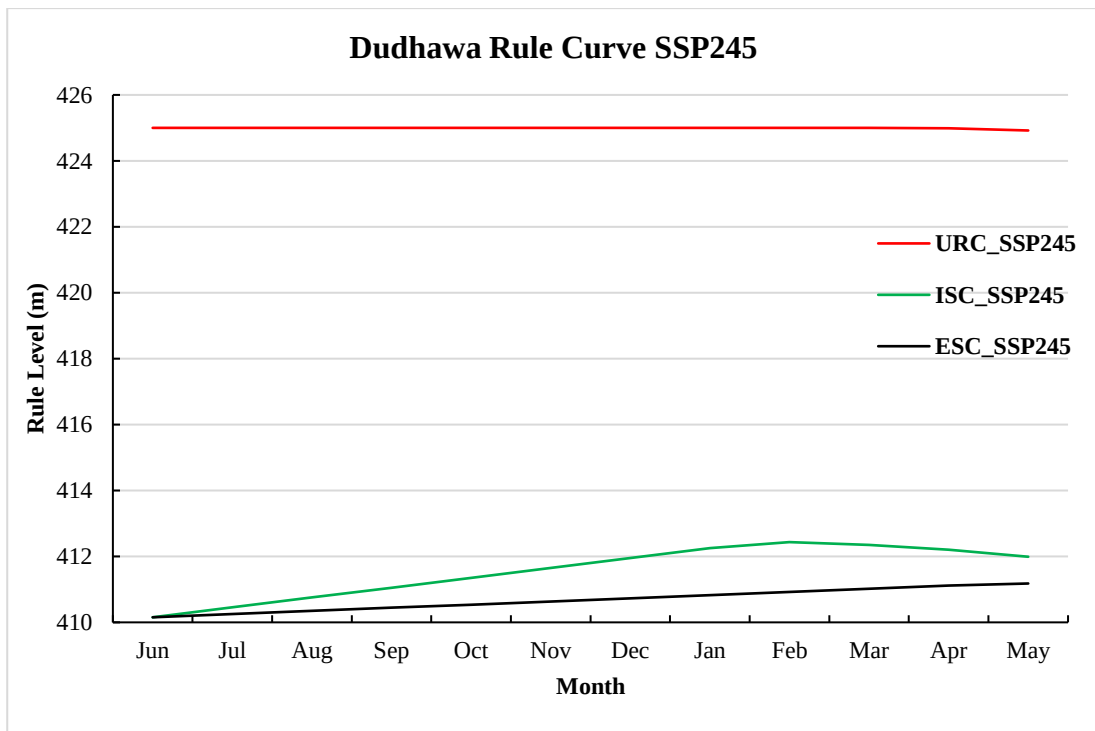


Figure 5.83 (b) Rule curve for Dudhawa reservoir under SSP245 scenario.

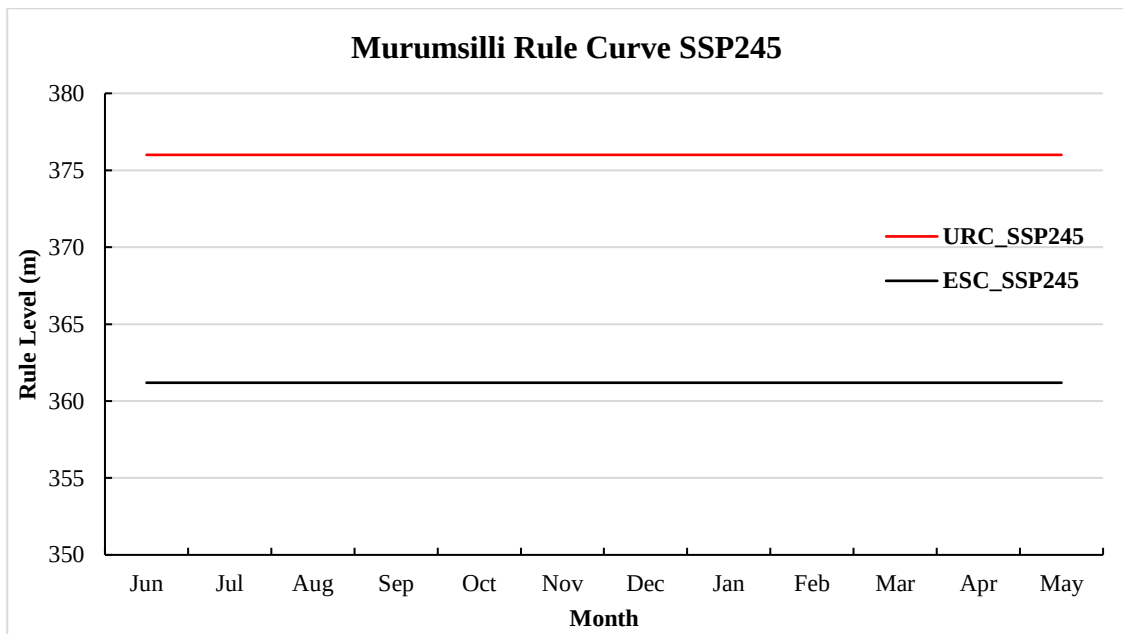


Figure 5.83 (c) Rule curve for Murumsilli reservoir under SSP245 scenario.

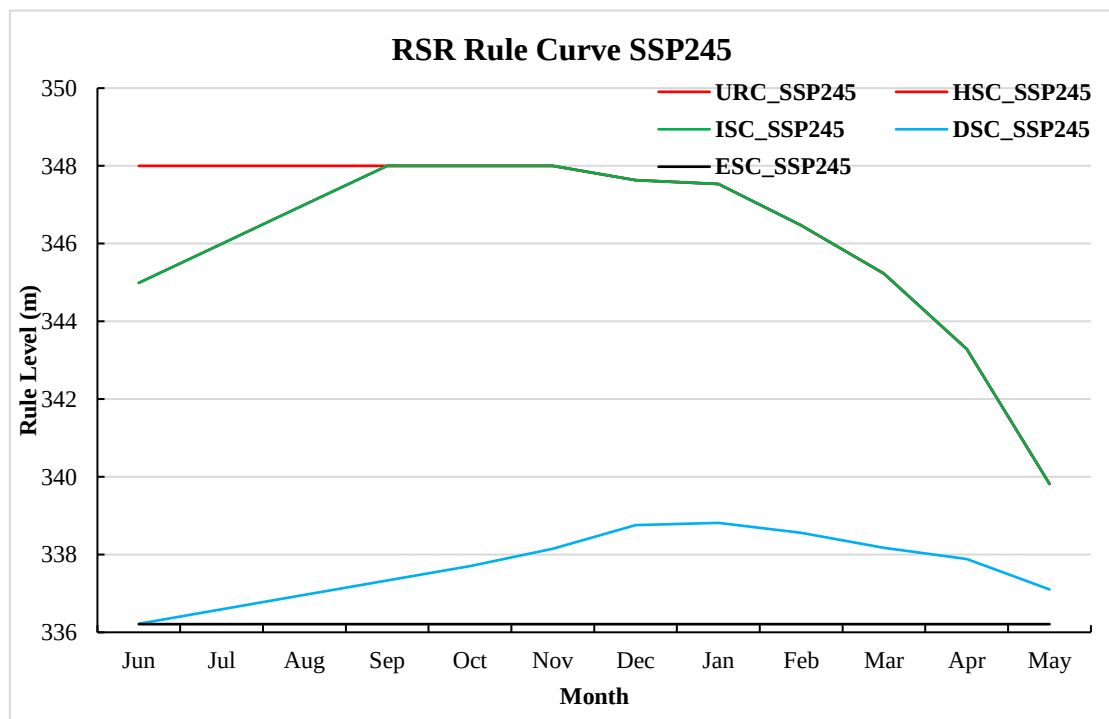


Figure 5.83 (d) Rule curve for Ravishankar Sagar reservoir under SSP245 scenario.

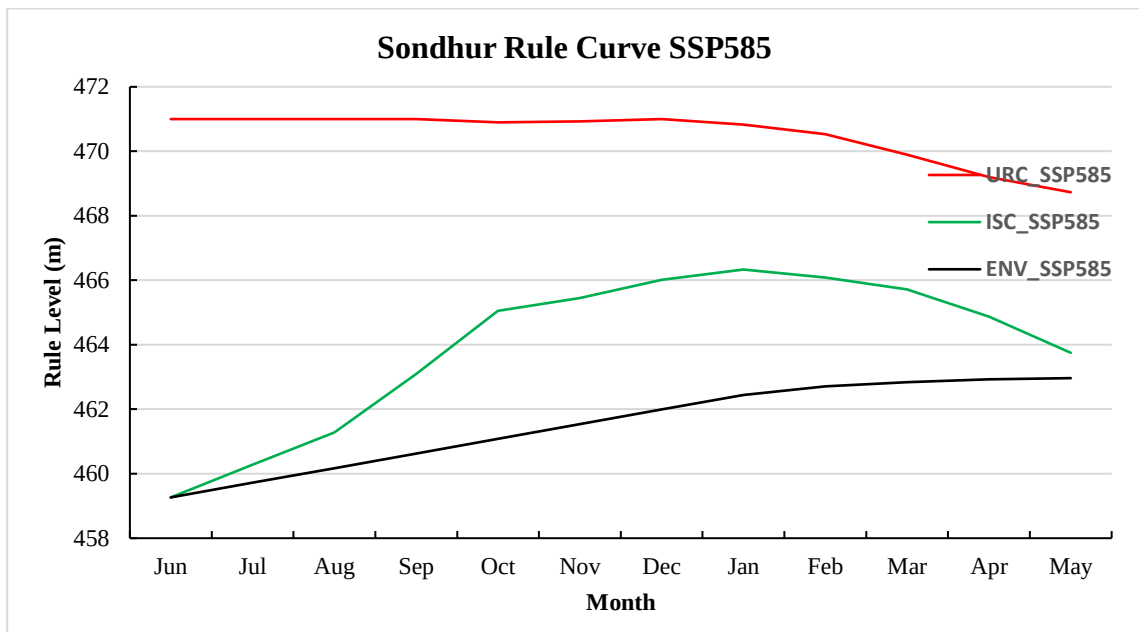


Figure 5.84 (a) Rule curve for Soundhur reservoir under SSP585 scenario.

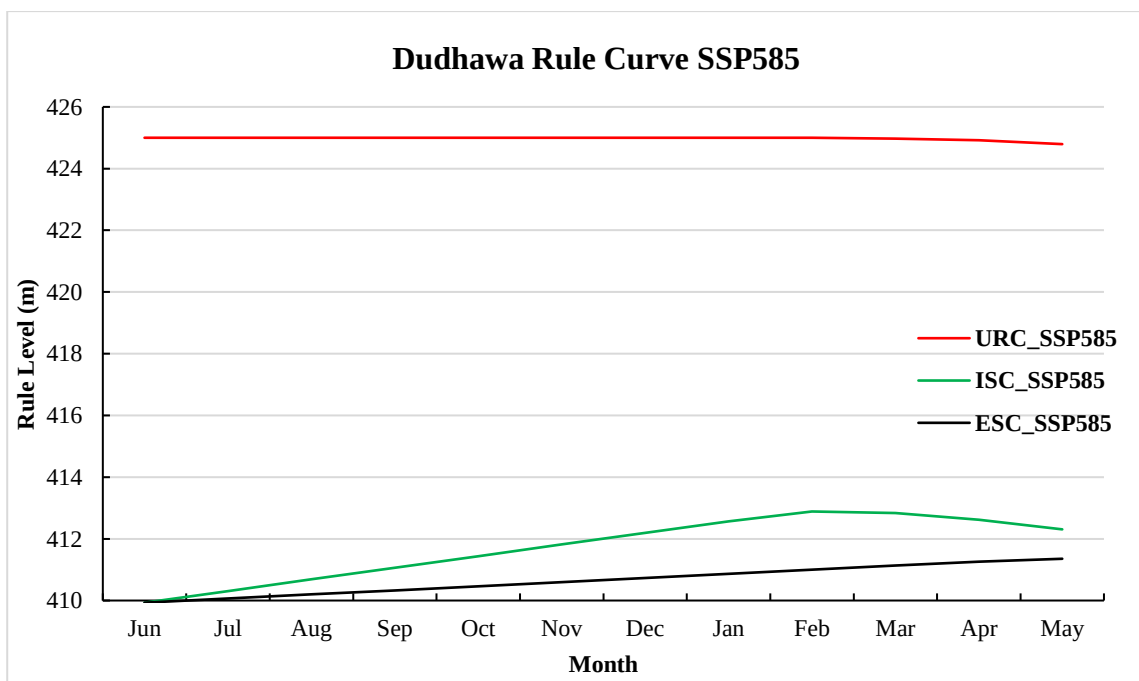


Figure 5.84 (b) Rule curve for Dudhawa reservoir under SSP585 scenario.

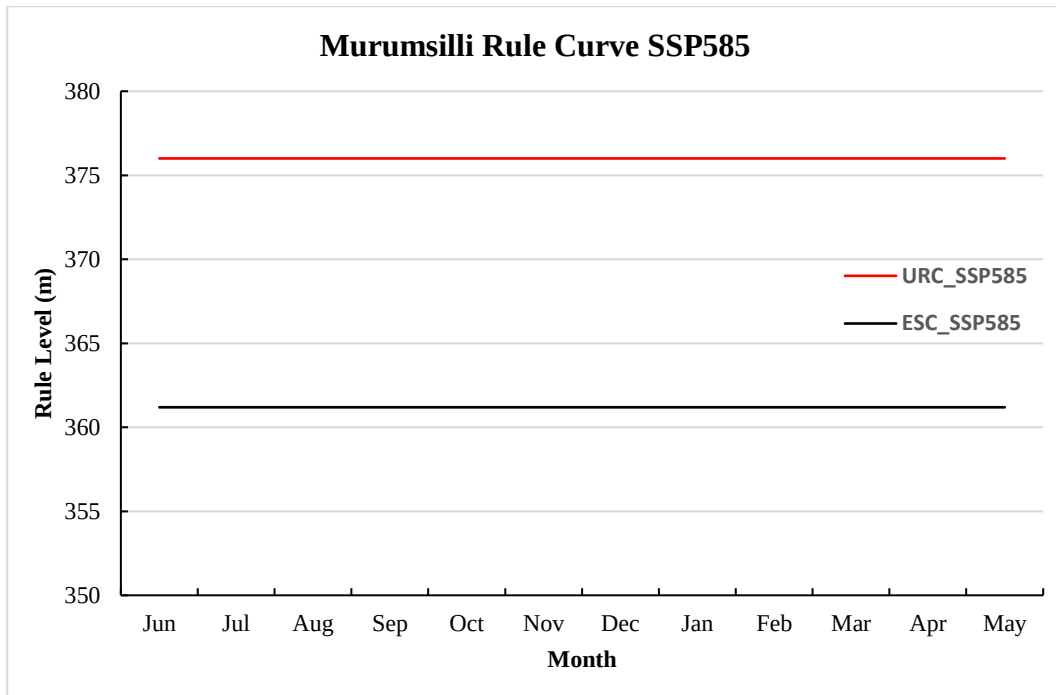


Figure 5.84 (c) Rule curve for Murumsilli reservoir under SSP585 scenario.

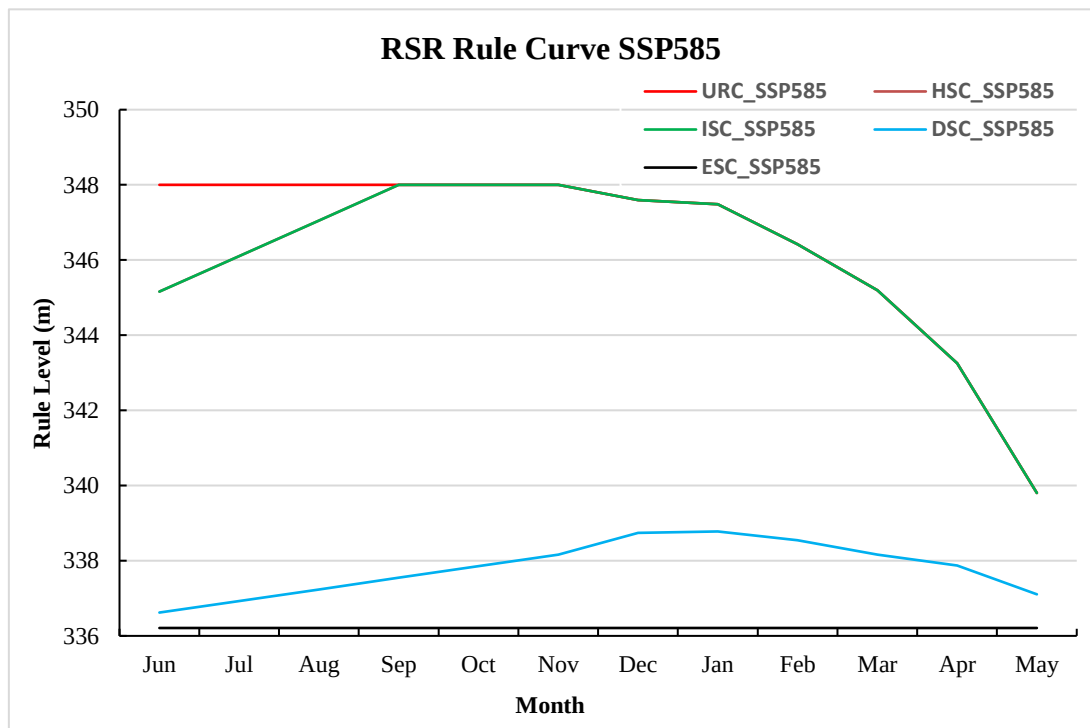


Figure 5.84 (d) Rule curve for Ravishankar Sagar reservoir under SSP585 scenario.

5.17.1 Methodology for integrated operation analysis for MRP system

NIH_ReSyP, a Software developed at NIH is used for the integrated simulation of various projects in the MRP. Each reservoir in the system is simulated as per the water balance approach:

$$S_{t+1} = S_t + \text{Inflow} - \text{Releases} - \text{Spill} - \text{Evaporation} \quad \dots(5.2)$$

The steps involved in the underlying methodology of computations are as follows:

- f) First, all the data for all the structures in the system is read and saved in specified variables.
- g) The simulation is started for a time step and all the projects are simulated as per their connectivity for that time step. The whole system is simulated for subsequent time steps till the end of the simulation period.
- h) In a time step, the projects are simulated from upstream to downstream. For each project, the demands are satisfied in the order of priority as per the water availability and the operating levels. The return flows and spills are transferred as inflow for the downstream projects.
- i) The evaporation is estimated iteratively. For a time step, some final elevation is assumed and the evaporation loss is computed. The project is simulated and the final elevation so obtained is compared with that initially assumed. Several iterations are made till the value converges.
- j) All the variables are recorded and an output file is created which gives a complete glimpse of the simulation analysis at each 10-daily time step for each project.

5.17.2 Operation guidelines suggested by WRD, Chhattisgarh

- 1. Sondhur Reservoir will continuously release water to Dudhawa Reservoir during monsoon after ensuring its own Kharif irrigation demands.
- 2. From the middle of September if required to take up the maintenance of spillway gates and head regulator gates balance storage of the Sondhur reservoir will be transferred to Dudhawa. Simultaneously water from Dudhawa and Murumsilli will also be transferred to Ravishnkar Sagar in case there is adequate storage space even after storing the Rabi and minimum carry-over requirement of the next year.
- 3. The rate of drawdown in all dams will be 10cm/day as per design requirements.

4. In the Sondhur reservoir, during high flow when the reservoir level is at 466 m the incoming water will be passed over the spillway taking care that the rate of outflow does not exceed the rate of inflow in the reservoir.
5. In Ravishankar Sagar, the operation during the flood period should be done in such a way that the reservoir is not depleted below 348.7 m by August end. It should be filled up to FRL 348.7 m from 1st September onward till the end of the monsoon.
6. No release from Murumsilli and Dudhawa is planned from June to September only spills will reach Ravishankar.

5.18 Integrated Operation of the System with Rule Curve under climate change scenarios

Climate change is expected to significantly influence both water availability and demand across different regions and sectors. Changes in temperature, precipitation patterns, and the frequency of extreme weather events like droughts and floods will likely lead to shifts in the timing and quantity of water supply. At the same time, rising temperatures and altered ecosystems may increase demand for water in areas such as agriculture, energy production, and domestic use.

As these changes unfold, it becomes essential to study how climate change will impact the balance between water supply and demand to ensure sustainable management. This requires an integrated approach that considers not only physical changes in water resources but also the competing needs of different sectors and the adaptation strategies that may be necessary. By examining the complex interactions between climate, water availability, and human usage, we can develop more resilient and adaptive water management systems to address near-term future challenges. The study examines three different climate scenarios—SSP126, SSP245, and SSP585 to explore near-term future changes in water availability and demands for the period 2025-2055.

5.18.1 SSP 126

SSP126 represents a scenario with low greenhouse gas emissions and a pathway towards sustainable development, which assumes significant efforts to mitigate climate change. This scenario generally predicts more stable water availability with moderate changes in water demand. For the integrated operation of the MRP under climate change

scenarios, the ReSyP model was initially used to develop rule curve levels for all reservoirs. Using the developed rule curves integrated operation is carried out. Water is released downstream once the reservoir levels exceed the rule curve thresholds. These rule curves are based on dependable water availability conditions and adjusted water demands. Future water supply demands were projected using population growth data, while irrigation demands were estimated by accounting for climate change variables and corresponding shifts in agricultural areas, utilizing the CROPWAT model. The integrated operation also performs reliability analyses for each project to assess its ability to meet both full and critical demands. Critical demands are defined as 90% of the full demand for domestic water supply and 75% for irrigation and other uses. This threshold signifies that water supply falling below this level of demand is considered a critical failure to meet demand. It helps evaluate a project's reliability in meeting essential water supply demands, ensuring that critical demands are consistently met. By identifying critical demand levels, planners can anticipate potential shortages and implement measures to enhance supply reliability before problems arise. Understanding where shortfalls may occur allows for making planning decisions, such as increasing storage capacity or improving distribution systems. Setting these thresholds encourages better management of water use, promoting conservation practices among consumers, reducing overall demand during peak periods, and implementing measures to enhance supply reliability. The results of this integrated operation under climate change scenarios are presented through various figures and tables.

Tables 5.44, 5.45, and 5.46 provide detailed insights into the reliability of several reservoirs—Sondhur, Dudhawa, Murumsilli, and Ravishankar—in meeting different water demands on various timescales: annually, monthly, and ten-daily basis. These demands include full and critical water supply (WS), minimum flow (MF), irrigation (Irr), link (Lnk), and power demands. The average volume reliability of various projects is given in **Table 5.47**

The annual reliability, as shown in **Table 5.44**, Ravishankar generally shows lower annual reliability in meeting full irrigation and power demands compared to other reservoirs in the integrated operation. While Sondhur, Dudhawa, and Murumsilli achieve full reliability in most categories, including critical and full water supply, Ravishankar falls behind, especially in irrigation and power demands, where its reliability is significantly lower. However, Ravishankar performs well in meeting critical water supply and critical minimum

flow demands, showing high reliability for these needs. Sondhur, while performing well, shows a lower reliability (80%) for full minimum flow and irrigation compared to the other reservoirs.

On a monthly basis, Ravishankar improves its performance but is still unable to meet full irrigation and power demands. Sondhur, Dudhawa, and Murumsilli show high reliability for both full and critical demands. Ravishankar, while not fully meeting all demands, demonstrates higher reliability for critical water supply and critical irrigation needs on a monthly scale. The ten-daily reliability analysis shows that the Ravishankar Sagar Reservoir exhibits improved performance compared to its annual and monthly reliability, particularly for full irrigation demands. Ravishankar remains highly reliable in meeting critical water supply and municipal demands, consistent with its performance in the other timescales. Sondhur, Dudhawa, and Murumsilli continue to exhibit full reliability across most categories. Full power supply reliability remains low on ten daily level too at Ravishankar.

Volume reliability is high across most demands. Ravishankar shows a higher irrigation reliability on a volumetric basis, though power supply reliability is still quite low. It performs well in meeting water supply and municipal demands but fails to meet irrigation and power demands, especially when considering full demands. Sondhur, Dudhawa, and Murumsilli Reservoirs exhibit high reliability across all demands. Reliability tends to improve when moving from annual to ten daily scales, particularly for Ravishankar Reservoir. Variability in water availability and demand due to changing climate patterns could affect the reservoir's ability to consistently meet all needs, particularly for irrigation and power.

Table 5.44 Average annual reliability in meeting demands of the projects for SSP126.

Demands	Annual Reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
Full WS demands	-	-	-	100
Full MF demands	80	100	100	73.333
Full Irr demands	80	100	100	0
Full Lnk demands	76.667	-	-	
Full Power demands	-	-	-	0
Critical WS demands	-	-	-	100

Critical MF demands	100	100	100	100
Critical Irr demands	86.667	100	100	80
Critical Power demands	-	-	-	56.667

Table 5.45 Average Monthly reliability in meeting demands of the projects for SSP126.

Demands	Monthly Reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
Full WS demands	-	-	-	100
Full MF demands	89.444	100	100	94.722
Full Irr demands	89.722	100	100	36.111
Full Link demands	86.389	-	-	
Full Power demands		-	-	29.167
Critical WS demands		-	-	100
Critical MF demands	100	100	100	100
Critical Irr demands	90	100	100	85.556
Critical Power demands	-	-	-	51.667

Table 5.46 Average ten daily reliability in meeting demands of the projects for SSP126.

Demands	Ten Daily Reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
Full WS demands	-	-	-	100
Full MF demands	92.315	100	100	97.13
Full Irr demands	93.519	100	100	43.056
Full Link demands	88.056	-	-	
Full Power demands		-	-	30
Critical WS demands		-	-	100
Critical MF demands	100	100	100	100
Critical Irr demands	93.519	100	100	89.259
Critical Power demands	-	-	-	53.148

Table 5.47. Volume reliability in meeting demands of the projects for SSP126

Demands	Volume reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
WS demands	-	-	-	100
MF demands	99.942	100	100	99.981
Irr demands	92.594	100	100	84.835
Link demands	90.04	-	-	-
Power demands	-	-	-	50.665

Figure 5.85 represents the storage and spill behavior of the reservoirs during the integrated operation of the system in the SSP126 scenario. **Figures 5.86-5.89** show the demand-supply plots for each demand of the reservoir for each of the projects.

The ten-daily average results show a pattern **Figure 5.90**, where Sondhur faces some irrigation demand deficits during the monsoon months of August and September. Additionally, the link transfer demand is not met from August to November. During the non-monsoon period, Sondhur provides sufficient water to meet the link demand, which is lower during this time. However, it is still unable to fully meet its own irrigation demands during the non-monsoon months. Applying rule curves therefore does not seem to give much advantage in the case of Sondhur and Dudhawa reservoir results show that on ten daily average basis, it can meet its total irrigation demands completely (See **Figure 5.91**).

The results indicate that Ravishankar requires more water from upstream reservoirs during the non-monsoon season compared to the monsoon season **Figure 5.91.1**. This could be because a significant portion of the monsoon water demand is met by spills from Dudhawa and Murumsilli, particularly from Murumsilli **Figure 5.91.2**. In terms of controlled water releases, **Figure 5.91.3** shows that approximately 63% of the water comes from Dudhawa, while 37% is released from Murumsilli to meet the rest of the deficit at Ravishankar, after accounting for the water used from spills. However, it should be noted that not all the water spilled from Dudhawa and Murumsilli is necessarily utilized at Ravishankar. If the water is not needed, it may also be spilled from Ravishankar.

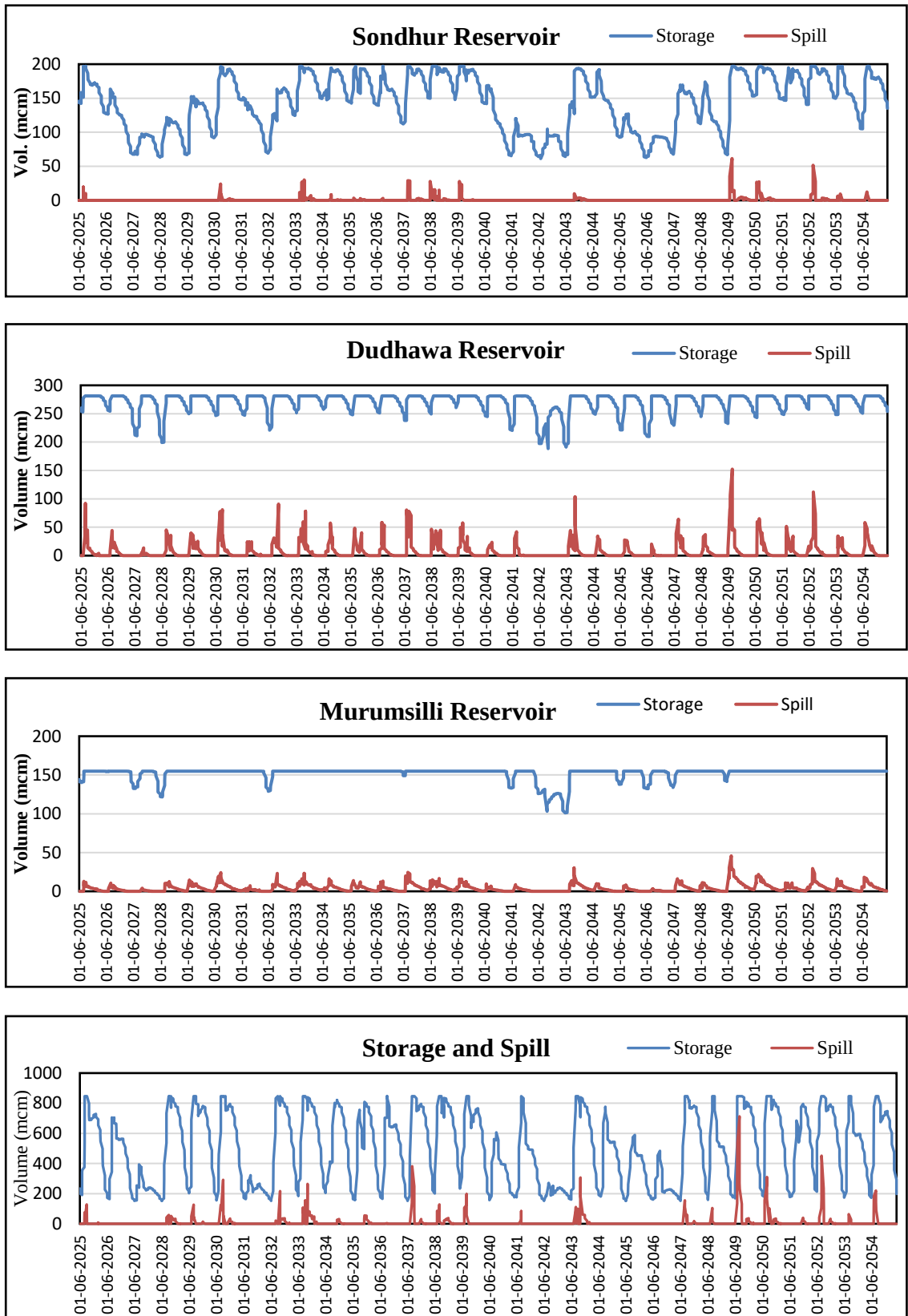


Figure 5.85 Storage and spill behaviors of the reservoirs during integrated operation (SSP126).

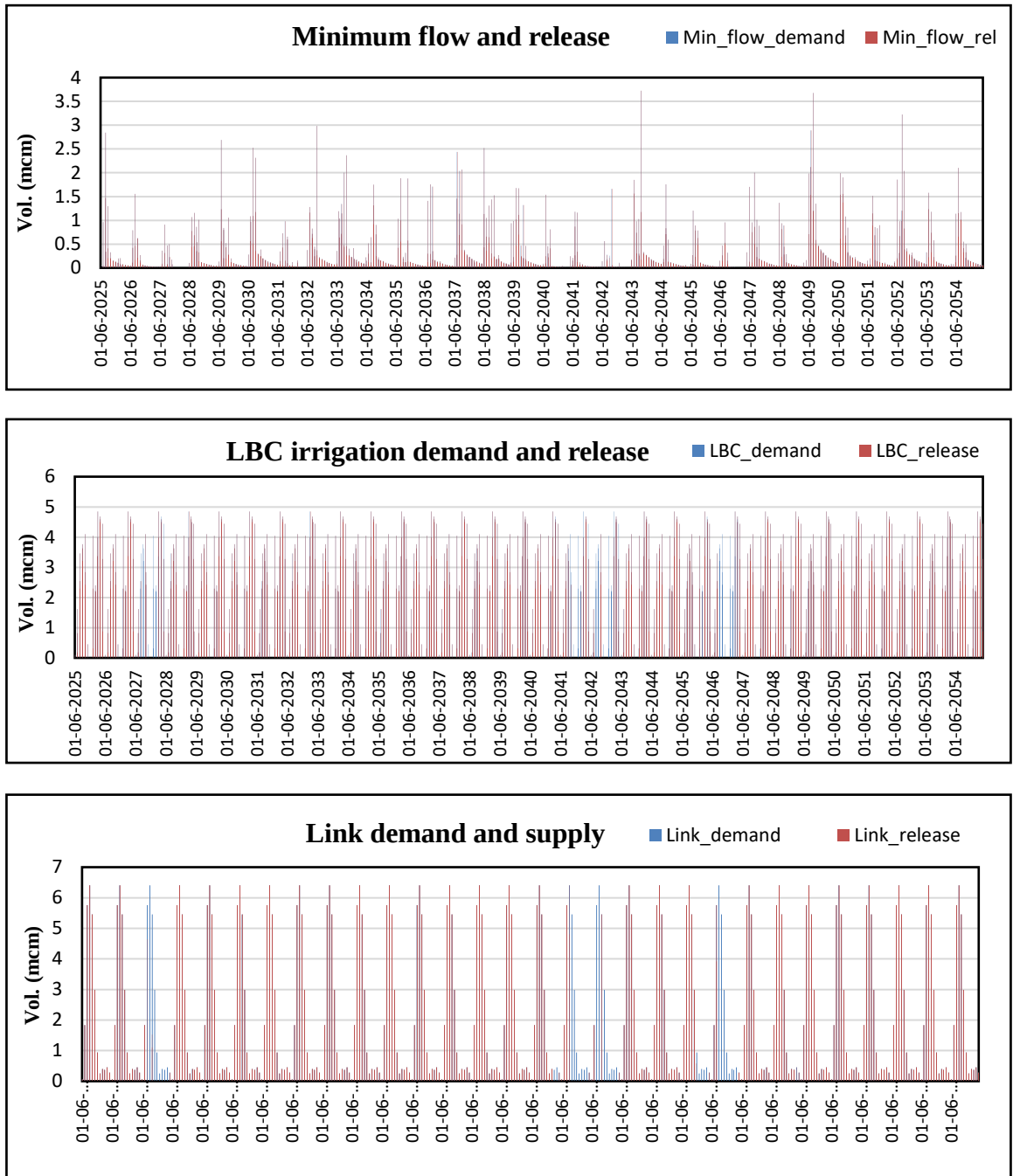


Figure 5.86 Sondhur reservoir operation results (SSP126).

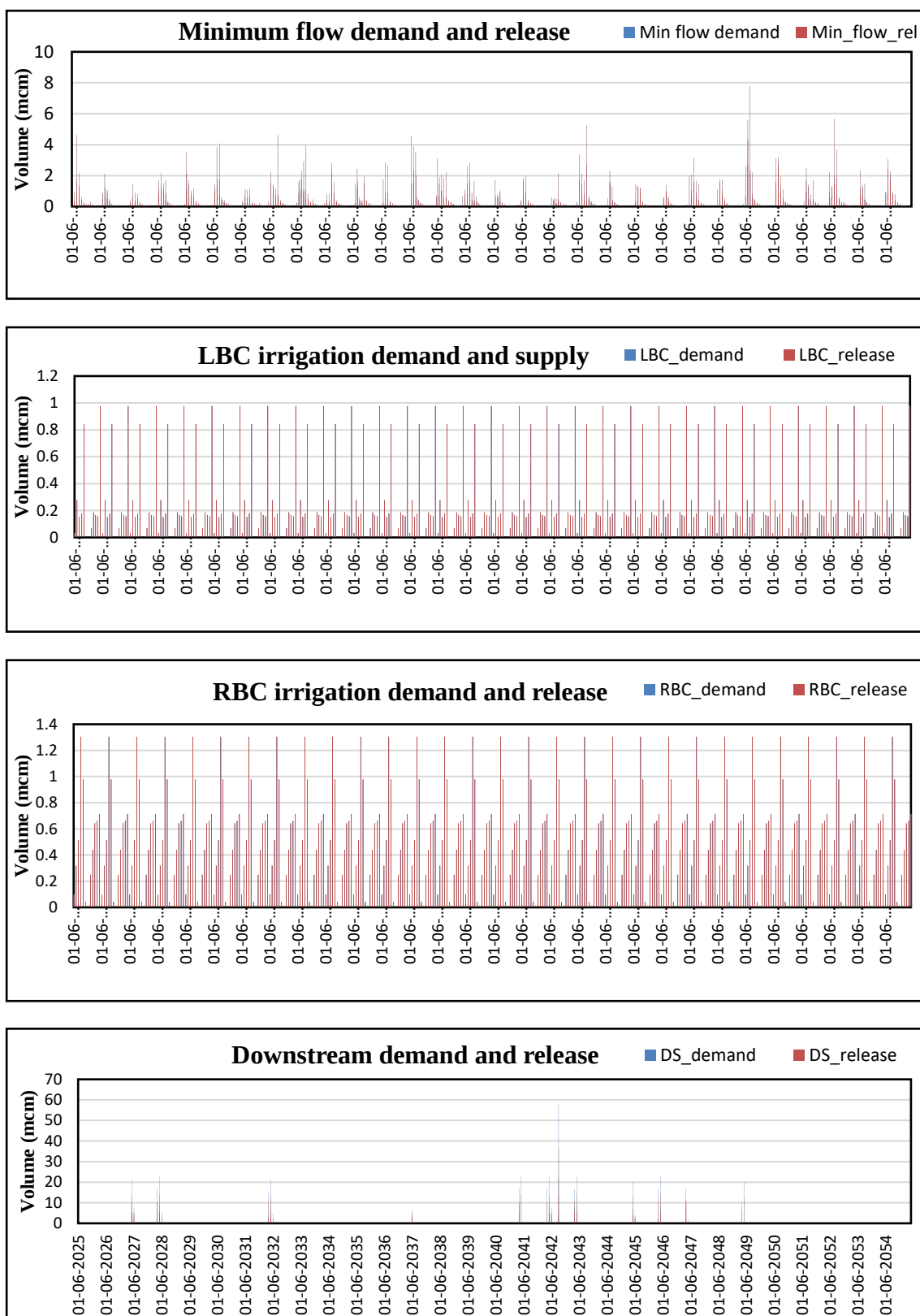


Figure 5.87 Dudhawa reservoir operation results (SSP126).

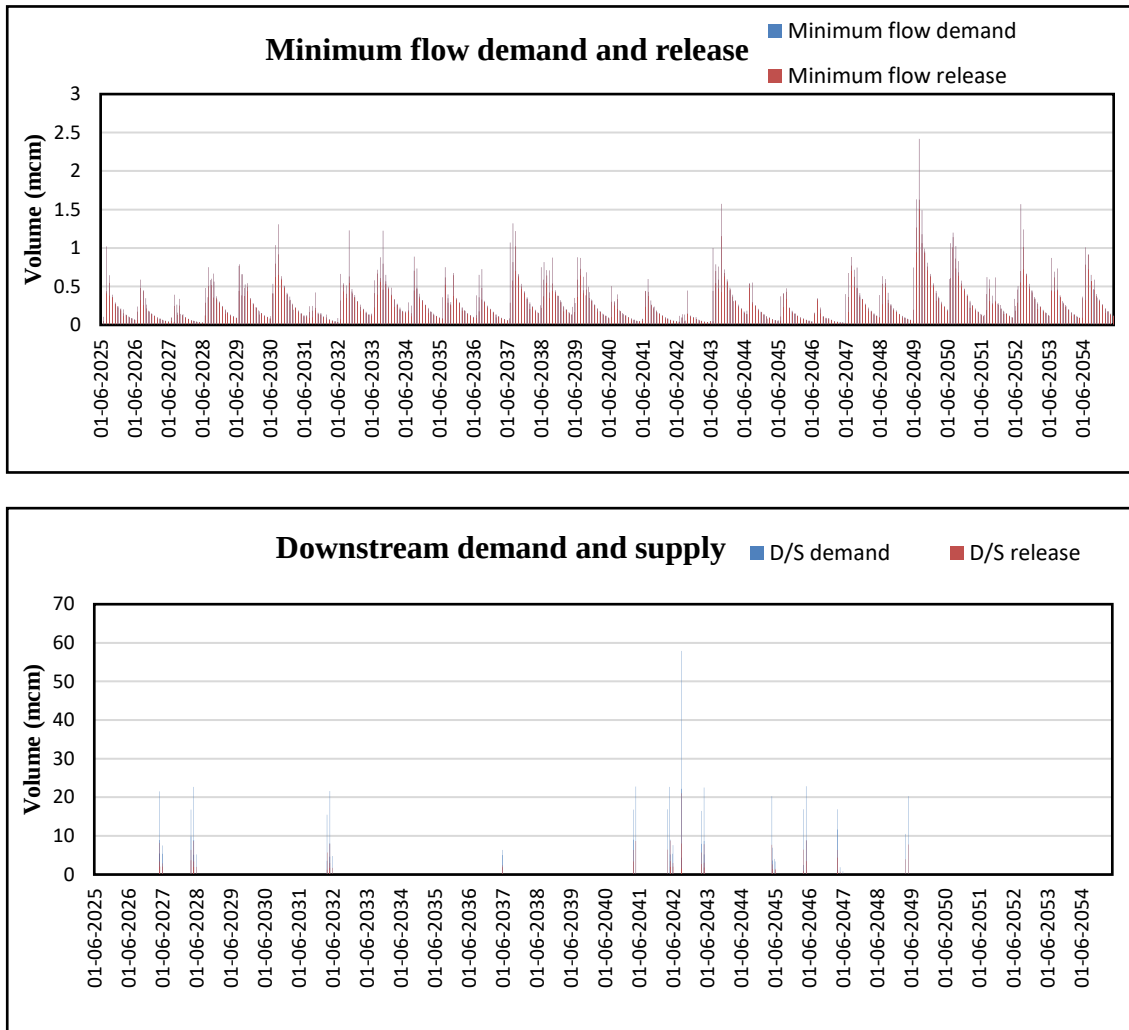


Figure 5.88 Murumsilli reservoir operation results SSP126.

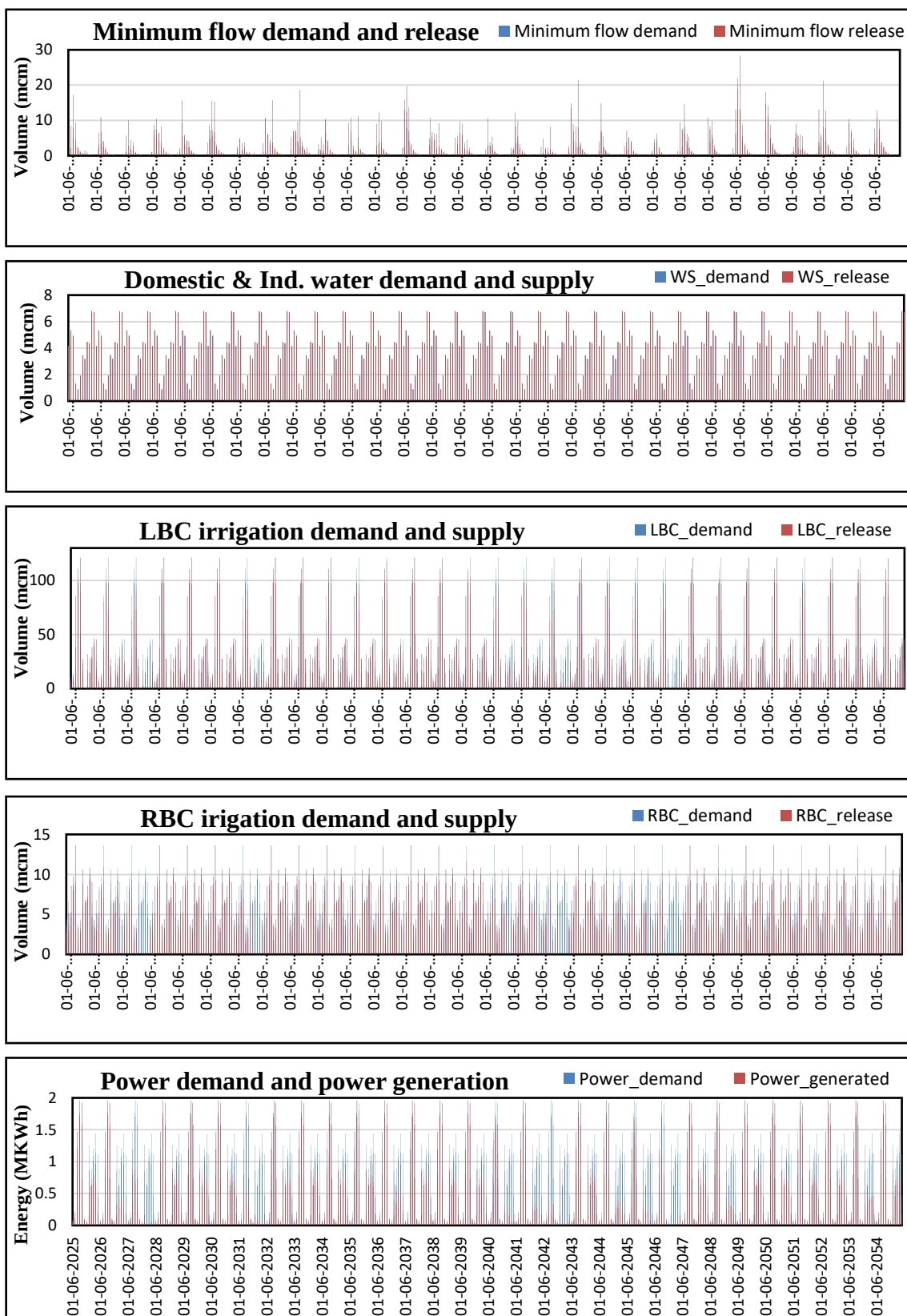


Figure 5.89 Ravi Shankar Sagar reservoir operation results (SSP126).

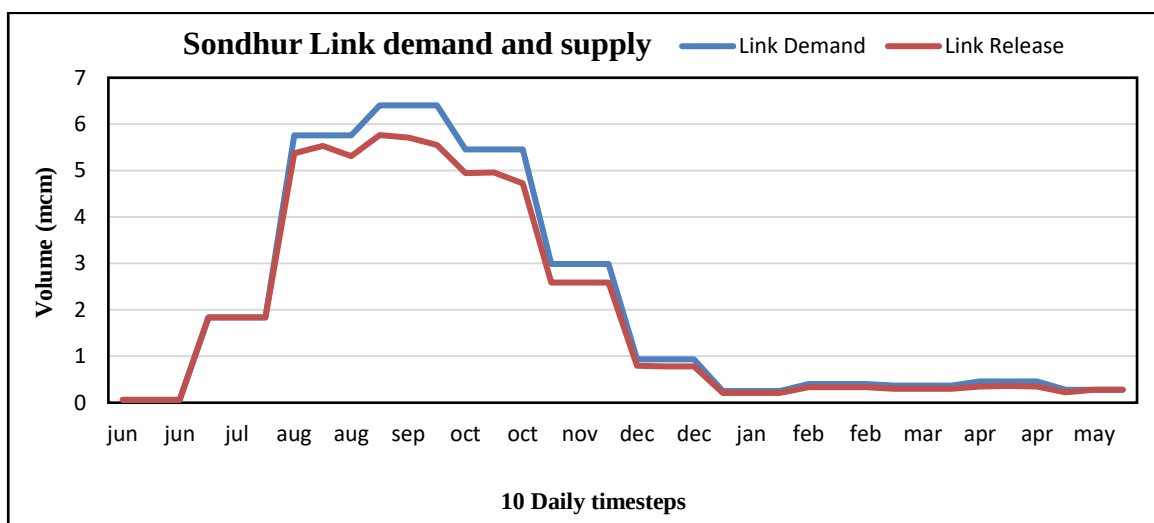
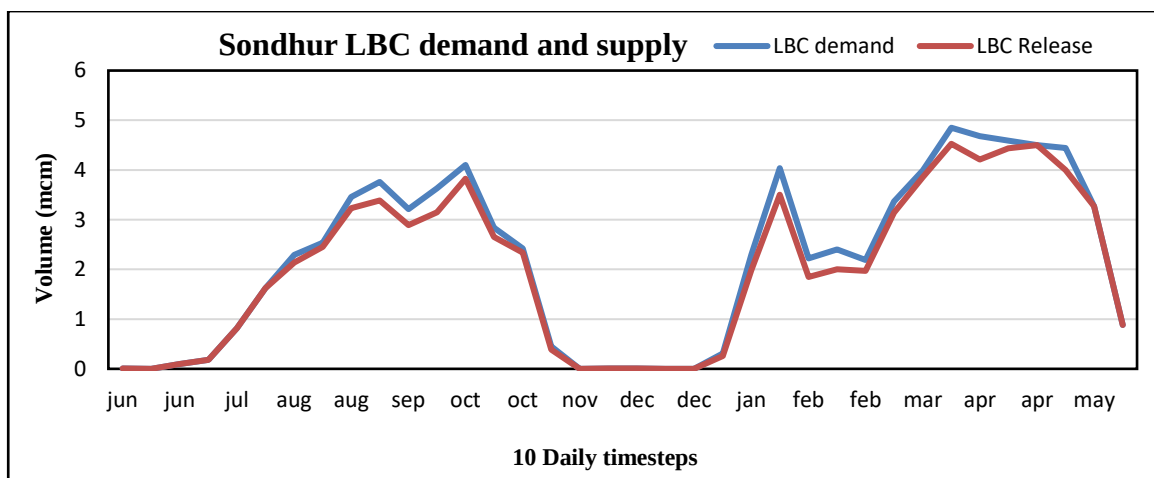


Figure 5.90 Average 10 daily analysis of demand and supply at Sondhur reservoir for SSP126.

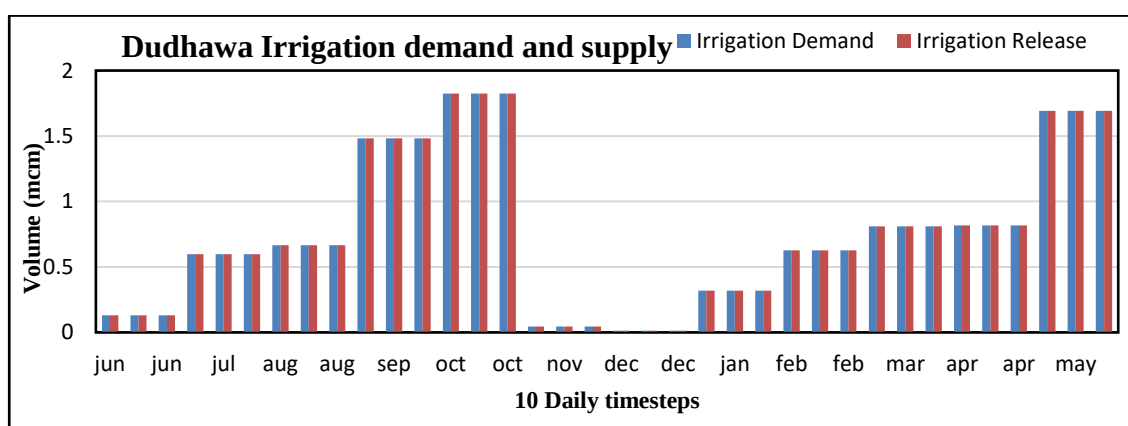


Figure 5.91 Average 10 daily analysis irrigation demand and supply at Dudhawa reservoir for SSP126.

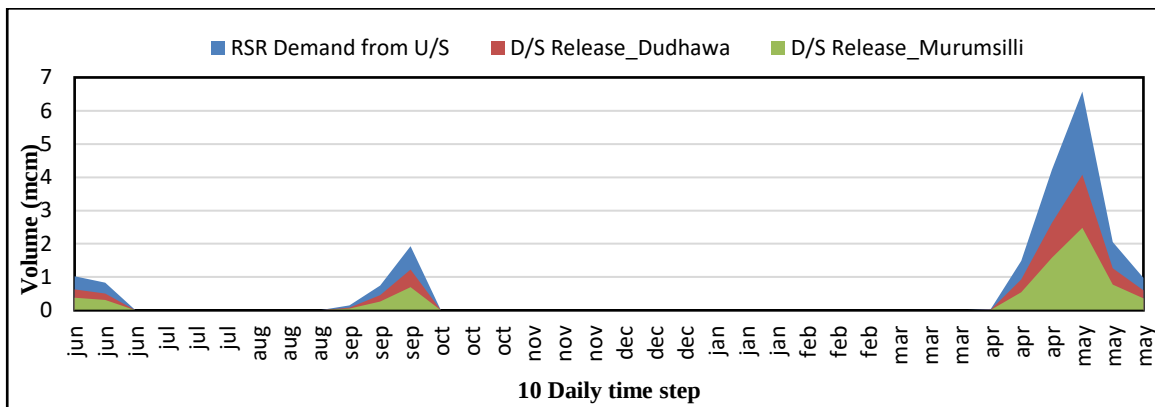


Figure 5.91.1 Average 10 daily water supplied from Murumsilli and Dudhawa to RSR in addition to spills.

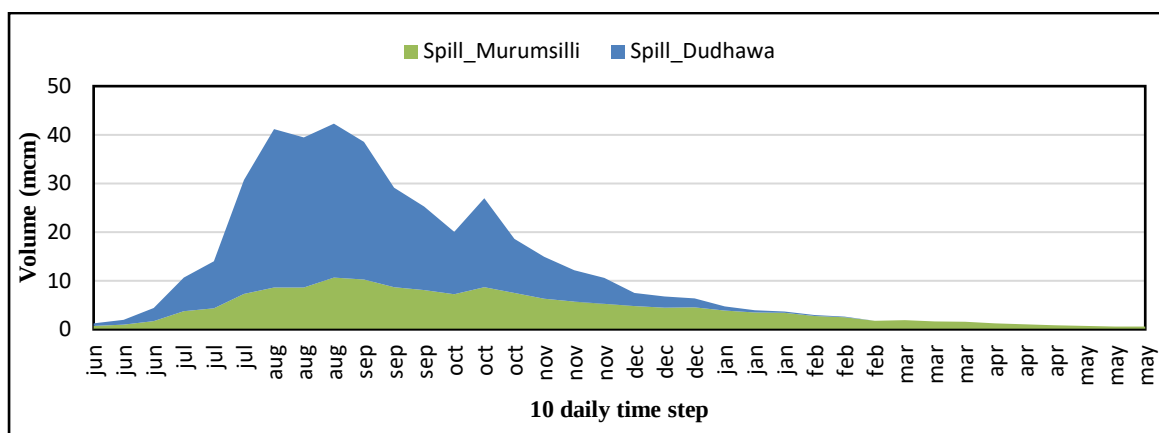


Figure 5.91.2 Spills from Dudhawa and Murumsilli to RSR.

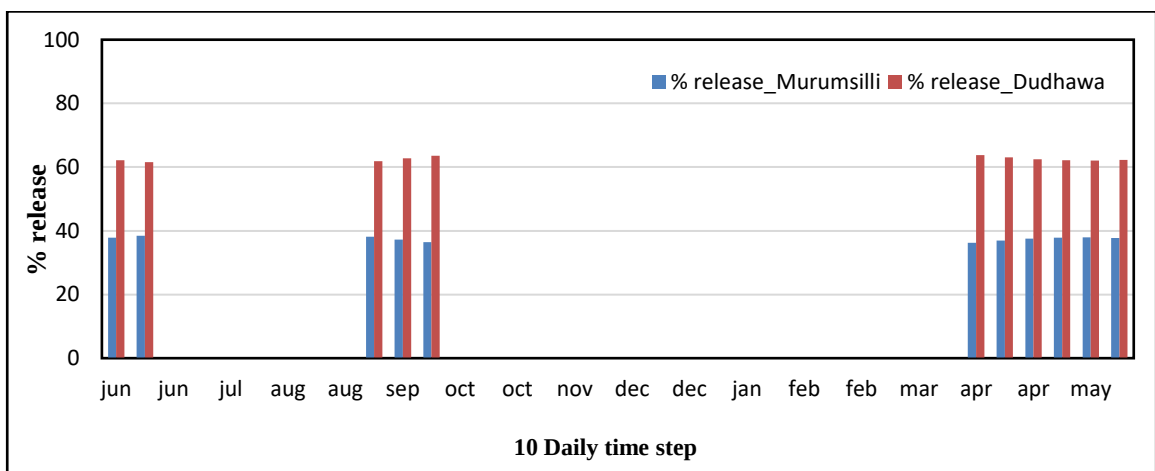


Figure 5.91.3 % Share of release from Dudhawa and Murumsilli to RSR in addition to spills.

Further, the operational results of the Ravishankar reservoir indicate that there remains a deficit in meeting irrigation demands during both the monsoon and non-monsoon seasons (see **Figure 5.92**). The deficits are more prominent in the non-monsoon season compared to the monsoon. A similar pattern is observed for power supply, as the reservoir struggles to meet power demands, particularly during the non-monsoon period **Figure 5.93**.

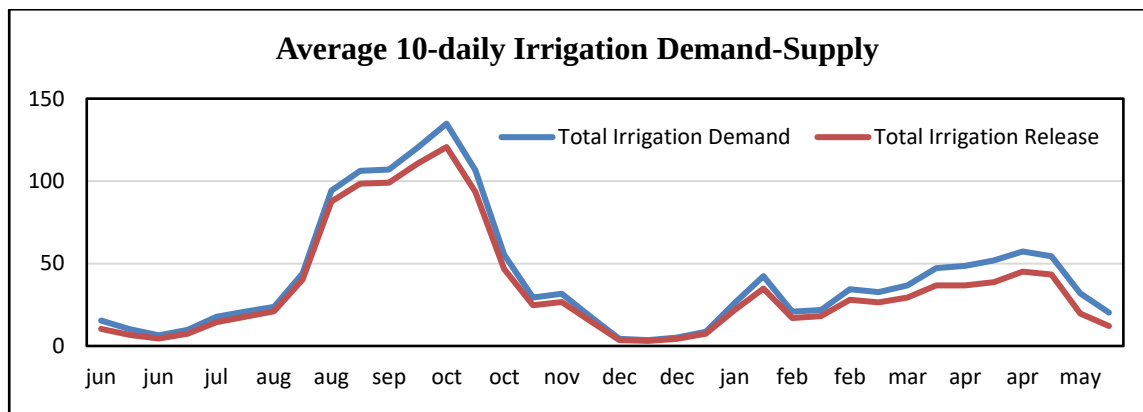


Figure 5.92 Average ten-daily irrigation demand and release at Ravishankar Sagar for SSP126.

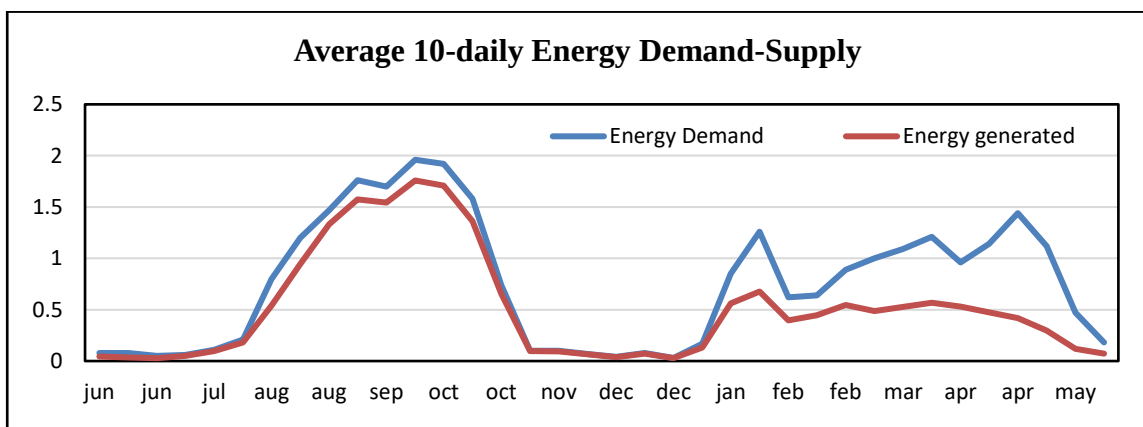


Figure 5.93 Average ten-daily energy demand and energy generation at Ravishankar Sagar for SSP126.

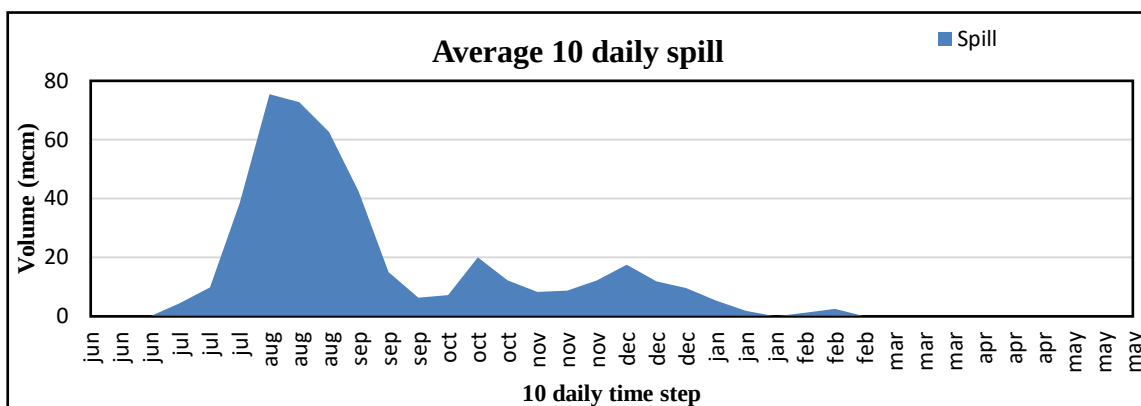


Figure 5.93.1 Average ten-daily spills from Ravishankar Sagar for SSP126.

Figure 5.93.1 illustrates that the Ravishankar reservoir is unable to accommodate all the water from upstream reservoirs or its own catchment inflow, leading to a significant amount of water being spilled, particularly during the monsoon season. This indicates the need for more efficient water management in the future to conserve this excess water. Since the current results are already based on rule curves, and the upper rule curve for all three reservoirs—Dudhawa, Murumsilli, and Ravishankar—is set at Full Reservoir Level (FRL) during the monsoon, managing spills by raising the rule curve to the maximum water level may not be a viable option due to flood control constraints.

5.18.2 SSP 245

SSP245 represents a scenario with intermediate greenhouse gas emissions and moderate challenges to both mitigation and adaptation. It forecasts more significant changes in water availability and demand reflecting moderate climate change impacts and a greater degree of variability in future water resources. Similar to the SSP 126 scenario, for the integrated operation of the MRP under the SSP245 scenario, the ReSyP model was initially employed to establish rule curve levels for all reservoirs. Water is released downstream whenever reservoir levels surpass the designated rule curve thresholds. These rule curves are derived from dependable water availability conditions and adjusted water demands. Future water supply demands were projected based on population growth, while irrigation demands were estimated by incorporating climate change variables and the resulting changes in agricultural areas, using the CROPWAT model. The outcomes of this integrated operation under the chosen climate scenario are illustrated through various figures and tables as

follows.

The tables **Tables 5.48, Table 5.49, and Table 5.50** provide detailed insights into the reliability of several reservoirs—Sondhur, Dudhawa, Murumsilli, and Ravishankar—in meeting different water demands on various timescales: annually, monthly, and ten-daily basis. These demands include full and critical water supply (WS), minimum flow (MF), irrigation (Irr), link (Lnk), and power demands. The average volume reliability of various projects is given in **Table 5.51**

The annual reliability analysis under the SSP245 scenario reveals that Ravishankar Reservoir faces significant challenges in meeting full irrigation and power demands. The reservoir is unable to meet both these demands consistently over the year (**Table 5.48**). For critical demands, Ravishankar performs better, particularly in meeting critical water supply and critical minimum flow demands, with 100% reliability. However, for critical irrigation (75% of full demand) results indicate that the reservoir can meet critical irrigation demands 76% of the time out of the entire study period. Sondhur Reservoir performs moderately with 53.33% annual reliability in meeting full irrigation and 50% for full link demands, however, it maintains high reliability across critical water supply, minimum flow, and irrigation demands. Both Dudhawa and Murumsilli display full reliability, for full as well as critical irrigation and minimum flow (MF) demands on an annual basis.

On a monthly scale, Ravishankar shows 100% reliability for full water supply and critical water supply. However, its ability to meet full irrigation and full power demands remains quite low (**Table 5.49**). Dudhawa and Murumsilli show full reliability for meeting full and critical demands on monthly basis for all demands. Sondhur exhibits higher reliability on monthly basis as compared to annual for full and critical irrigation demands. The ten-daily reliability analysis (**see Table 5.50**) shows improvements for Ravishankar, particularly in full irrigation demands, where reliability rises to 37.04%, compared to lower values on annual and monthly scales. The reservoir also achieves 97.87% reliability for full minimum flow and 100% reliability for critical water supply and minimum flow, underscoring its ability to meet these essential demands fully. Dudhawa, and Murumsilli continue to show excellent performance across most categories. Sondhur's full irrigation reliability improves to 91.94%, and it achieves 100% reliability for critical irrigation demands on ten daily scale. Ravishankar remains less reliable in meeting full power demands, as well as critical power supply reliability.

In terms of volume reliability, Ravishankar shows better performance in meeting irrigation demands, with 86.06% reliability, although power supply reliability remains low at 53.45% while water supply and minimum flow demands are met fully (**Table 5.51**). Sondhur, Dudhawa, and Murumsilli meet the minimum flow and irrigation demands fully on a volumetric basis. Sondhur performs well in meeting link demands in terms of volume. The reliability analysis for the SSP245 scenario highlights that while Ravishankar Reservoir is effective in meeting critical demands for water supply and minimum flow, it is unable to meet full irrigation and power demands considerably, especially on an annual and monthly basis.

Table 5.48 Average annual reliability in meeting demands of the projects for SSP245.

Demands	Annual Reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
Full WS demands	-	-	-	100
Full MF demands	100	100	100	80
Full Irr demands	53.333	100	100	0
Full Lnk demands	50	-	-	-
Full Power demands	-	-	-	0
Critical WS demands	-	-	-	100
Critical MF demands	100	100	100	100
Critical Irr demands	100	100	100	76.667
Critical Power demands	-	-	-	56.667

Table 5.49 Average Monthly reliability in meeting demands of the projects for SSP245.

Demands	Monthly Reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
Full WS demands	-	-	-	100
Full MF demands	100	100	100	96.389
Full Irr demands	87.778	100	100	30.278
Full Link demands	85	-	-	-
Full Power demands	-	-	-	29.167
Critical WS demands	-	-	-	100
Critical MF demands	100	100	100	100
Critical Irr demands	96.944	100	100	88.611
Critical Power demands	-	-	-	54.167

Table 5.50 Average ten daily reliability in meeting demands of the projects for

SSP245.

Demands	Ten Daily Reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
Full WS demands	-	-	-	100
Full MF demands	100	100	100	97.87
Full Irr demands	91.944	100	100	37.037
Full Link demands	87.13	-	-	-
Full Power demands	-	-	-	33.981
Critical WS demands	-	-	-	100
Critical MF demands	100	100	100	100
Critical Irr demands	98.056	100	100	91.667
Critical Power demands	-	-	-	55.37

Table 5.51 Volume reliability in meeting demands of the projects for SSP245.

Demands	Volume reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
WS demands	-	-	-	100
MF demands	100	100	100	99.991
Irr demands	97.267	100	100	86.059
Link demands	93.78	-	-	-
Power demands	-	-	-	53.449

Figure 5.94 represents the storage and spill behaviour of the reservoirs during integrated operation of the system in SSP245 scenario. **Figures 5.95-5.98** show the demand-supply plots for each demand of the reservoir for each of the projects.

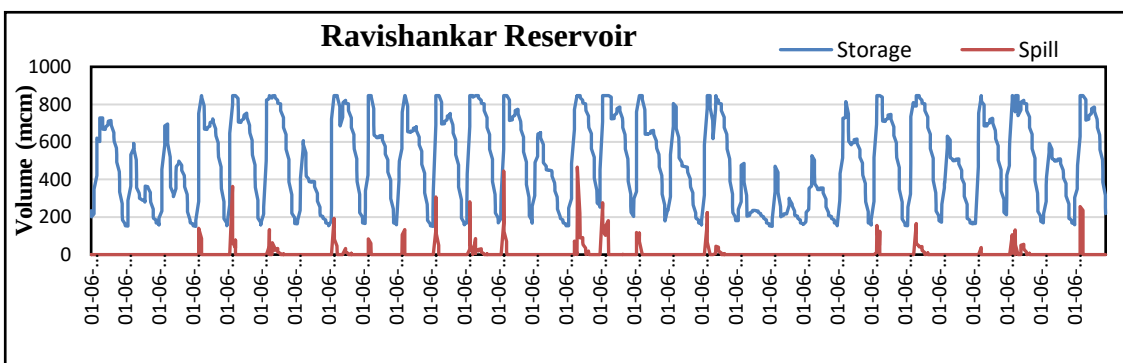
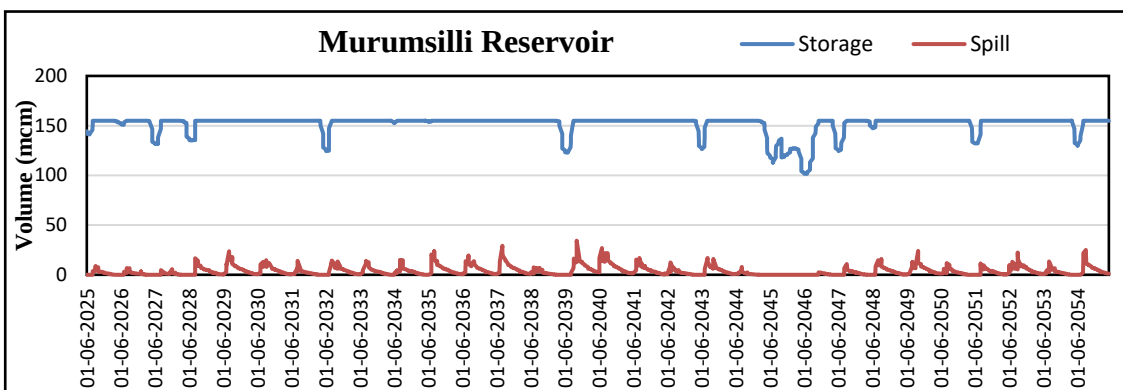
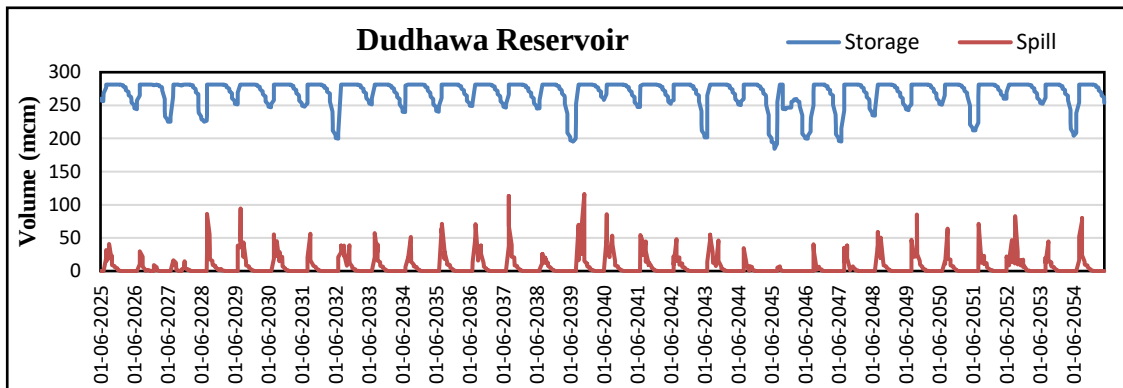
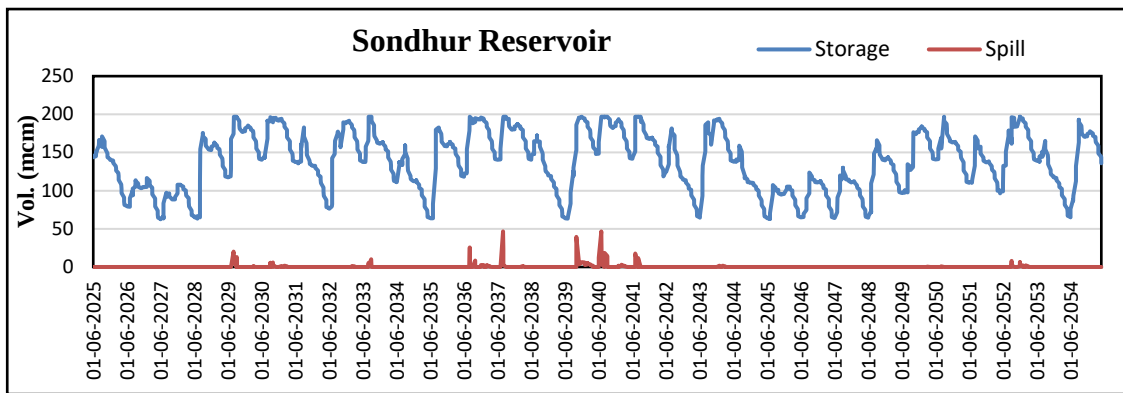


Figure 5.94 Storage and spill behaviors of the reservoirs during integrated operation (SSP245).

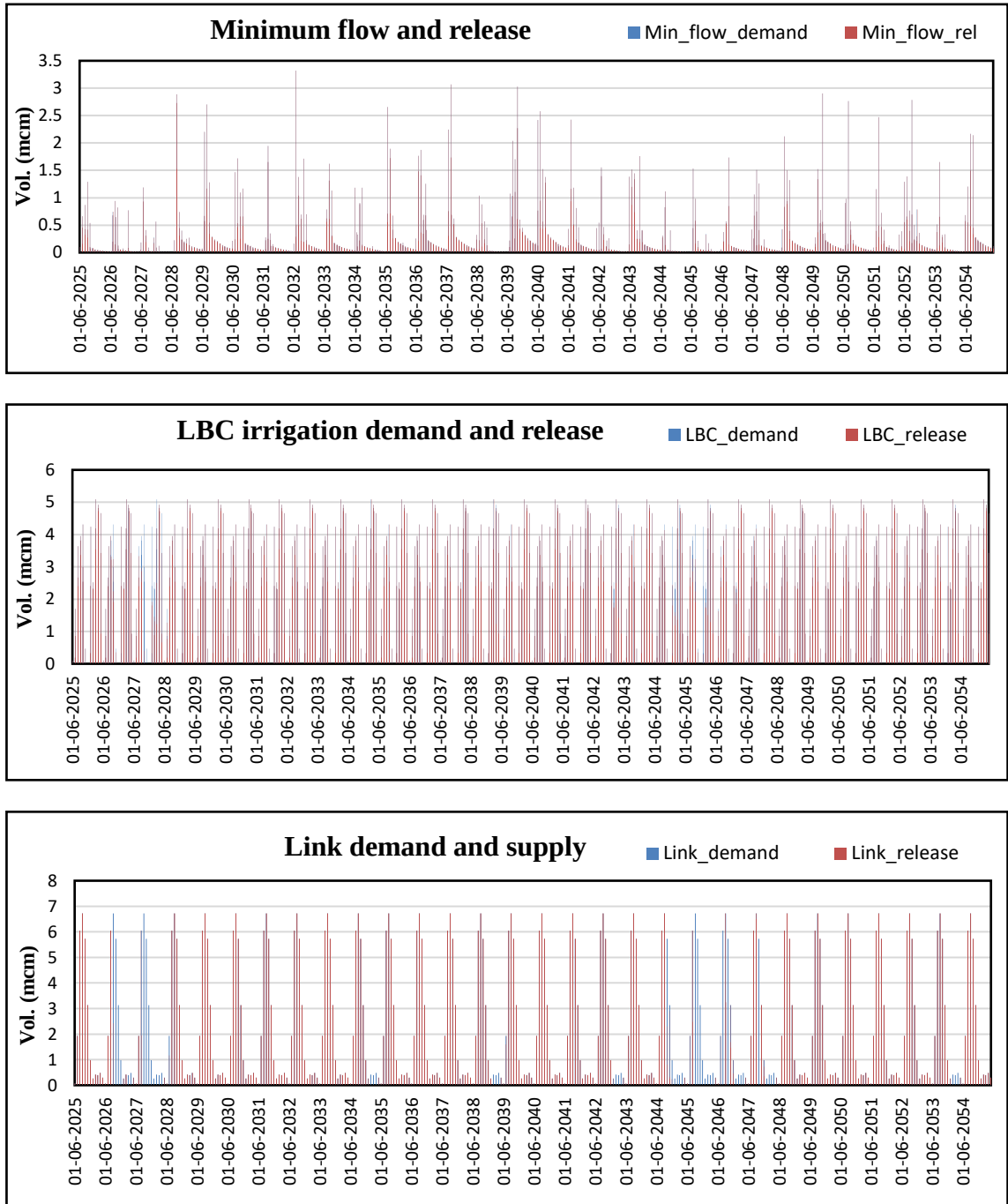


Figure 5.95 Sondhur reservoir operation results (SSP245).

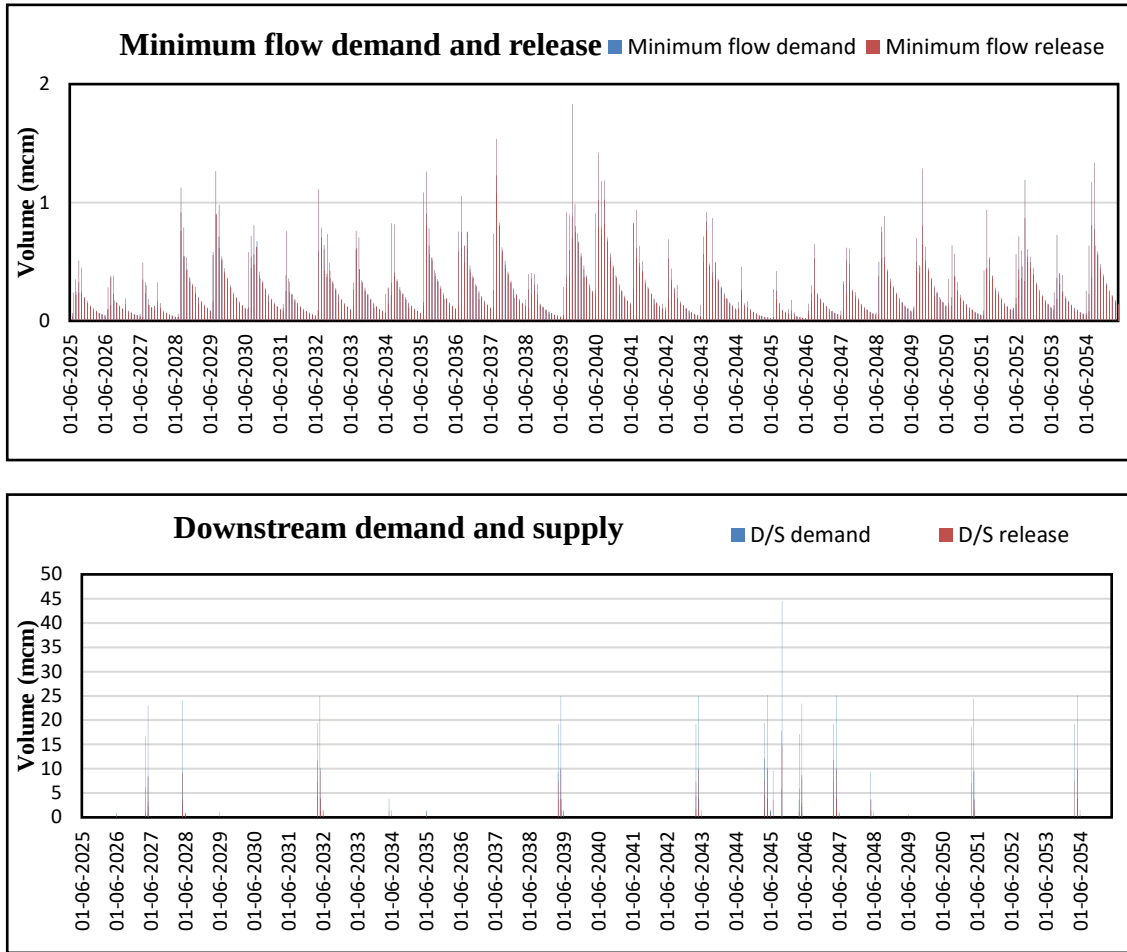


Figure 5.97 Murumsilli reservoir operation results SSP245.

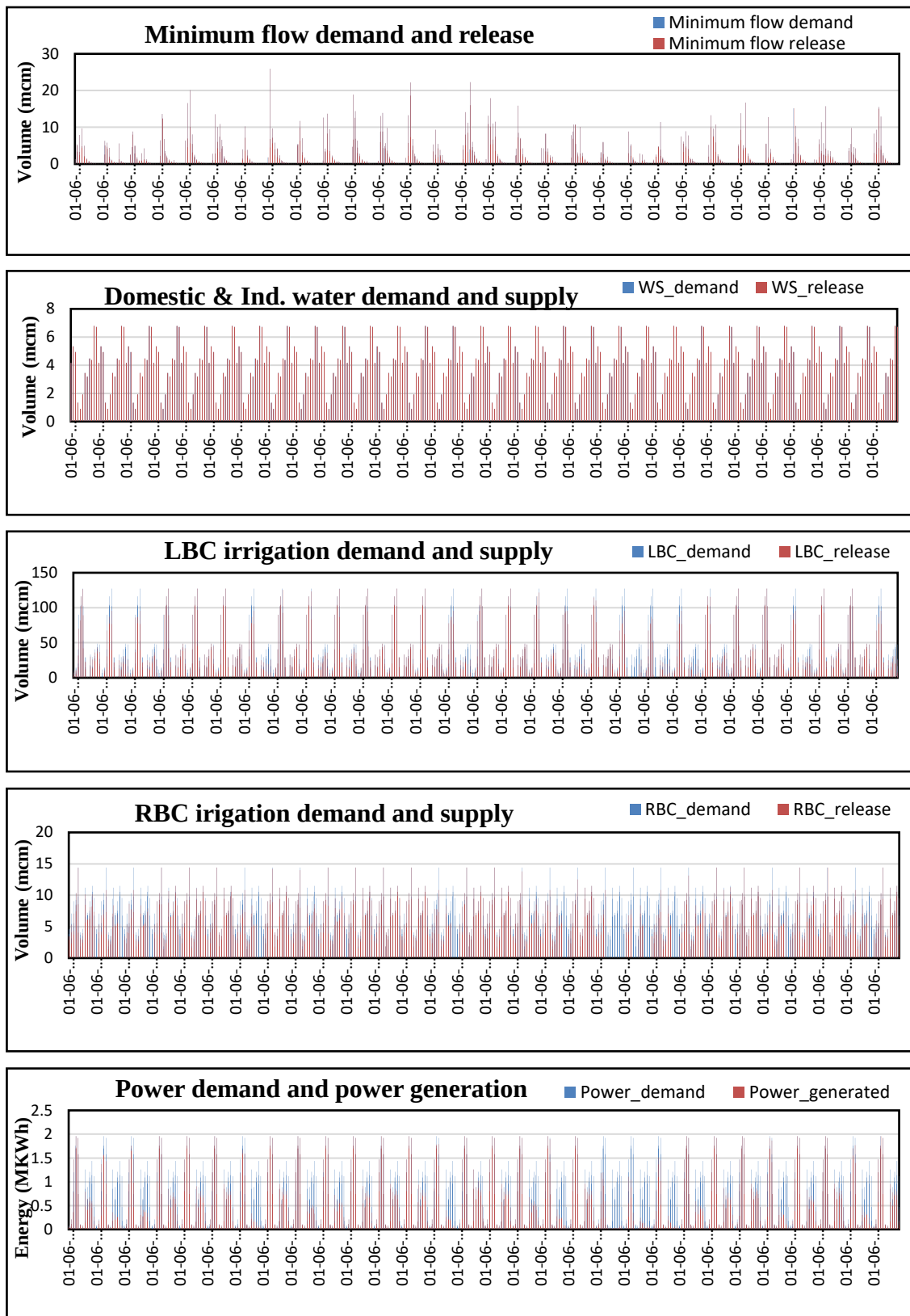


Figure 5.98 Ravi Shankar Sagar reservoir operation results (SSP245).

The average ten-daily results show (Figures 5.99) that small deficits occur during non-monsoon in meeting the irrigation demand of Sondhur. In contrast, the link transfer demand deficit occurs during monsoon in particular from July to September. During the non-monsoon period, Sondhur provides sufficient water to meet the link demand. Dudhawa reservoir results show that on ten daily average basis, total irrigation demands are met completely. (See in Figure 5.100).

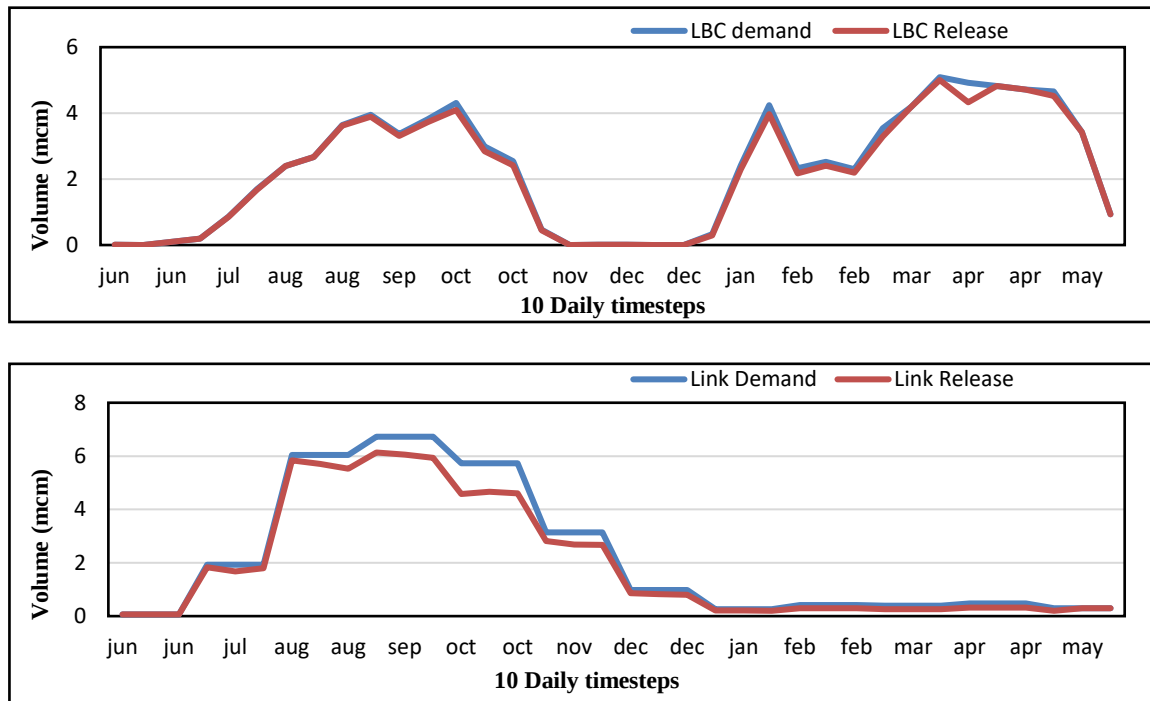


Figure 5.99 Average 10 daily analysis of demand and supply at Sondhur reservoir for SSP245.

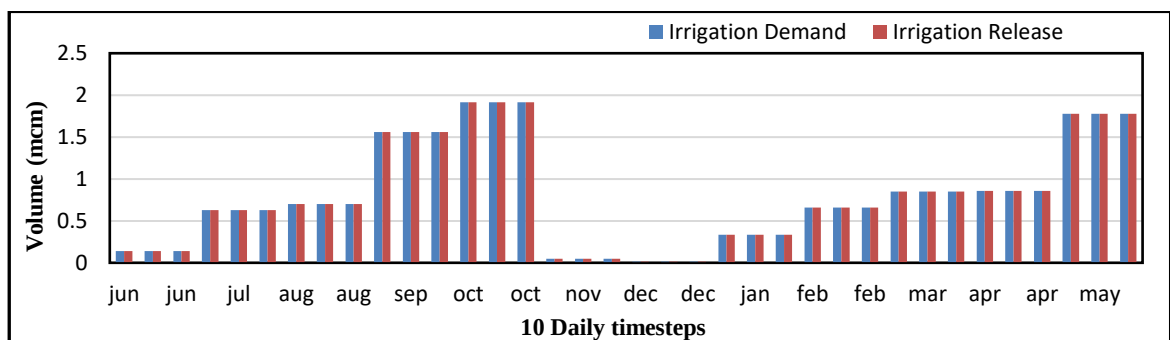


Figure 5.100 Average 10 daily irrigation demand and supply at Dudhawa reservoir for SSP245 scenario.

Dudhawa and Murumsilli supply water for demands at Ravishankar in addition to water spilled from these reservoirs. **Figure 5.100.1** and **Figure 5.100.2** indicates that in general, the spilled water is sufficient to meet the demands at Ravishankar during July to February as no additional water demand occurs during this season at RSR. Water needs to be delivered from Dudhawa and Murumsilli only during April to June, (see **Figure 5.100.1**). **Figure 5.100.3** shows that the share of water supplied from Dudhawa and Murumsilli to Ravishankar is 62% and 38%, respectively, to meet the rest of the deficit at Ravishankar, after accounting for the water used from spills. These results are quite similar to the SSP126 scenario where this share was 63% and 37% for the same. However, it should be noted that not all the water spilled from Dudhawa and Murumsilli may necessarily be utilized at Ravishankar and may further get spilled from Ravishankar.

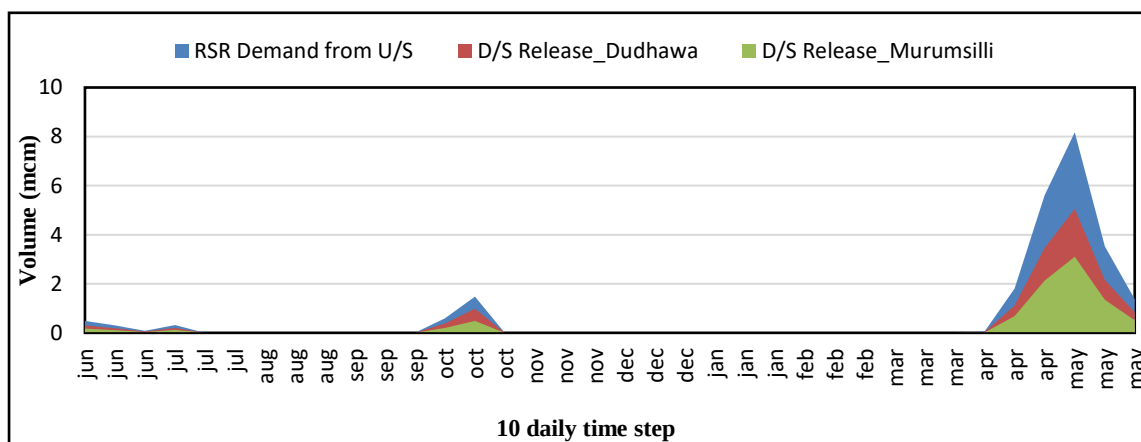


Figure 5.100.1 Average 10 daily water supplied from Murumsilli and Dudhawa to RSR in addition to spills in SSP245 scenario.

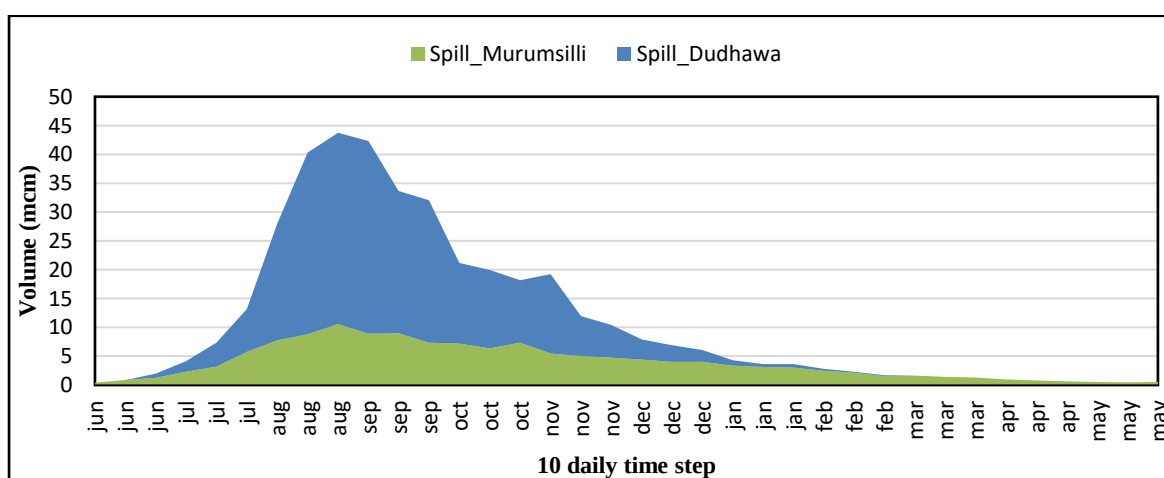


Figure 5.100.2 Spills from Dudhawa and Murumsilli to RSR in SSP245 scenario

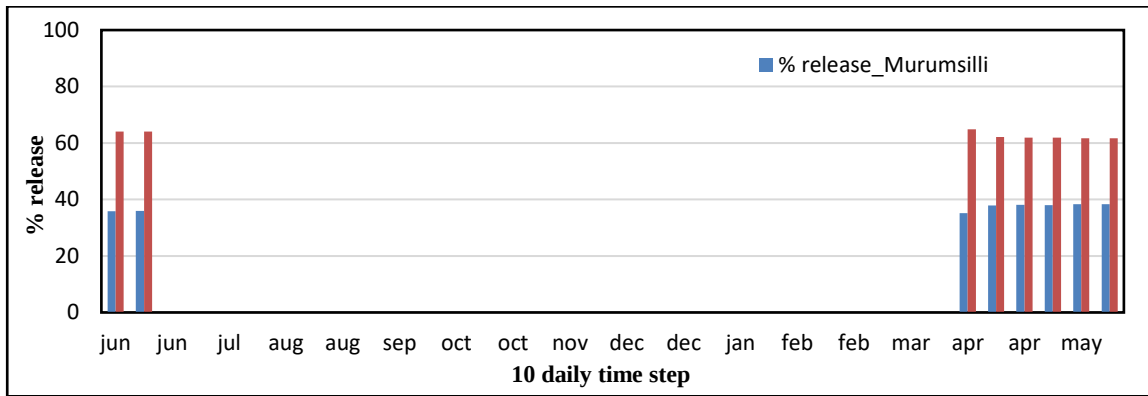


Figure 5.100.3 % Share of release from Dudhawa and Murumsilli to RSR in addition to spills.

Further, the operational results of the Ravishankar reservoir indicate that there remains a deficit in meeting irrigation demands during both the monsoon and non-monsoon seasons (see Figure 5.101). The deficits are more prominent in the non-monsoon season compared to the monsoon. A similar pattern is observed for power supply, significant deficit may be seen in meeting power demands, particularly during the non-monsoon period Figure 5.102.

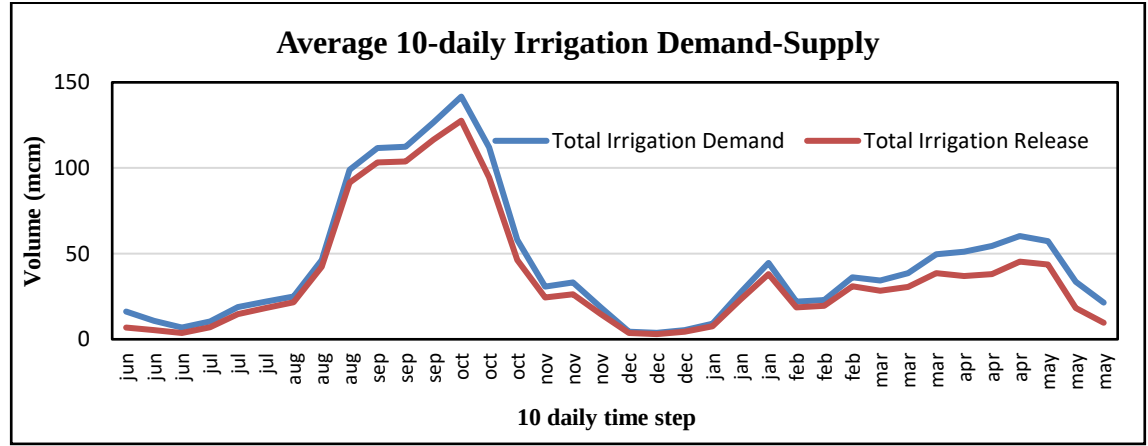


Figure 5.101 Average ten-daily irrigation demand and release at Ravishankar Sagar for SSP245 scenario.

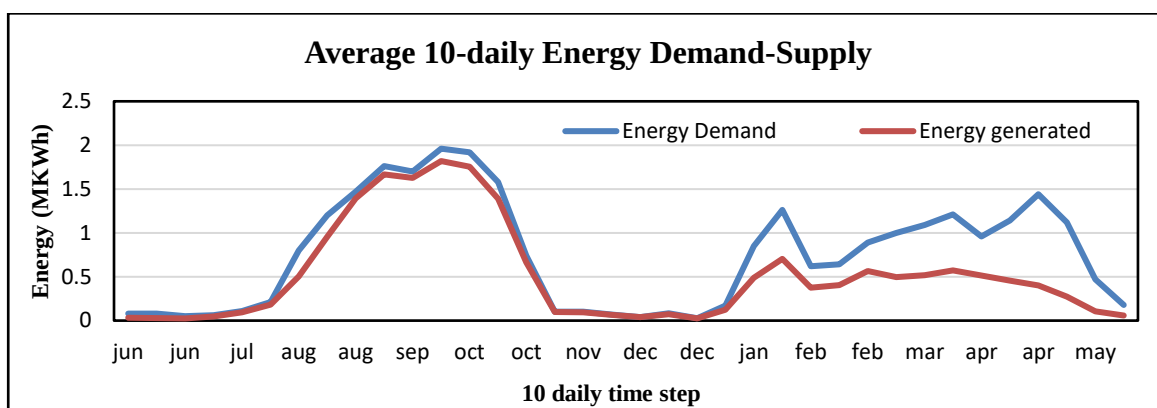


Figure 5.102 Average ten-daily energy demand and energy generation at Ravishankar Sagar for SSP245 scenario.

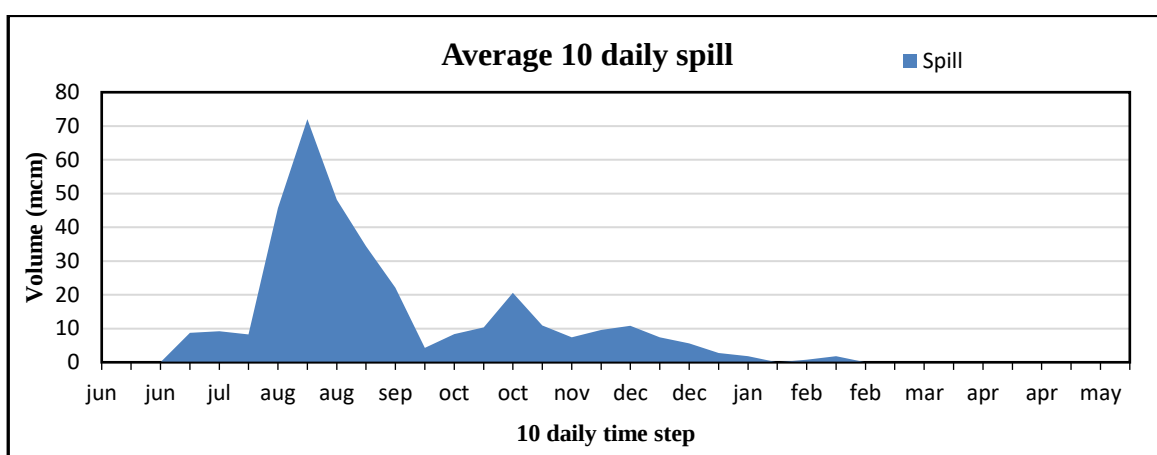


Figure 5.102.1 Average ten-daily spills from Ravishankar Sagar for SSP245 scenario.

Similar to scenario SSP126, (Figure 5.102.1) illustrates that the Ravishankar reservoir is unable to accommodate all the water from upstream reservoirs or its own catchment inflow, leading to a significant amount of water being spilled, particularly during the monsoon season. This indicates the need for more efficient water management in the future to conserve this excess water. For meeting irrigation demands during monsoon lowering irrigation rule curve level during this period may be helpful in fulfilling more demands during monsoon. The upper rule curve for all three reservoirs—Dudhawa, Murumsilli, and Ravishankar is set at Full Reservoir Level (FRL) during the monsoon, managing spills by raising the rule curve to the maximum water level may not a viable option due to flood control constraints.

5.18.3 SSP 585

SSP585 corresponds to a scenario with high greenhouse gas emissions and significant challenges to mitigation efforts. This scenario forecasts considerable changes in water availability and demand, with increased variability and more severe impacts due to climate change. Similar to the other scenarios, for integrated operation of the MRP under the SSP585 scenario, the ReSyP model was initially employed to establish rule curve levels for all reservoirs. Water is released downstream whenever reservoir levels surpass the designated rule curve thresholds. These rule curves are derived from dependable water availability conditions and adjusted water demands for future. Future water supply demands were projected based on population growth, while irrigation demands were estimated by incorporating climate change variables and the resulting changes in agricultural areas, using the CROPWAT model. The outcomes of the integrated operation under this climate scenario are illustrated through various figures and tables as follows.

The tables **Tables 5.52, Table 5.53, and Table 5.54** provide detailed insights into the reliability of several reservoirs—Sondhur, Dudhawa, Murumsilli, and Ravishankar—in meeting different water demands on various timescales: annually, monthly, and ten-daily basis. These demands include full and critical water supply (WS), minimum flow (MF), irrigation (Irr), link (Lnk), and power demands. The average volume reliability of various projects is given in **Table 5.55**

Annual reliability analysis suggests that under the SSP585 scenario, the reservoirs' ability to meet water demands varies significantly (**Table 5.52**). Ravishankar Reservoir is unable to meet both full irrigation and power demands. While it meets 100% of full water supply demands, its reliability for full minimum flow demand is only 56.67%. Slight improvement occurs in the case of critical demands where 100% reliability for critical water supply and minimum flow, and 66.67% for critical irrigation are achieved. Sondhur Reservoir shows moderate performance, achieving 60% reliability for both full irrigation and link demands. It meets 90% of full minimum flow needs and performs well with 96.67% reliability for critical irrigation. Dudhawa and Murumsilli outperform the others, consistently meeting full and critical demands across all demands, demonstrating strong resilience under severe climate change impacts.

Monthly reliability analysis of the reservoir's performance shows that Ravishankar

Reservoir continues to face challenges (**Table 5.53**), with 22.5% reliability for full irrigation and 28.06% for full power demands, though it achieves 100% reliability for full water supply. For critical demands, water supply and minimum flow can be met fully, while reliability for critical irrigation is 82.78%. Sondhur Reservoir shows 87.78% reliability for full irrigation and 78.61% for full link demands. For critical demands, Sondhur achieves 96.11% reliability for critical irrigation and 100% for critical minimum flow. Dudhawa and Murumsilli reservoirs maintain 100% reliability across full and critical demands.

The ten-daily reliability analysis (**see Table 5.54**) shows Ravishankar Reservoir shows 29.17% reliability for full irrigation and 31.39% for full power demands, indicating ongoing deficits in meeting on ten daily basis too. However, it performs better in meeting full and critical, water supply and minimum flows. Reliability in meeting critical demand is 87.31%. Sondhur Reservoir performs well, with 92.5% reliability for full irrigation and 82.31% for full link demands, while maintaining 100% reliability for critical minimum flow and 97.13% for critical irrigation. Dudhawa and Murumsilli reservoirs maintain 100% reliability across all full and critical demands.

In terms of volume reliability, Ravishankar meets water supply and minimum flow needs but fails to fully meet irrigation and power demands fully, while Dudhawa and Murumsilli remain fully reliable. (**Table 5.55**). Sondhur performs well in meeting irrigation and link demands in terms of volume. The reliability analysis for the SSP585 scenario highlights that while Ravishankar Reservoir is effective in meeting critical demands for water supply and minimum flow, it is unable to meet full irrigation and power demands considerably on annual, monthly and ten-daily basis.

Table 5.52 Average annual reliability in meeting demands of the projects for SSP585.

Demands	Annual Reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
Full WS demands	-	-	-	100
Full MF demands	90	100	100	56.667
Full Irr demands	60	100	100	0
Full Lnk demands	60	-	-	
Full Power demands		-	-	0
Critical WS demands		-	-	100
Critical MF demands	100	100	100	100
Critical Irr demands	96.667	100	100	66.667
Critical Power demands	-	-	-	50

Table 5.53 Average Monthly reliability in meeting demands of the projects for SSP585.

Demands	Monthly Reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
Full WS demands	-	-	-	100
Full MF demands	97.778	100	100	92.222
Full Irr demands	87.778	100	100	22.5
Full Link demands	78.611	-	-	
Full Power demands		-	-	28.056
Critical WS demands		-	-	100
Critical MF demands	100	100	100	100
Critical Irr demands	96.111	100	100	82.778
Critical Power demands	-	-	-	48.889

Table 5.54 Average ten daily reliability in meeting demands of the projects for SSP585.

Demands	Ten Daily Reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
Full WS demands	-	-	-	100
Full MF demands	98.611	100	100	95.926
Full Irr demands	92.5	100	100	29.167
Full Link demands	82.315	-	-	
Full Power demands		-	-	31.389
Critical WS demands		-	-	100
Critical MF demands	100	100	100	100
Critical Irr demands	97.13	100	100	87.315
Critical Power demands	-	-	-	51.296

Table 5.55 Volume reliability in meeting demands of the projects for SSP585.

Demands	Volume reliability (%)			
	Sondhur	Dudhawa	Murumsilli	Ravishankar
WS demands	-	-	-	100
MF demands	99.978	100	100	99.972
Irr demands	96.851	100	100	82.927
Link demands	87.195	-	-	
Power demands	-	-	-	50.875

Figure 5.103 represents the storage and spill behavior of the reservoirs during the integrated operation of the system in the SSP585 scenario. **Figures 5.104-5.107** show the demand-supply plots for each demand of the reservoir for each of the projects.

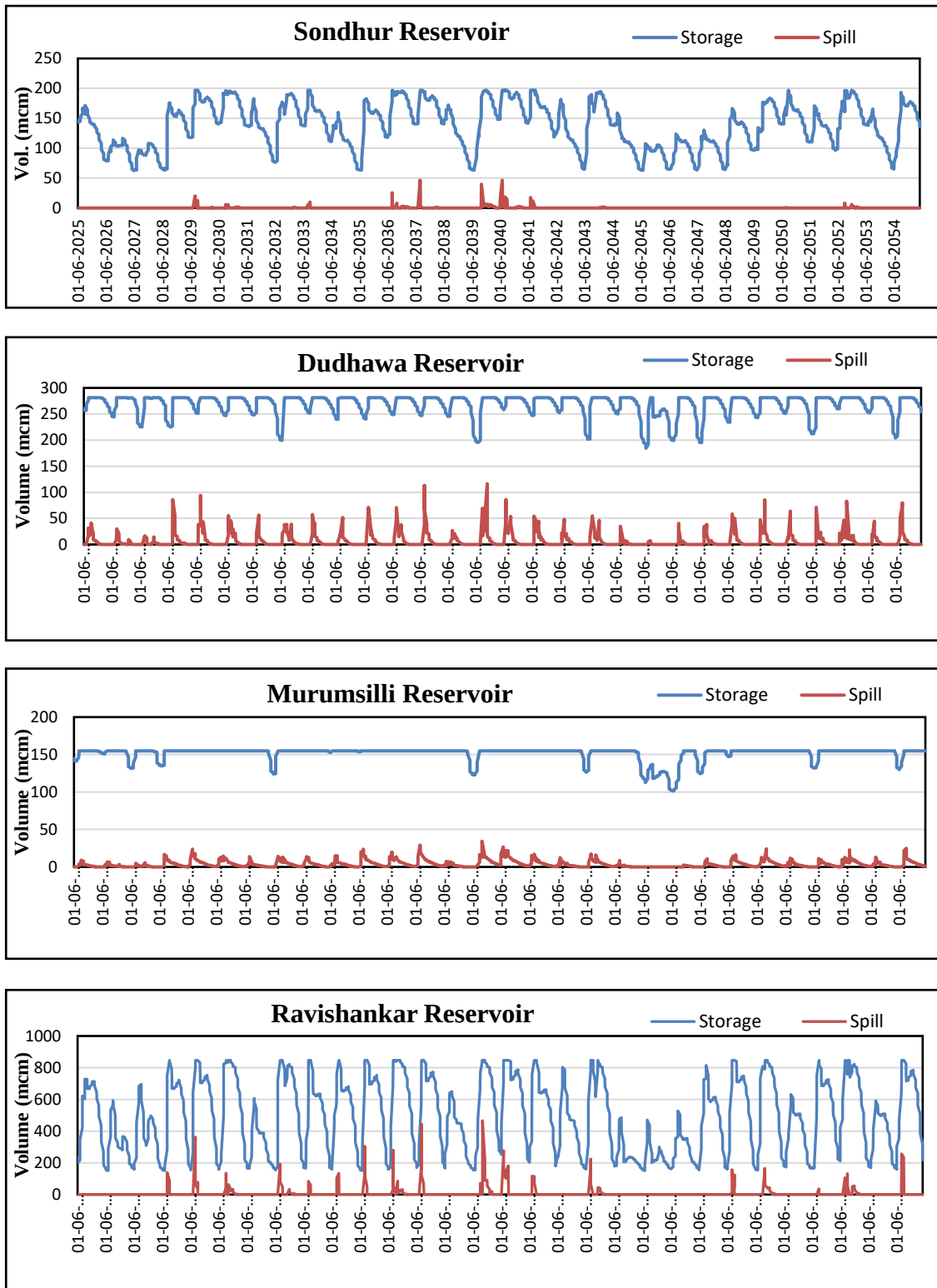


Figure 5.103 Storage and spill behaviors of the reservoirs during integrated operation (SSP585).

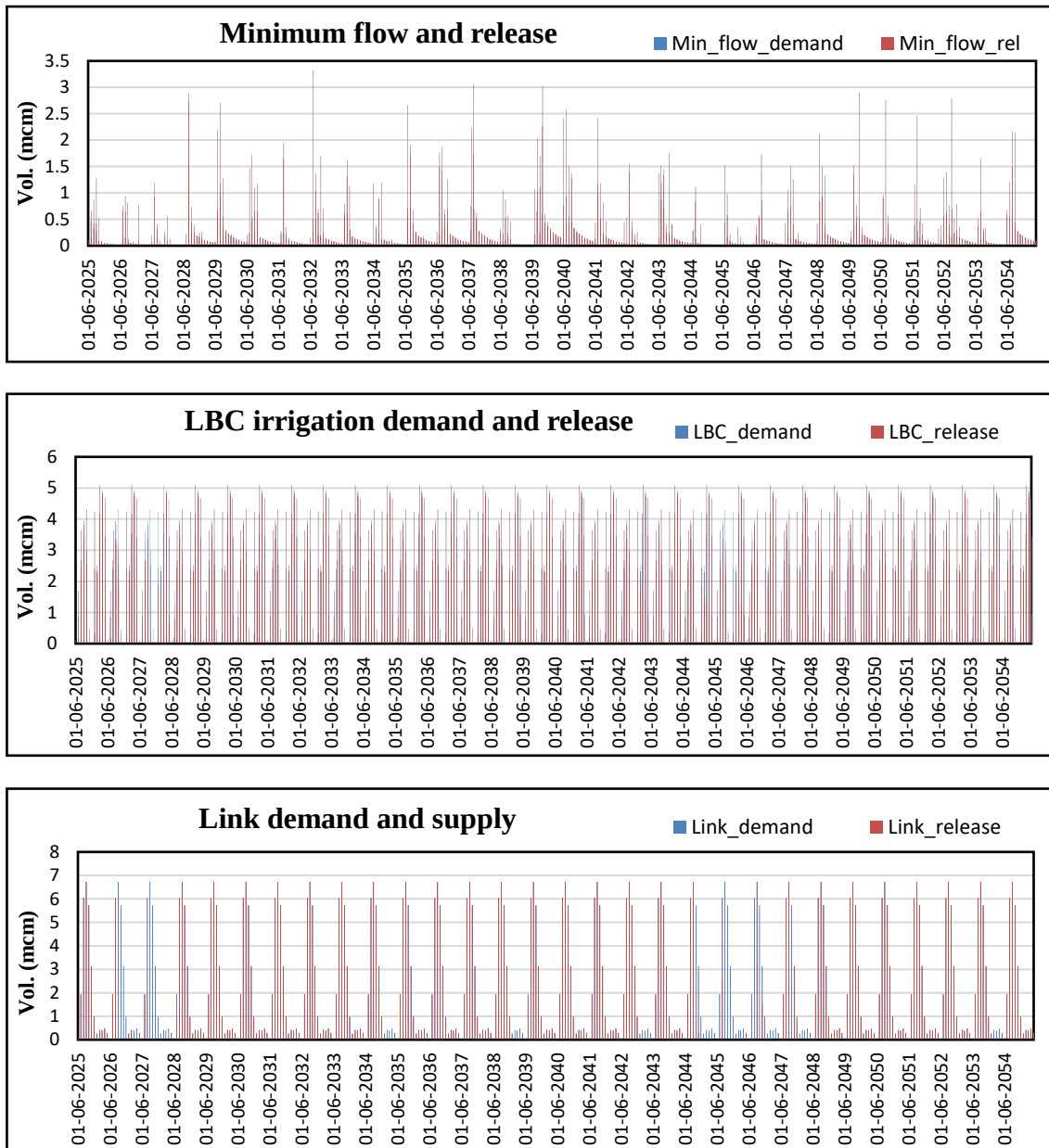


Figure 5.104 Sondhur reservoir operation results (SSP585).

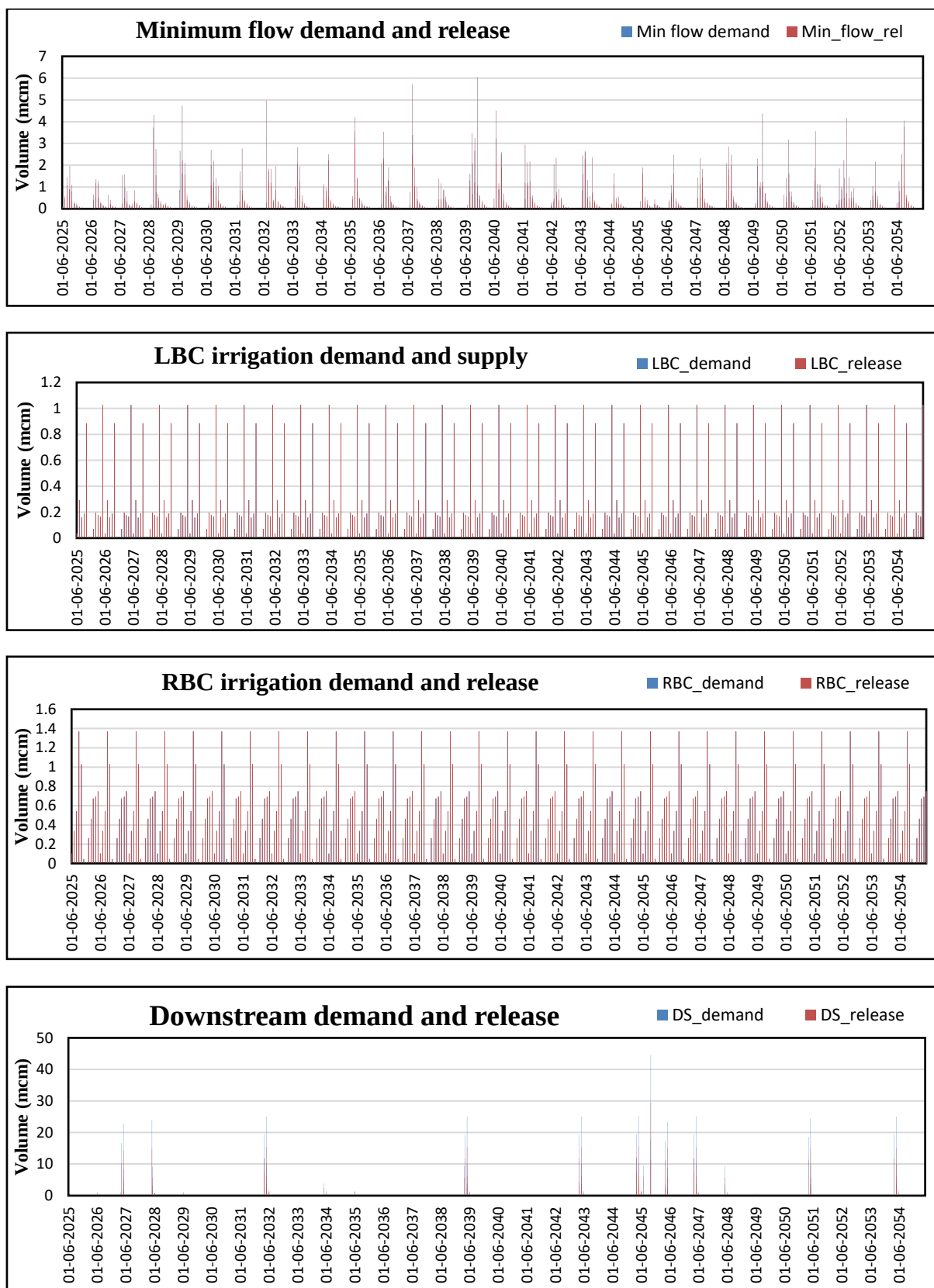


Figure 5.105 Dudhawa reservoir operation results (SSP585).

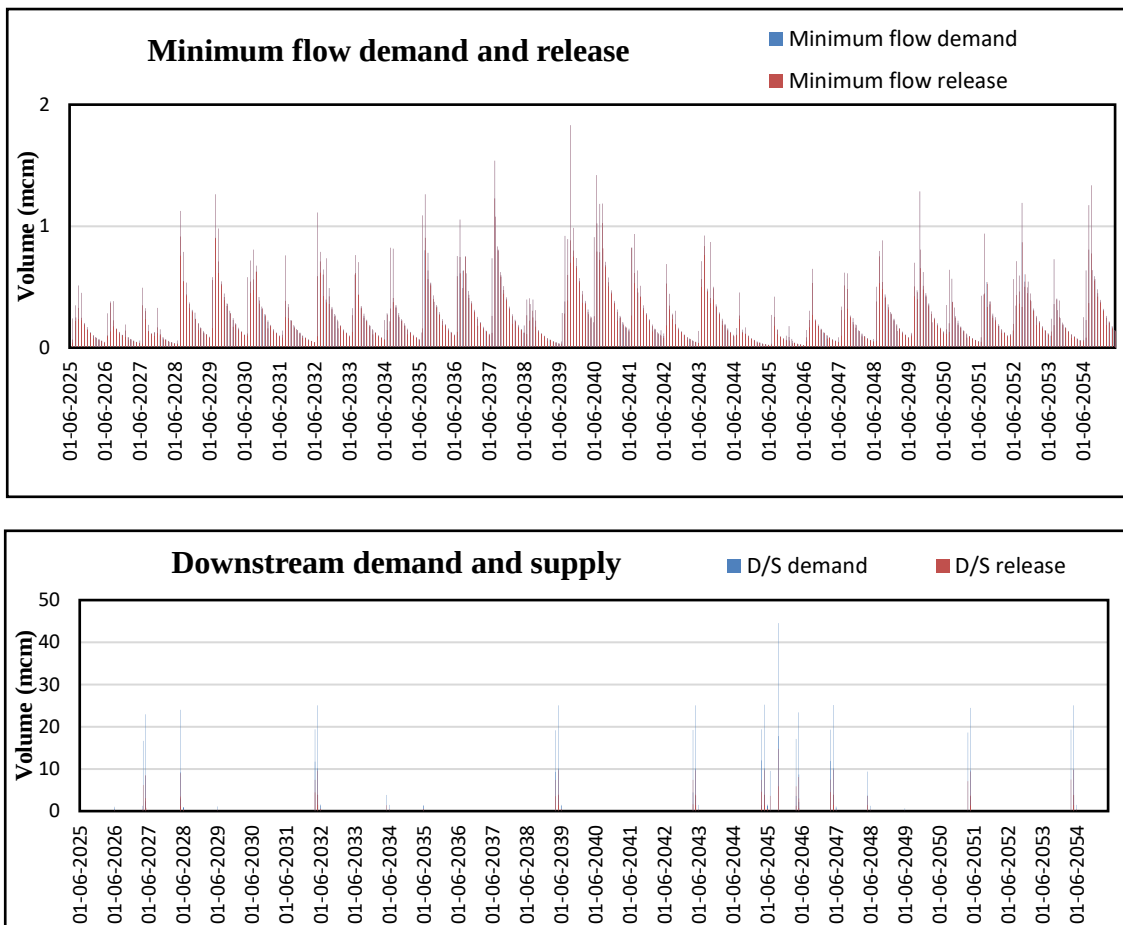


Figure 5.106 Murumsilli reservoir operation results SSP585.

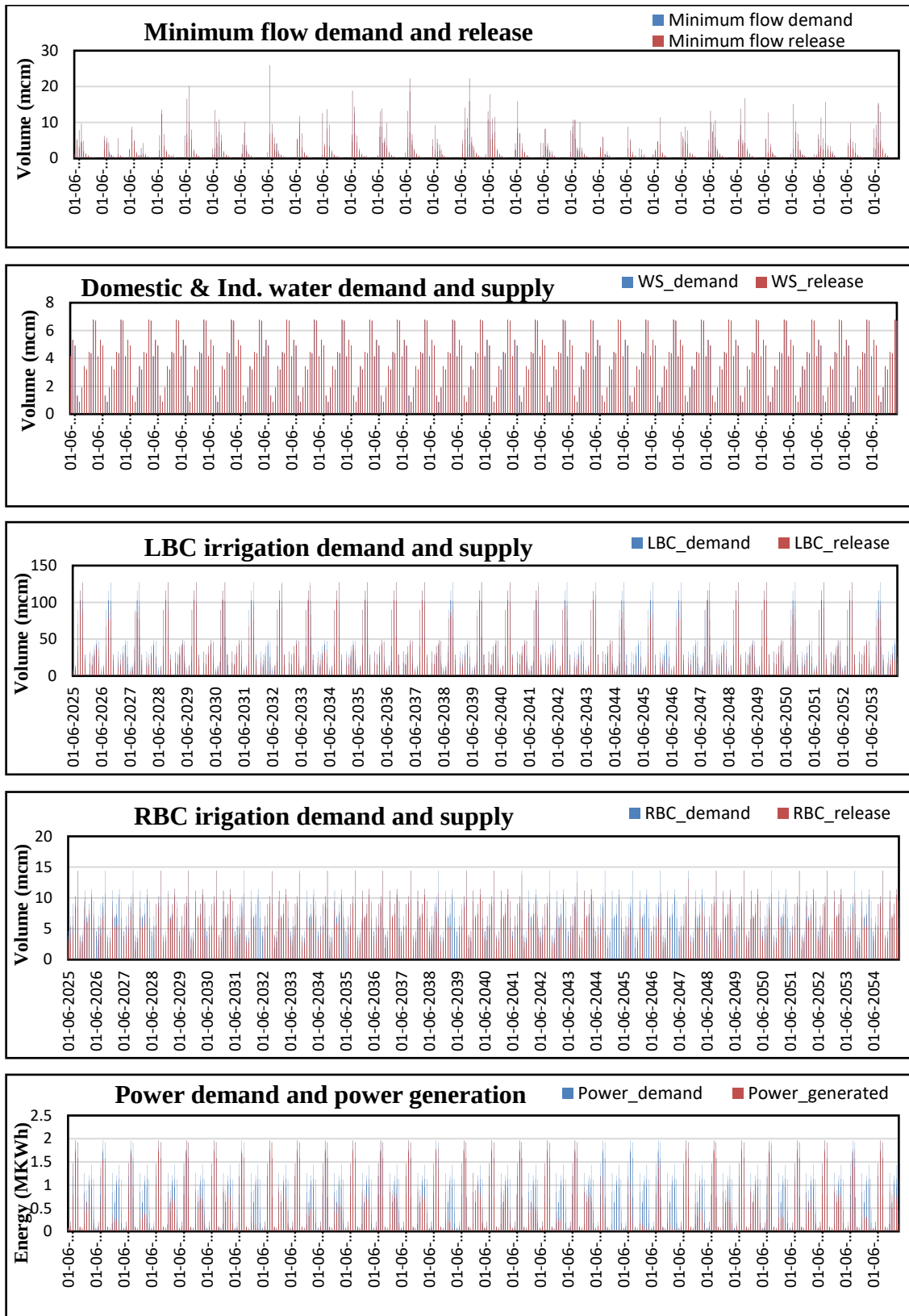


Figure 5.107 Ravi Shankar Sagar reservoir operation results (SSP585).

The average ten-daily results show **Figure 5.108** that a very small deficit occurs during non-monsoon in meeting the irrigation demand of Sondhur. In contrast, a significant link transfer demand deficit occurs during August to November. From December to May, Sondhur provides sufficient water to meet the link demand. Dudhawa reservoir results show that on ten-daily average basis total irrigation demands are met completely (See **Figure 5.109**).

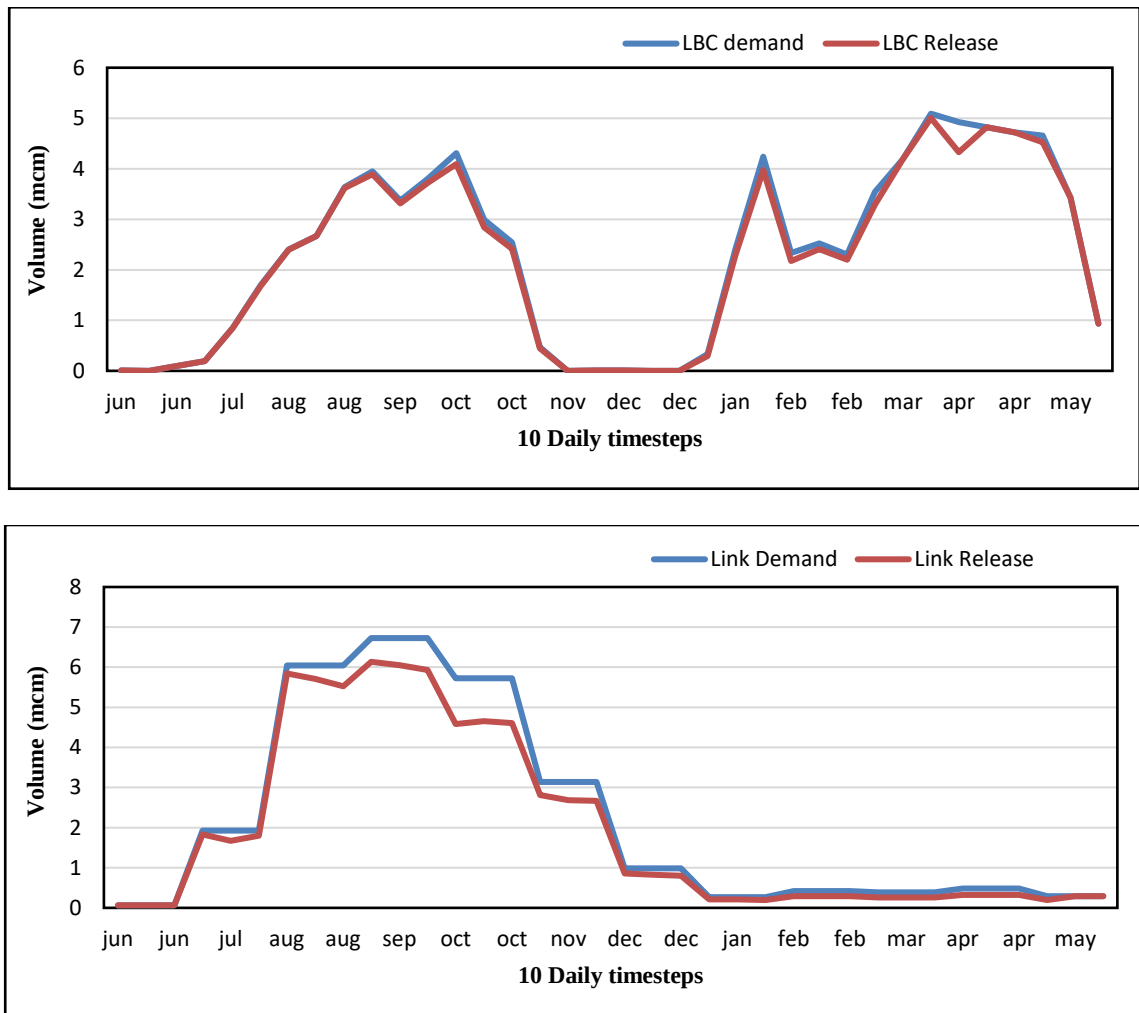


Figure 5.108 Average 10 daily analysis of demand and supply at Sondhur reservoir for SSP585.

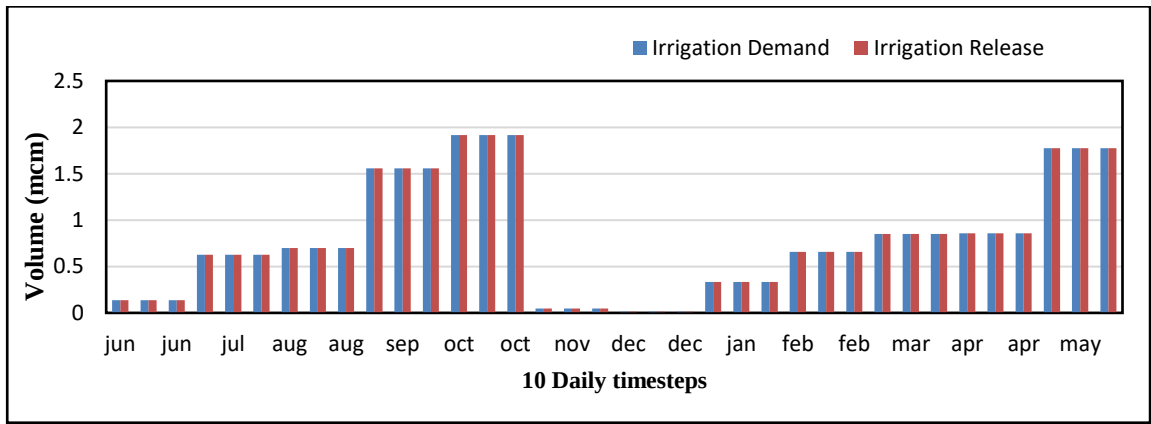


Figure 5.109 Average 10 daily irrigation demand and supply at Dudhawa reservoir for the SSP585 scenario.

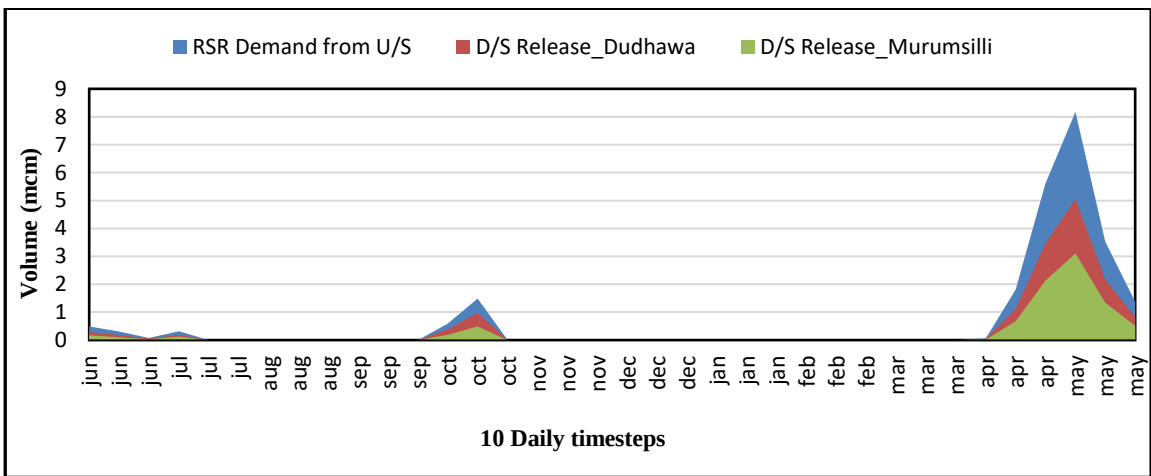


Figure 5.109.1 Average 10 daily water supplied from Murumsilli and Dudhawa to RSR in addition to spills in the SSP585 scenario.

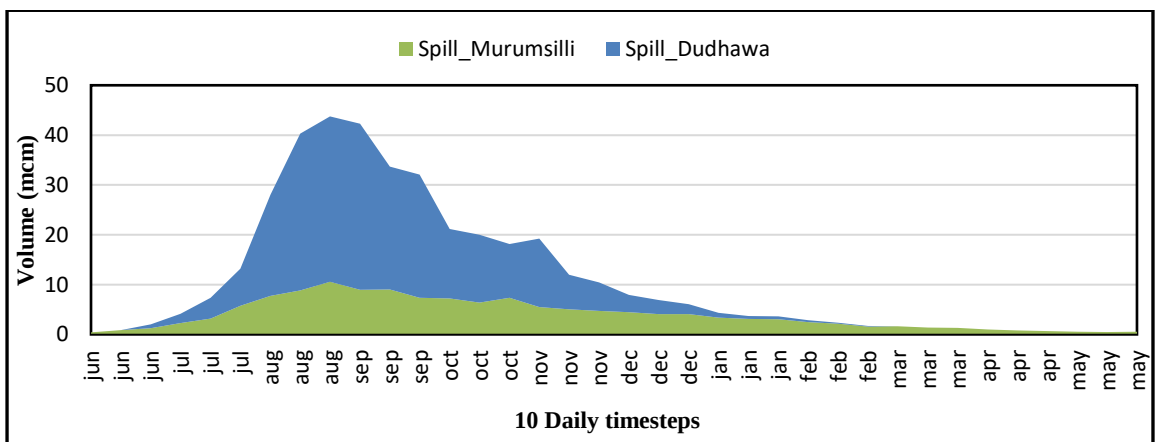


Figure 5.109.2 Spills from Dudhawa and Murumsilli to RSR in the SSP585 scenario.

Dudhawa and Murumsilli supply water for demands at Ravishankar in addition to water spilled from these reservoirs. **Figure 5.109.1** and **Figure 5.109.2** indicate that in general, the spilled water is sufficient to meet the demands at Ravishankar from July to February as no additional water demand occurs during this season at RSR except September and October when some demand occurs at RSR from upstream reservoirs. Water needs to be delivered significantly from Dudhawa and Murumsilli from April to June, see **Figure 5.109.1**.

Figure 5.109.3 shows that the share of water supplied from Dudhawa and Murumsilli to Ravishankar is 63% and 37%, respectively, to meet the rest of the deficit at Ravishankar, after accounting for the water used from spills. These results are the same as those of SSP126 scenario. However, it should be noted that not all the water spilled from Dudhawa and Murumsilli may necessarily be utilized at Ravishankar and may further get spilled from Ravishankar. Further, the operational results of the Ravishankar reservoir indicate that there remains a deficit in meeting irrigation demands during both the monsoon and non-monsoon seasons (see **Figure 5.110**). The deficits are more prominent in the non-monsoon season compared to the monsoon. A similar pattern is observed for power supply, significant deficit may be seen in meeting power demands, particularly during the non-monsoon period **Figure 5.111**.

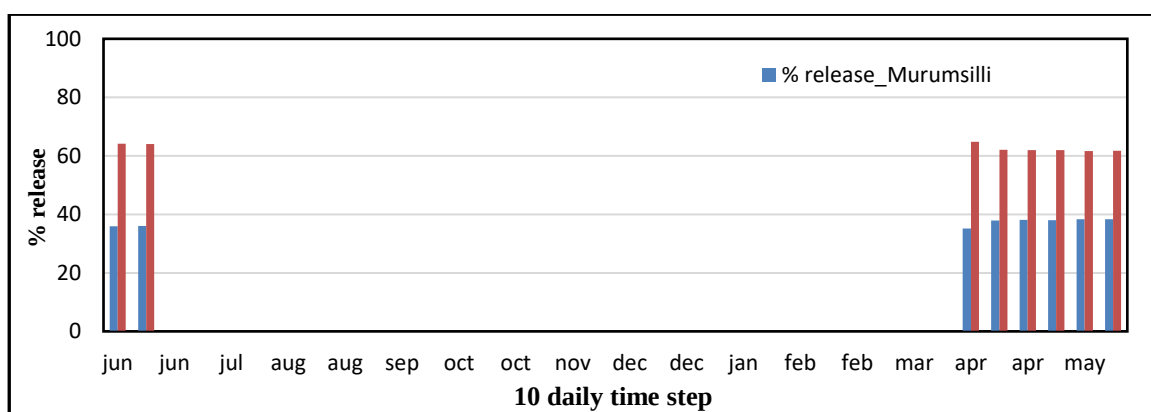


Figure 5.109.3 % Share of release from Dudhawa and Murumsilli to RSR in addition to spills

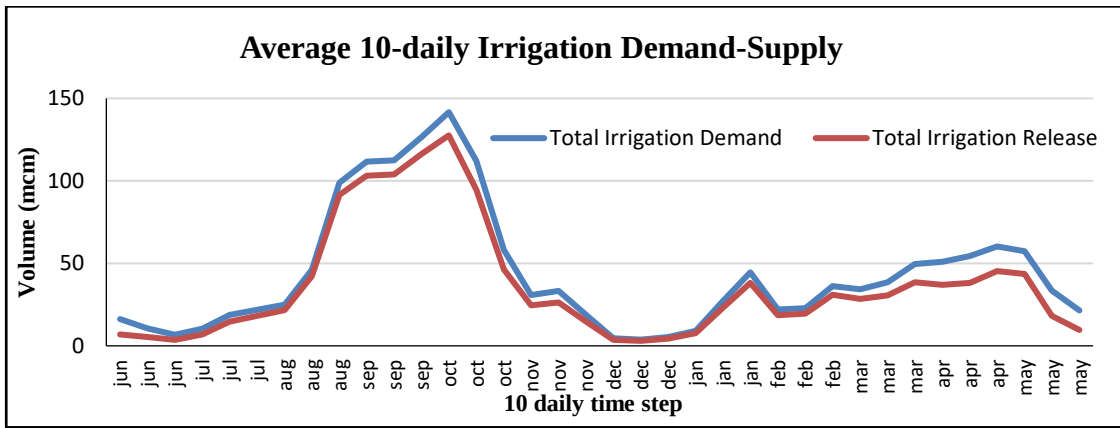


Figure 5.110 Average ten-daily irrigation demand and release at Ravishankar Sagar for the SSP585 scenario.

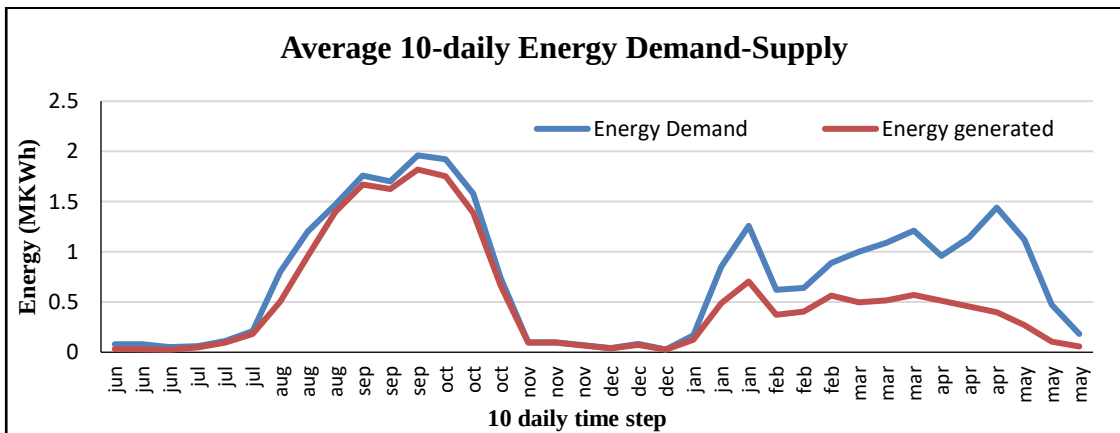


Figure 5.111 Average ten-daily energy demand and energy generation at Ravishankar Sagar for the SSP585 scenario.

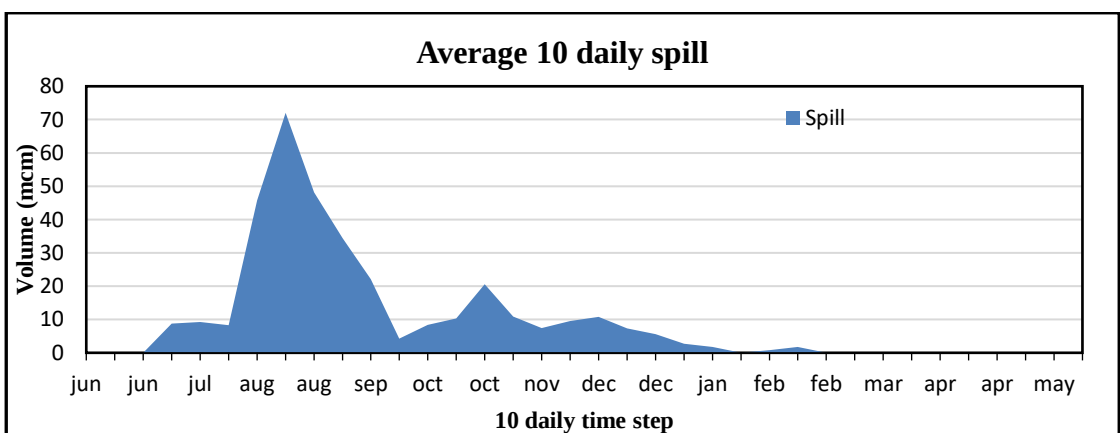


Figure 5.111.1 Average ten-daily spills from Ravishankar Sagar for the SSP585 scenario.

Similar to scenarios SSP126 and SSP245, **Figure 5.111.1** illustrates that the Ravishankar reservoir is unable to accommodate all the water from upstream reservoirs or its own catchment inflow, leading to a significant amount of water being spilled, particularly during the monsoon season. This indicates the need for more efficient water management in the future to conserve this excess water. For meeting irrigation demands during monsoon lowering the irrigation rule curve level during this period may be helpful in fulfilling more demands during monsoon. The upper rule curve for all three reservoirs—Dudhawa, Murumsilli, and Ravishankar—is set at Full Reservoir Level (FRL) during the monsoon, managing spills by raising the rule curve to the maximum water level may not be a viable option due to flood control constraints.

5.18.4 Reliability Analysis

In order to further make an analysis of these results, the monthly volume reliability of various demands for each of the reservoirs is analyzed for different scenarios of climate change and base scenario. It can be seen that Dudhawa and Murumsilli can meet their irrigation demands without any fail and exhibit full reliability in meeting their own demands in the base as well as each of the climate change scenarios on a monthly scale. While Sondhur which has shown 100% reliability in meeting its own irrigation demands during the base period for each month, shows that in the SSP126 scenario from February to July reliability of meeting its irrigation demand is less than 90% while in the rest of the months, it is less than 95% (**Figure 5.112**). SSP 585 scenario also shows a similar pattern, that is, less reliability during March to June (90-95%) but higher in the rest of the months (95-100%). SSP 245 results are contrary to this where better reliability is achieved during December to June (above 97%) while lower values during July to November (90-95%), however the overall reliability is above 94%. This shows that this scenario is less vulnerable as compared to the other in Sondhur reservoir case for meeting monthly irrigation requirements especially in non-monsoon months. Similar results are seen for link transfer (**Figure 5.113**) suggesting that in the future Sondhur will not be able to meet link transfer demands.

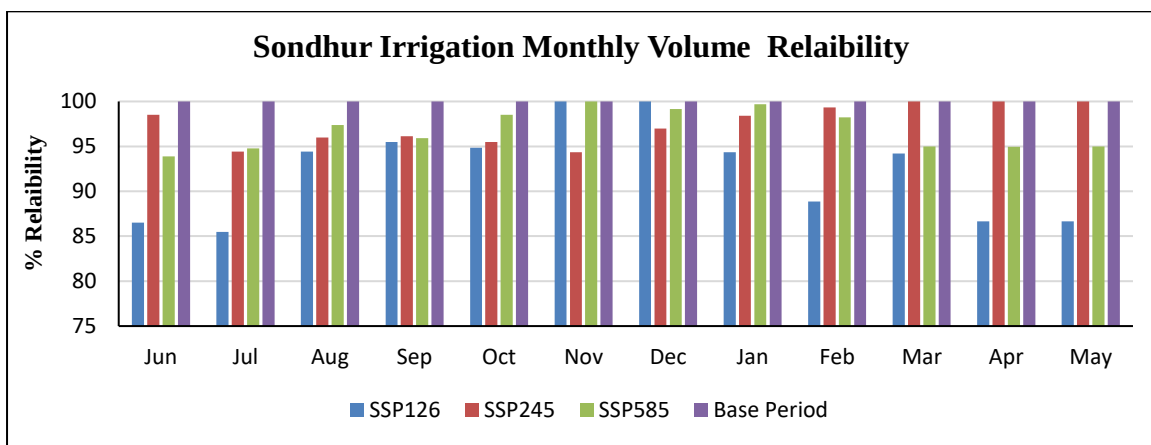


Figure 5.112 Monthly volume reliability for irrigation supply at Sondhur base period and under various near-term climate change scenarios.

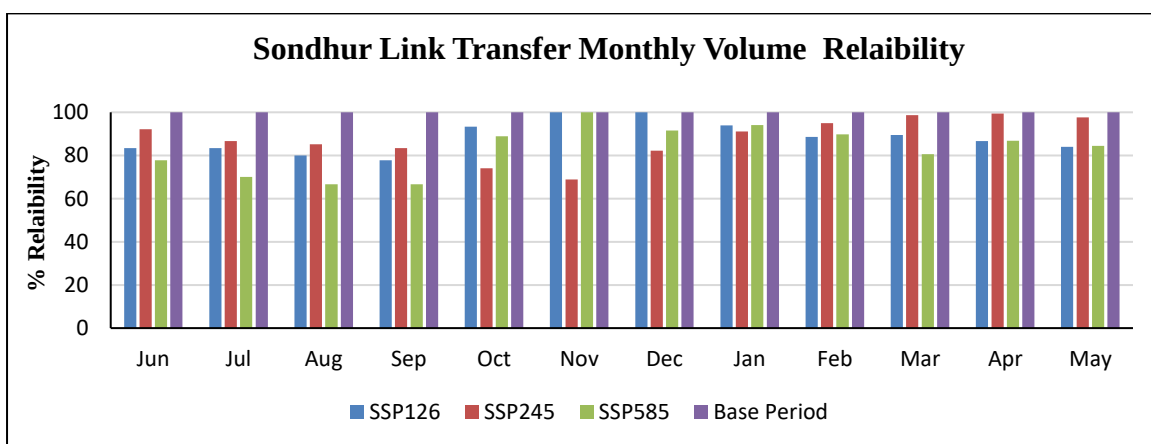


Figure 5.113 Monthly volume reliability for link transfer at Sondhur base period and under various near-term climate change scenarios.

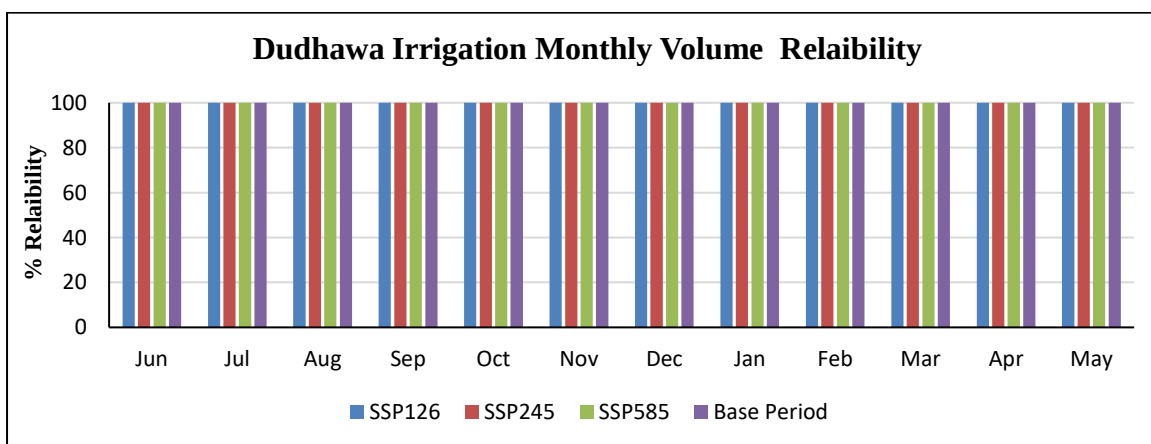


Figure 5.114 Monthly volume reliability for irrigation supply at Dudhawa base period and under various near-term climate change scenarios.

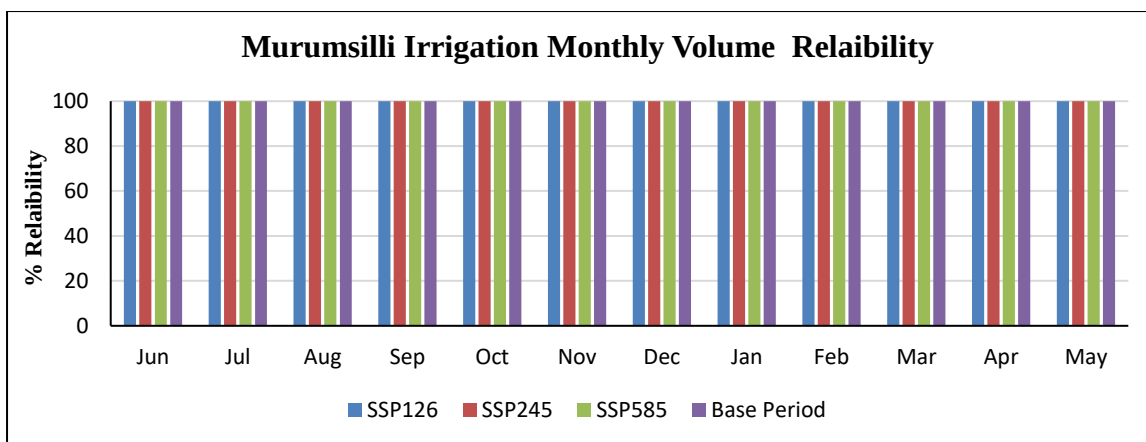


Figure 5.115 Monthly volume reliability for irrigation supply at Murumsilli base period and under various near-term climate change scenarios.

In the case of Ravishankar's domestic and industrial supply, 100% reliability may be achieved in each scenario for each month **Figure 5.116**. For minimum flow except SSP245 the demand can be met fully for remaining scenarios for each month, SSP245 in general shows less reliability during monsoon months **Figure 5.117**.

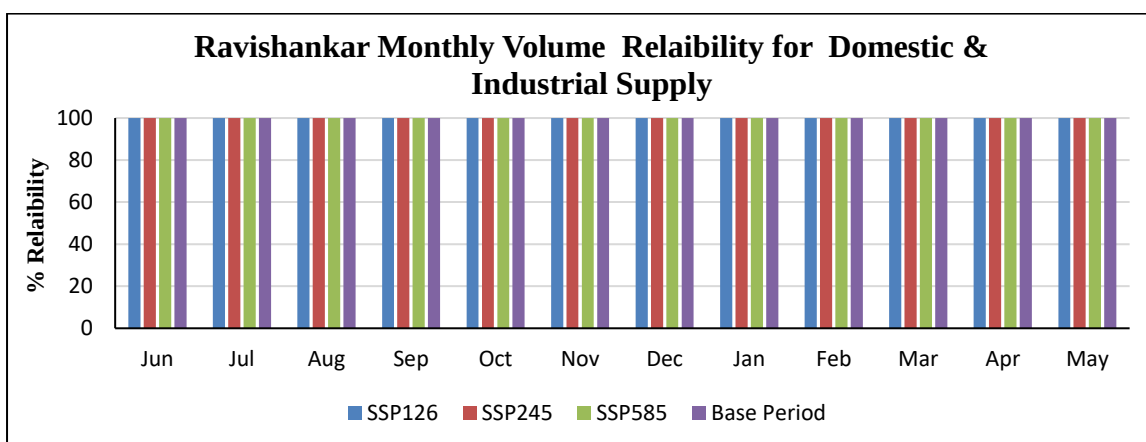


Figure 5.116 Monthly volume reliability for domestic and industrial water supply at Ravishankar base period and under various near-term climate change scenarios.

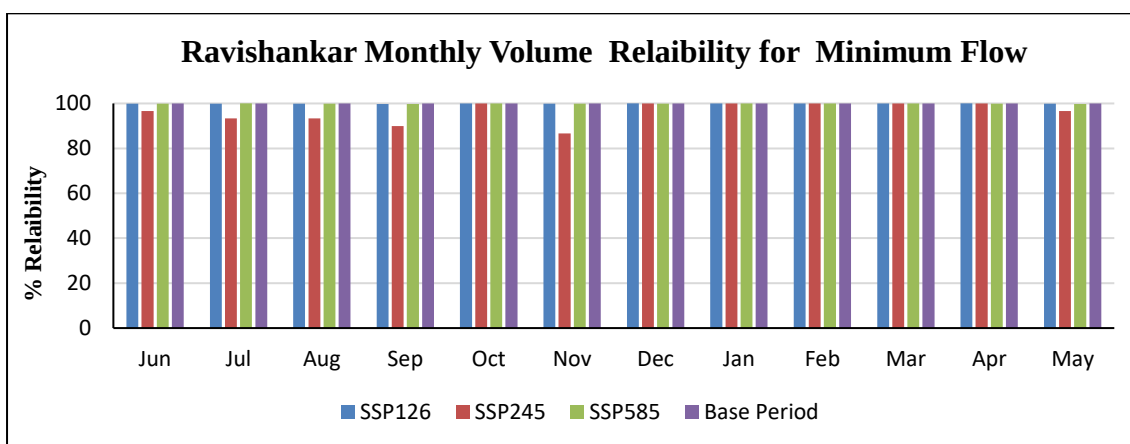


Figure 5.117 Monthly volume reliability for minimum flow at Ravishankar base period and under various near-term climate change scenarios.

On Ravishankar in general volume reliability in meeting irrigation demand is (more than 80%) except from September to November where reliability is below 80% in each scenario of climate change. In meeting irrigation requirements all the scenarios SSP126, SSP245, and SSP585 show quite similar results (**Figure 5.118**).

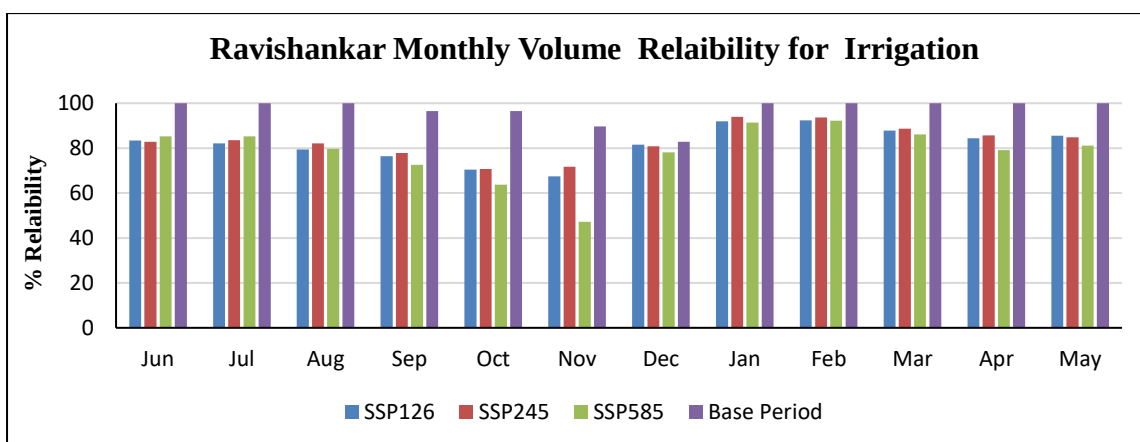


Figure 5.118 Monthly volume reliability for irrigation supply at Ravishankar base period and under various near-term climate change scenarios

In the case of hydropower, better results with reliability (more than 90% during February to May during non-monsoon) are seen in general for each scenario. During June to November, the reliability is very poor in general less than 60%. From October to January, results are better as compared to the base period, however, a very similar pattern is seen for

all three climate scenarios for each month (**Figure 5.119**).

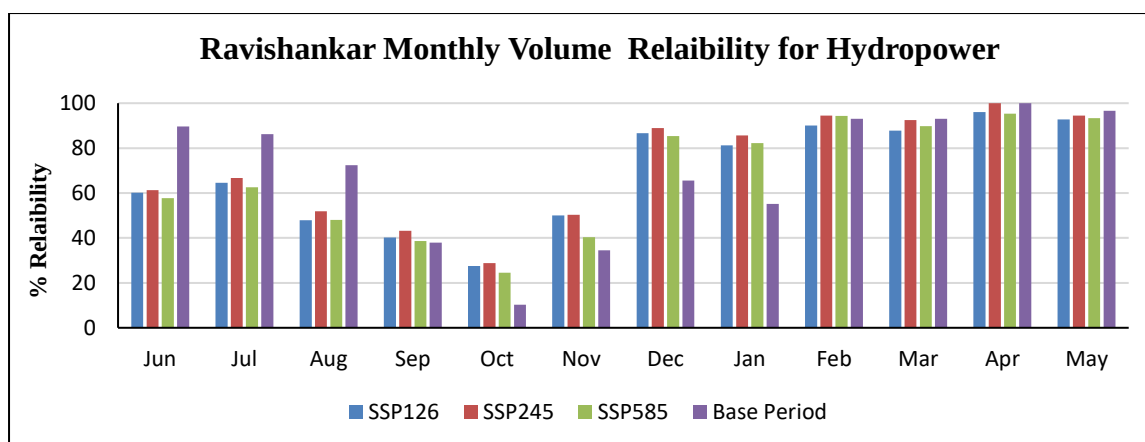


Figure 5.119 Monthly volume reliability for hydropower at Ravishankar base period and under various near-term climate change scenarios.

Figure 5.120 (a) to (d) compares the annual reliability of each reservoir in meeting various demands associated with the reservoir under various climate change scenarios and base periods. The results show that reservoirs, especially Murumsilli and Dudhawa, remain resilient across all scenarios, maintaining 100% reliability for full as well as critical irrigation supply and minimum flows. Sondhur reservoir's reliability decreases across the scenarios showing more sensitivity to SSP245, particularly in meeting link demands, but still manages to meet critical irrigation and minimum flow demands. The Ravishankar Reservoir, while consistent in meeting minimum flow and municipal water supply needs, continues to struggle significantly in supplying agricultural and power demands. Ravishankar Sagar shows strong performance for water supply under all scenarios but struggles with full irrigation and power demands. Under SSP126, minimum flow demands are mostly met, but as emissions increase in SSP245 and SSP585, reliability for full minimum flow demand, irrigation, and power demands declines significantly. However, it consistently meets critical water supply and minimum flow needs across all scenarios.

The analysis of the three climate scenarios (SSP126, SSP245, SSP585) reveals a decline in reservoir performance as climate change intensifies. While Murumsilli and Dudhawa remain highly reliable across all scenarios, Sondhur and Ravishankar show increasing vulnerability, particularly in meeting full irrigation and power demands. The worsening performance under

SSP585 highlights the growing challenges that reservoirs will face in maintaining operational efficiency, especially under severe climate impacts.

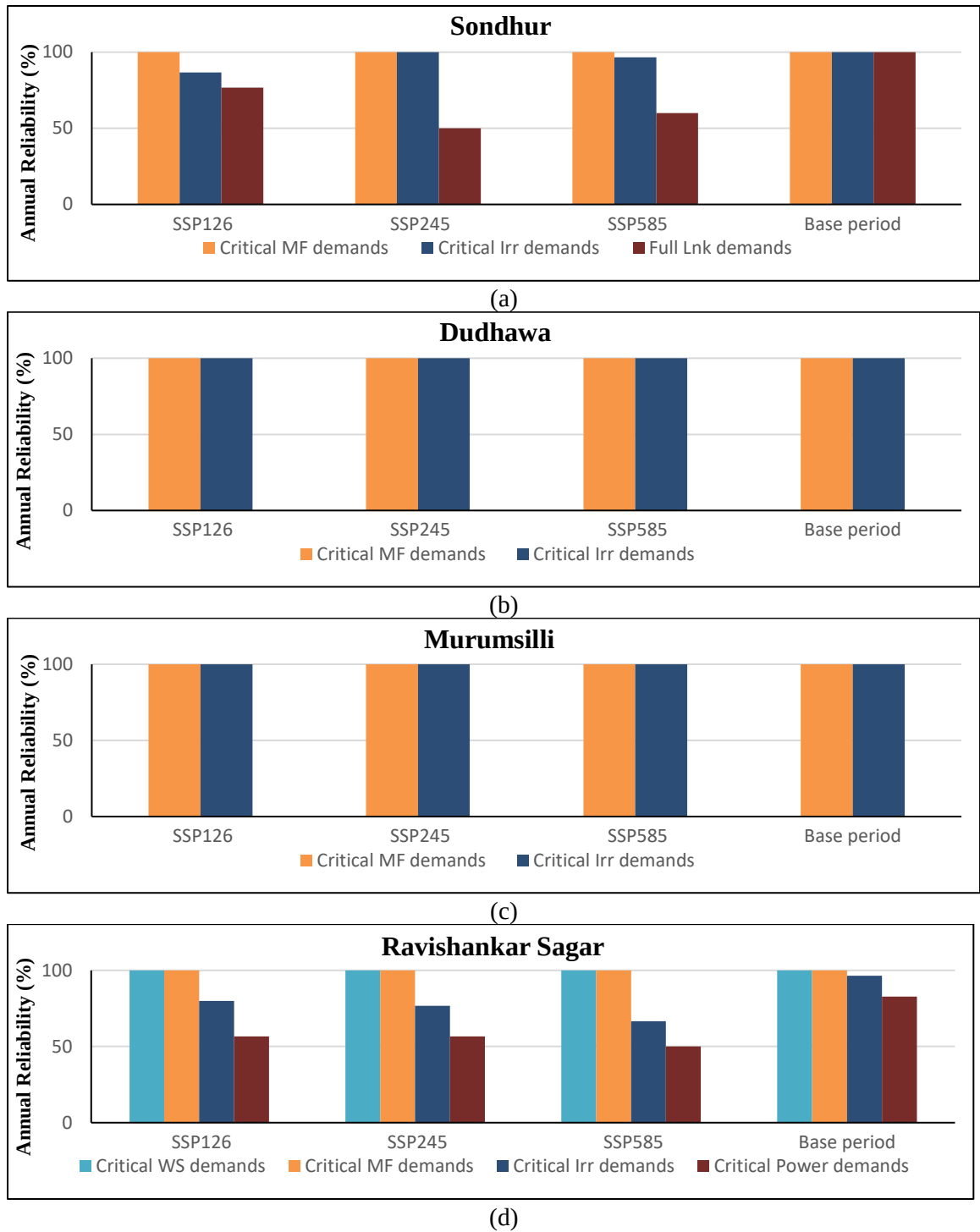


Figure 5.120 (a) to (d) Annual reliability of meeting various demands (critical) for the base period and various near-term climate change scenarios.

The Mahanadi Reservoir Complex, a pivotal hydrological structure in India, plays a multifaceted role in supporting agriculture, providing potable water, serving industrial needs, and generating hydropower. This complex primarily centered on the Mahanadi River, one of India's major Rivers, includes several dams and barrages that contribute to its multifunctional utility. The strategic management of the Mahanadi Reservoir Complex ensures that the water resources are utilized efficiently to support the region's comprehensive needs. Balancing these needs for agricultural, potable, industrial, and energy generation highlights the complex's vital role in the sustainable development and well-being of the communities it serves. The development of a Rule Curve for the Mahanadi Reservoir Complex involves creating a systematic plan or guideline that dictates the optimal storage levels within the reservoirs throughout the year, balancing various demands like irrigation, drinking water, industrial use, and hydropower generation, against the need to manage flood risks and maintain ecological health. This process is crucial for the effective and sustainable management of water resources in the complex.

In the present study, Water water-balancing Excel sheet was used for the estimation of inflow, the MIKE-11 NAM model was calibrated and validated, the revised capacity of the reservoir was estimated by GEE (Google Earth Engine), LULC change detection and forecasting using GEE and hybrid Markov CA model, Rule curve developed by using NIH_ReSyP and GCM model of CMIP6 selected for all reservoirs.

The water balance analysis for Sondhur, Dudhawa, Murumsilli, and Ravishankar Sagar reservoirs involved determining daily inflows from these catchments utilizing reservoir levels, canal outflows, spills, inflows from other catchments, rainfall, and evaporation. This analysis was conducted daily. Specific water balance models adjusted to each reservoir were developed using Excel programming, considering reservoir levels, outflows, and transfers of water from other reservoirs. The analysis spanned from Jun 2003 to May 2021 for the Sondhur, Dudhawa, Murumsilli, and Ravishankar Sagar reservoirs. From the analysis, it has been observed that percentage errors in water balance varied in the range of -6.38 to -7.21 % for the Sondhur reservoir, -6.09 to 6.40 %, for Dudhawa reservoir for Murumsilli reservoir -1.98 to 0.425 and -7.72 to 8.36 % for Ravishankar Sagar reservoir. The results of water balance for reservoirs indicated average annual inflow may be 272.58 ± 188.629 MCM from Sondhur, 522.52 ± 214.95 MCM from Dudhawa, 216.74 ± 112.65 MCM

from Murumsilli catchment, and 2995.74 ± 1980.76 from Ravishankar Sagar reservoir.

The MIKE-11NAM for Sondhur, Dudhawa, Murumsilli, and RS Sagar reservoir catchment up to the dam site was set up and the model was calibrated and validated for the period from 2003 to 20015 and validated from 2016 to 2020. The coefficient of determination (R^2) found during calibration and validation for daily modeling was 0.73, 0.76, 0.70, and 0.74 for Sondhur, Dudhawa, Murumsilli, and Ravishankar Sagar respectively, and 0.73, 0.69, 0.69, and 0.83 respectively. Which was a good match between observed and simulated. After calibrating and validating the MIKE NAM model for all catchments within the MRP complex, the calibrated parameters have been applied to simulate inflows from 1991 to 2020 for the Sondhur, Murumsilli, and Dudhawa catchments. The simulated inflows have been used in NIH_ResyP to develop rule curves for all the dams.

The sediment resultant due to soil erosion from the catchment of the reservoir may affect the intended benefits and needs to be assessed frequently to take appropriate measures well in time. In the study, the Otsu-based segmentation technique is proposed and applied to four reservoirs in India, and the results were compared with the bathymetric survey. These reservoirs were classified into different classes as insignificant (up to 0.1%), significant (0.1 to 0.5%), or serious (more than 0.5%) suggested in IS 12182 by the Bureau of Indian Standard (BIS). Also, the same standard devised a way to select a reservoir catchment for soil conservation by a concept of prescribed limit which can be expressed by the following equation.

$$PL = \frac{\text{Dead Storage}}{\text{Life of reservoir}} \quad (6.1)$$

If the rate of loss of dead storage is higher than the prescribed limit, it is necessary to adopt soil conservation measures in the catchments of the reservoir.

The revised capacity and the rate of sedimentation in different reservoirs of MRP of the Chhattisgarh state of India with the proposed technology and compared with the bathymetric survey (**Table 6.1**). From the analysis, all reservoirs have an annual loss in the range of 0.1 to 0.23%, which can be categorized in the significant class. Also based on the 100-year life period, the Sondhur and Dudhawa reservoirs need soil conservation measures to arrest excessive sediment in the reservoirs.

The predicted changes in land use from 2005 to 2025 and 2050 show significant

trends in the region, with some areas experiencing increases while others are decreasing. The expansion of built-up areas suggests that urbanization and infrastructure development are rapidly taking place in the region, which may have both positive and negative impacts on the environment and the communities living in these areas. The slight increase in barren land class may be a result of human activities such as mining or quarrying or natural factors such as erosion.

On the other hand, the small increase in the water area is a positive sign, indicating that natural hydrological processes are taking place or artificial water bodies are being created. The increase in crop area may suggest that agricultural activities are becoming more efficient and productive, leading to more sustainable use of land. However, the significant decrease in forest area is a cause for concern, as deforestation can have severe impacts on the environment, including soil erosion, loss of biodiversity, and reduced carbon sequestration.

Therefore, it is essential to monitor these changes in land use closely and take appropriate measures to mitigate the negative impacts while promoting sustainable land use practices. This may include reforestation and afforestation programs, promoting agroforestry, and implementing sustainable urban planning strategies. It is vital to balance economic development with environmental sustainability and social equity to ensure the long-term well-being of both the environment and the communities living in the region.

Rule curve has been developed for all four reservoirs for smooth functioning of reservoir operation using NIH_ReSyP reservoir system package. The NIH_ReSyP was estimated rule curve using the EAC Table, demand series (such as irrigation, industrial, domestic, and power demand), and inflow series derived from water balancing based Excel sheet and other meteorological data like, Rainfall, ET. The domestic supply is considered as priority demand, environmental flow is the second priority, irrigation is third and hydropower is considered as fourth priority demand. Integrated operation of the MRP system was carried out using NIH_ReSyP with Standard Operating Policy (SLOP) and Rule Curve. Month-wise reliability suggests that Sondhur, Dudhawa, and Murumsilli reservoirs maintain perfect reliability for each month for all relevant demands using both SLOP and rule curves. A significant improvement in meeting irrigation demands under rule curves compared to SLOP, especially during non-monsoon months. The reliability analysis suggests that irrigation supply can be considerably enhanced using rule curves, making them

a more promising option for agricultural needs in drier periods. The use of rule curves for the integrated operation of the Ravishankar Sagar reservoir generally leads to better outcomes for minimum flow, domestic, industrial, and irrigation demands, particularly in non-monsoon months. The improvement comes at the expense of reduced reliability in meeting power demands during the same period, although power reliability improves during the monsoon months. The results suggest that while rule curves provide a more balanced and flexible approach overall, specific adjustments might be needed to better manage power generation, especially during non-monsoon months.

The study also examines the best GCM for future climate projection over the study area, the performance of 13 Global Climate Models (GCMs) of CMIP6 during 1991-2014 was evaluated against the observed dataset to identify the best climate model to reproduce rainfall and temperature time series. The BCC-CSM2-MR was selected as the model for projecting future rainfall and temperature.

The future projection Tmax, Tmin, and Precipitation for all reservoirs during the near century (2025-2055) under different emission scenarios SSPs i.e. SSP126, SSP245, SSP370 & SSP585 are obtained from the best climate model of CMIP6. In the sondhur catchment, the average Tmax and Tmin during the base period are estimated at 32.64 °C and 19.70 °C respectively. The future projection indicated an increase in Tmax by +2.21%, +2.49%, +2.06% & +2.73% in different SSP scenarios similarly Tmin may be increased by +9.90%, +9.40%, +10.64% & +11.58% during the near century in SSP scenarios (SSP1, SSP2, SSP3 & SSP5). The average annual rainfall during the base period is estimated at 1125.53 mm. Future projections showed an increase in rainfall within the range of +3.81-11.64% under different SSP scenarios. The highest percentage increase in annual rainfall is found under SSP1-2.6. The monthly analysis showed an overall increase in rainfall during October to February. In the Dudhawa catchment, the average Tmax and Tmin during the base period are estimated at 32.64 °C and 19.70 °C respectively. The future projection indicated an increase in Tmax by +1.71%, +1.61%, +1.77% & +1.03% in different SSP scenarios similarly Tmin may be increased by +5.98%, +5.54%, +6.66% & +7.66% during the near century in SSP scenarios (SSP1, SSP2, SSP3 & SSP5). The average annual rainfall during the base period is estimated at 1219.01 mm. Future projections showed an increase in rainfall within the range of +0.02-7.47% under different SSP scenarios. The highest percentage increase in annual rainfall is found under SSP126. The monthly analysis showed

an overall increase in rainfall from November to February. In the Murumsilli catchment, the average Tmax and Tmin during the base period are estimated at 32.64 °C and 19.70 °C respectively. The future projection indicated an increase in Tmax by +2.10%, +2.44%, +2.266% & +2.95% in different SSP scenarios similarly Tmin may be increased by +8.97%, +8.39%, +9.61% & +10.58% during the near century in SSP scenarios (SSP1, SSP2, SSP3 & SSP5). The average annual rainfall during the base period is estimated at 1125.53 mm. Future projections showed an increase in rainfall within the range of +9.13-17.69% under different SSP scenarios. The highest percentage increase in annual rainfall is found under SSP1-2.6. The monthly analysis showed an overall increase in rainfall from October to February. In the Ravishankar Sagar catchment, the average Tmax and Tmin during the base period are estimated at 32.64 °C and 19.70 °C respectively. The future projection indicated an increase in Tmax by +1.15%, +1.32%, +0.58% & +0.63% in different SSP scenarios similarly Tmin may be increased by +3.70%, +3.17%, +4.29% & +5.38% during the near century in SSP scenarios (SSP1, SSP2, SSP3 & SSP5). The overall high increase has been shown in minimum temperature (Tmin) compared to maximum temperature (Tmax). The average annual rainfall during the base period is estimated at 1274.64 mm. Future projections showed an increase in rainfall under SSP1&SSP2 scenarios. The increase percentage of rainfall by +3.58% and +1.09% under SSP1 and SSP2 scenarios. The future projection indicated a decrease in rainfall by -0.765% and -3.49% under SSP3 and SSP5 scenarios. The highest percentage increase in annual rainfall is found under SSP126.

The calibrated MIKE11 NAM model is interfaced with future climate projections to predict the future inflow for all catchments of MRP. Inflow is decreasing in all of the SSPs scenarios over the Ravishankar and Sondhur catchments. Murumsilli and Dudhawa are showing a decreasing trend in SSP126, SSP370, and SSP585 and increasing in SSP245.

The impact of climate change on irrigation water requirements under projected scenarios (SSP126, SSP245, SSP370, and SSP585) using a selected climatic model. By comparing the irrigation water requirements during a base period with those projected under different scenarios, it can assess the potential changes in water demand due to climate change. The future projection indicated an increase in average irrigation water requirement by +20.2%, +26.9%, +26.6% & +26.7% in different SSP scenarios. Predicting future populations and adjusting the reservoir rule curve accordingly helps ensure that the water supply infrastructure can meet future demands. The domestic water supply is projected to

increase by 1.92 times in the future.

The computed inflow, Irrigation water requirement, domestic water supply, projected rainfall, and projected evapotranspiration have been used in NIH_ReSyP to develop future rule curves for all reservoirs under SSP126, SSP245, and SSP585 scenarios. The results show that reservoirs, especially Murumsilli and Dudhawa, remain resilient across all scenarios, maintaining 100% reliability for full as well as critical irrigation supply and minimum flows. Sondhur reservoir's reliability decreases across the scenarios showing more sensitivity to SSP245, particularly in meeting link demands, but still manages to meet critical irrigation and minimum flow demands. The Ravishankar Reservoir, while consistent in meeting minimum flow and municipal water supply needs, continues to struggle significantly in supplying agricultural and power demands. Ravishankar Sagar shows strong performance for water supply under all scenarios but struggles with full irrigation and power demands. Under SSP126, minimum flow demands are mostly met, but as emissions increase in SSP245 and SSP585, reliability for full minimum flow demand, irrigation, and power demands declines significantly. However, it consistently meets critical water supply and minimum flow needs across all scenarios.

The analysis of the three climate scenarios (SSP126, SSP245 & SSP585) reveals a decline in reservoir performance as climate change intensifies. While Murumsilli and Dudhawa remain highly reliable across all scenarios, Sondhur and Ravishankar show increasing vulnerability, particularly in meeting full irrigation and power demands. The worsening performance under SSP585 highlights the growing challenges that reservoirs will face in maintaining operational efficiency, especially under severe climate impacts.

These findings have significant implications for various applications, including water resource planning, reservoir operation, and irrigation scheduling. The future projections based on the selected GCMs and SSP data can be utilized for informed decision-making, development of future rule curves, and improved utilization of available resources.

Overall, the study emphasizes the importance of balancing economic development with environmental sustainability and social equity to ensure the long-term well-being of both the environment and the communities living in the region. It highlights the need for proactive measures to address the challenges posed by sedimentation in reservoirs and land use changes to ensure that they do not compromise the intended benefits and negatively impact the environment and communities.

Table 6.1 Comparison of revised capacities with hydrographic survey.

Salient features Name	Unit	Ravishankar Sagar		Muramsilli		Sondhur		Dudhawa	
		RS Survey	Bath. Survey	RS Survey	Bath Survey	RS Survey	Bath Survey	RS Survey	Bath. Survey
Year of assessment		2019	2021	2021		2020		2020	
Rev. Storage at DSL	MCM	118.26	125.54	0.63	0.08	2.01		1.788	2.113
Rev. Storage at FSL	MCM	826.249	825.89	148.127	148.748	172.11		257.575	252.002
Loss of storage at DSL	MCM	25.34	18.06	1.268	0.548	4.19		3.002	2.677
Loss of storage at FSL	MCM	84.26	84.62	17.14	17.27	25.99		31.04	36.61
Loss of Live storage	MCM	58.92	66.56	15.87	16.72	21.80		28.03	33.93
Rate of Loss at DSL	MCM/Year	0.62	0.42	0.013	0.006	0.086		0.053	0.046
Rate of Live Storage	MCM/Year	1.44	1.55	0.160	0.169	0.445		0.492	0.585
Rate of Loss at FSL	MCM/Year	2.06	1.97	0.173	0.174	0.530		0.544	0.631
Silt Index	ham/100 sq km/year	5.68	5.44	3.563	3.589	10.240		8.712	10.099
Annual % Loss	Percentage	0.226	0.216	0.104	0.105	0.268		0.189	0.219
Class of reservoir		Significa nt	Significant	Significa nt	Significa nt	Significa nt		Significa nt	Significant
Life		100	100	100	100	100		100	100
PL		1.44	1.44	0.013	0.013	0.062		0.048	0.048
Present Rate		0.62	0.42	0.013	0.01	0.086		0.053	0.046
Need of CAT plan		No	No	No	No	Yes		Yes	No

RS: Remote Sensing, Bath: Bathymetric, PL: Prescribed limit, PL: Prescribed limit, Res: Reservoir, DSL: Dead storage level, FSL: Full supply le

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ANNEXURE-I SALIENT FEATURS
C.G. MAJOR IRRIGATION PROJECT MRP COMPLEX
SONDHUR RESERVOIR PROJECT
SALIENT FEATURS

1. LOCATION

1.1	Basin	:-	Mahanadi Basin.
1.2	State	:-	Chhattisgarh
1.3	Village /Taluka /District	:-	Mechka/Nagri/Dhamtari
1.4	Latitude		20°-14'
1.5	Longitude		82°-06' (Toposheet No. 64L-3, 64H-15, 64H-16)
1.6	Name of River	:-	Sondhur
1.7	Tribal / Non Tribal	:-	Tribal
1.8	Distance from District head quarter (K.m.)	:-	90 km.
1.9	Project Site	:-	Near village Mechka, 3Km south from village Arsikanhar and 25 Km south from Nagri town.

2 *HYDROLOGICAL DATA*

2.1	Catchment area (Sq. K.m.)	:-	512
2.2	Maximum flood discharge (cumecs)	:-	5163.12

2.2 *ANNUAL RAINFALL*

2.2.1	Maximum	:-	1955.54mm/76.99inch
2.2.2	Minimum	:-	585.72mm/23.06 inche
2.2.3	Average	:-	1419.70mm/55.89 inche

2.3 *MONSOON RAINFALL*

2.3.1	Maximum	:-	1850.89mm/72.87inch
2.3.2	Minimum	:-	519.17mm/20.44 inche
2.3.3	Average	:-	1295.91mm/51.02 inche

2.3 *MONSOON YEILD*

2.3.1	Maximum (before constn. of Dam)	:-	16.44 Mcum/580 Mcft.
2.3.2	Minimum	:-	1.15 Mcum/42 Mcft.
2.3.3	Average	:-	8.22 Mcum/290 Mcft
2.3.4	Maximum (after constn. of Dam) in 1994	:-	4012Mcum/141673 Mcft.

2.3.5	75% dependable Yield	:-	6.37 Mcum/225 Mcft.
2.3.6	50% dependable Yield	:-	4.24 Mcum/150 Mcft
2.3.7	90% dependable Yield	:-	7.65 Mcum/270 Mcft
2.4	FLOODS		
2.4.1	Maximum observed at Dam site	:-	2320 Cumecs/0.82 L Cusecs.
2.4.2	Designed Flood	:-	5163 Cumecs/1.82 L Cusecs.
2.4.3	Moderate design flood through spillway	:-	6513 Cumecs/2.30 L Cusecs.
2.4.4	Designed flood capacity of spillway	:-	5407 Cumecs/1.91 L Cusecs.
3.	RESERVOIR DATA		
3.1	Gross storage at F.R.L.	:-	198.10 MCum 6995.70 Mcft.
3.1	Live storage at F.R.L.	:-	179.6112 MCum 6342.74 Mcft.
3.2	Dead Storage	:-	18.49 MCum/ 653.00 Mcft
3.3	Submergence at FRL (ha.)	:-	2412 Ha.
4.	DAM		
4.1	Total Length of dam (meters)	:-	3330 M
4.	Length of Masonry Dam	-	191.20 M
	Length of Earthen Dam		3138.80 M
	Maximum height of dam (meters)		38.20 M
	Top width of dam (meters)	:	4.57 M
5	PRINCIPAL LEVELS (Meters)		
5.1	Lowest River bed level	:-	447.065
5.2	Crest Level of spillway	:-	461.065
5.3	Crest Level of Head sluice	:-	459.265
5.4	Deepest foundation Level	:-	436.065
5.5	Full reservoir level (FRL)	:-	471.065
5.6	Maximum water level (MWL)	:-	471.965
5.7	Top bund level (TBL)	:-	474.265
6.	CANAL		
6.1	Head Regulator gates	:-	2 Nos. (Size 1.75m x 1.50m.)

6.2	Head discharge (cumece)	:-	28.30 Cumecs
6.3	Length of main canal (k.m)	:-	15.0 Km.
6.4	Number of structure	:-	33
6.5	Length of distributaries and minors	:-	159.58 Km.
6.6	Number of structures	:-	675

7. ***AREA PROPOSED UNDER IRRIGATION
(ha.) (CCA)***

7.1	Perennial	:-	Nil
7.2	Kharif	:-	12703
7.3	Rabi	:-	Nil
7.4	Annual irrigated	:-	12703
7.5	Net area to be irrigated	:-	12510
7.6	Irrigated intensity (%)	:-	98%

C.G. MAJOR IRRIGATION PROJECT MRP COMPLEX
SALIENT FEATURES OF MOORAMSILLI DAM

1.	<u>Location</u>	
1.1	State	:- Chhattisgarh
1.2	District	:- Dhamtari
1.3	River/River Basin	:- Siliyari/Mahanadi Basin.
1.4	Nearest Village	:- Muramsilli in Nagri Tahsil
1.5	Latitude	:- 20°32'27"
1.6	Longitude	:- 81°40'54"
1.7	Top sheet No.	:- 64 H/10
1.8	Year of Completion	:- 1923
1.9	Name of Dam Owner	:- Water Resources Department
1.10	Full Address of Dam Owner	:- E.E., W.M. Dn. Rudri
1.11	Identification Code	:- CG3HH0008
2.	<u>Hydrology</u>	:-
2.1	Catchment area	:- 187 sq.miles (484.33sq.m)
2.2	Average annual rainfall	:- 52" (1320.78 mm)
2.3	Mean Monsoon Rainfall	:- -
2.4	Mean Monsoon Yield	:- 10303.7 Mcft. (291.80 m.cum)
2.5	Design flood revised	:- 4480.00 cumecs
2.6	Design flood	:- 2011.00 cumecs. (71008
(a)		cusecs)
(b)	Observed flood	:- 3908.00 Cumecs.
	(Spillway Capacity)	(1132.68 Cumecs.)
	Average of gross/mean Monsoon.	:- 56.39%
3.	<u>Reservoir Data</u>	:-
3.1	Gross storage capacity	:- 165.343 mm ³ (5839 mcft.)
3.2	Dead storage capacity	:- 3.43 mm ³ (121 mcft.)
3.3	Live storage	:- 161.916 mm ³ (5718 mcft.)
(a)	Maximum water level (MWL)	:- 377.04 m. (1237 ft.)
(b)	Maximum water level revised	:- 378.25 m. (1241.04')
3.4	Ht. (m) above deepest foundation level	:- 34.15 m.
3.5	Ht. (m) above NBL	:- 17.68 m.
3.6	Length of Dam (m) Earthen	:- 2590.80 m. (Gravity Dam
		94.10 m.)
3.7	Length of crest (m) of spillway	:- 94.10 m.
3.8	Bottom width (m)	:- 33.00 m.
3.9	Top width (m)	:- 5.00 m.
3.10	Water spread area (Ha.)	:- LSL (361.19 m) 261.15 Ha., FRL (376.28 m.) 2378.50 Ha. MWL (377.04 m.) 2525.24 Ha.
4.	Full Reservoir level (FRL)	:- 376.28 m. (1234.60 ft.)
5.	Lowest sill level (LSL)	:- 361.19 m. (1185 ft.)

6	Top bund level (TBL)	:-	378.87 m. (1243 ft.)
7	Maximum hight of bund above River bed.	:-	25.53 (83.76 ft.)
8	Water spread area at MWL	:-	-
9	Water spread area at FRL	:-	25.25 sq.km. (9.75 sq. miles)
10	Maximum discharge over waste weir.	:-	40,000 cusecs (1132.68 cumecs)
11	Gross submergence area	:-	2600 hector (6424.6 acres)
12	Cumulative commanded area	:-	80192.60 acres (32453.50 hector)
	(i) Total village effected	:-	-
	(ii) Dhamtari / Nagri Tahsil	:-	-
	(iii) Total cost of Project	:-	-
	(iv) After completion	:-	Rs. 31,17,537.00
13.	<u>Syphon Details</u>	:-	
13.1	'A' Type syphon 28 Nos.	:-	Batteries consisting of 28 syphon each.
13.2	'B' Type	:-	(3+3) =6 Nos. (2 Batteries)
13.3	Discharge 'A' type.	:-	1050 cusecs each.
13.4	Discharge 'B' type.	:-	1338 cusecs each.
13.5	R.L. of syphon D/s floor	:-	366.37m. (1202ft.)
13.6	Down stream	:-	150 & 300.67
13.7	First fall.	:-	19.83' (6.04 m.)
13.8	Second fall	:-	22' (6.70 m.)
13.9	Second fall crest R.L. Length.	:-	360.27m. (1182.00 ft.)
13.10	Total discharge capacity	:-	45245 cusecs (1281.21 cumecs)
13.11	Cost of syphon	:-	691000
13.12	Note :- 'B' Type siphons are at slightly lover level than 'A' type each syphon is provided with ababy syphon on 1" lift which is for priming purpose.		
13.13	Sluice gate.	:-	3 Nos. are 10' x 8'.9" (2.65x3.05 m.)

WORKING R.L. OF MURAMSILLI SYPHON BABY SYPHON 'B' TYPE

'B' type main syphon.		Prime gate R.L. 1234.54
No.	33	: 1234.50 to 1234.54 ft.
No.	2	: 1234.60 to 1234.63 ft.
No.	1	: 1234.0 to 1234.65 ft.
No.	32 & 34	: 1234.70 to 1234.75 ft.
No.	3	: 1234.80 to 1234.85 ft.
	Baby syphon 'A' type 'A' type main syphon	: Between R.L. 1234.55 to 1234.80 working R.L.
No.	7, 10, 16, 17	: 1235.50 to 1235.55
No.	21,22,23,25,29	: 1235.55 to 1235.60
No.	5, 6, 7, 11, 12, 13, 14, 15, 18, 19, 20, 24, 26, 27, 29, 30, 31	: 1235.60 to 1235.80
No.	4, 8	: 1236.00

C.G. MAJOR IRRIGATION PROJECT MRP COMPLEX
DUDHAWA TANK PROJECT
SALIENT FEATURES

1. LOCATION :

1.1	District.	:	Kanker
1.2	Tahsil.	:	Narharpur
1.3	River/Basin.	:	Mahanadi River/Mahanadi Basin
1.4	Location of Dam.	:	21 K.m. West of Sihawa nesr the origin of Mahanadi River & 29 K.m. esst of Kanker which is on 141 K.m. of Raipur Jagdalpur National Highway No. 30 Nearest Dudhawa Village.
1.5	Latitude & Longitude	:	20°-18' / Top sheet No. 81°-46'/64H/15
	(a) Year of Start	:	1953-54
	(b) Year of Completion	:	1963-64

2. HYDROLOGICAL DATA

(A) RAINFALL

2.1	Average (1928-1953)	:	(1248.66 mm) 49.16"
2.2	Maximum (1936)	:	70.84" (1799.34 mm)
2.3	Maximum (1941)	:	32.90" (835.66 mm)
2.4	Mean Monsoon Yield.	:	12173 Mcft. (344.77 Mcum)
2.5	Mean Monsoon	:	54.04" (1372.62 mm)
2.6	Rainfall in Catchment	:	

(B) FLOOD.

2.7	Maximum Observed. (21.08.2001)	:	(2375.49 Cusecs) 83878 Cusecs
2.8	Maximum adopted for design (Design Flood)	:	85800 Cusecs, (2429.90 Cumecs) Revised PMF 176974.00 Cusecs (5012.00 Cumecs)
2.9	Moderated Flood	:	18400 Cusecs 80800 Cusecs (521.10 Cumecs) (2288.30 Cumecs)
2.10	Designed S.P.F.	:	4,118 Cumecs

(C) RUN OFF

2.11	Average annual Monsoon Run-off as per binner percentage (43.70%)	:	337.55 Mcum (12099 Mcft.)
2.12	Run Off as per actual observed at Dudhawa Minimum.	:	234.83 Mcum (8292 Mcft.)
2.13	Maximum.	:	454.48 Mcum (16048 Mcft.)
2.14	Average.	:	344.75 M. Cum. (12173 Mcft.)
2.15	Run-Off as per gauging as on at Station average for 38 years.	:	285.44 M. Cum. (10079 Mcft.)

3. RESERVOIR DATA

(A) STORAGE.

3.1	Catchments area.	:	241.8 Sq. Miles. (625.27 Sq. Km.)
3.2	Mean monsoon yield Dinnies percentage.	:	242.67 M. Cum. (12099.80 Mcft.)
3.3	Gross storage capacity.	:	288.65 M. Cum. (10192.50 Mcft.)
3.4	Dead storage capacity.	:	4.53 M. Cum. (160.00 Mcft.)
3.5	Live storage capacity.	:	284.13 M. Cum. (10032 Mcft.)
3.6	Percentage of gross storage to normal monsoon yield.	:	82.82 %
	Percentage of dead storage gross storage capacity.	:	1.43 %

(B) LEVELS

3.7	Top of Bund level	:	
	a. (T.B.L.) Main Bund.	:	(430.00 m.) 1410.83'
	b. Sub sidiary bund	:	(428.64 m.) 1406.25'
3.8	Maximum water level (M.W.L.)	:	(427.11m.) 1401.25'
3.9	Full Reservoir Level (F.R.L.)	:	(425.12 m.) 1394.75'
3.10	Lowest sill level (L.S.L.)	:	(409.95 m.) 1345.00'
3.11	River Bed Level.	:	(404.38 m.) 1326.77'
3.12	Water spread area at F.R.L. (1394.75)	:	11087 acres. (4486.85 Hact.)
3.13	Water spread area at M.W.L. (1401.25)	:	13994 Acres. (5663.29 Hact.)

(C) DETAILS OF SUBMERGENCE

3.14	Culturable area at MWL. FRL.	:	(426.26 Hac.)1053.3 Acres.
3.15	Forest area MWL/FRL	:	(416.09 Hac.) 1028.16 Acres.
3.16	Gross Submergence area. (MWL)	:	(5663.00 Hac.) 13993.27 Acres.
3.17	Reserve Forest	:	(192.71 Hac.) 476.19 Acres.
3.18	Other Forest	:	(223.38 Hac.) 551.97 Acres.
3.19	Other Land (Dun cultural area)	:	(223.39 Hect.) 552.00 Acres.
3.20	No. of village effected.	:	4 Nos. forest village + 18 Nos. revenue village of Dhamtari Tahsil of Raipur & 8 Nos. revenue village in Kanker Tahsil of Bastar District.

4. DAM DATA

4.1	Type of Dam.	:	Earthen Dam.
4.2	Maximum height of Main Dam.	:	(24.53 m.) 80.5 ft.
4.3	Subsidiary Bund I.	:	(6.06 m.) 19.9 ft.
	II.	:	(2.83 m.) 9.28 ft.
4.4	Length of Main Dam.	:	(2906.43 m.) 9536 ft.
4.5	Subsidiary Bund I.	:	(568.42 m.) 1865 ft.
	II.	:	(426.70 m.) 1400 ft.
4.6	Quantity of work in main Dam Earth Work.	:	(28.18 L. Cum) 995 Lacs cft.
4.7	Subsidiary bund E/work I.	:	(0.318 L. Cum.) 11.24 Lacs cft.
	II.	:	(0.065 L. Cum.) 2.3 Lacs cft.
4.8	Length of waste weir.	:	(121.92 m.) 400 ft.
4.9	Maximum discharge of waste weir proposed Revised PMF	:	(1132.82 Cumecs) 40000 cusecs. 5012 Cumec (17994 Cusecs)
5.	<u>COMMAND DATA :</u>		Under existing Proposed after Mahanadi canal implementation system of Dudhawa.
5.1	Gross command area.	:	826042 Acres. (334294 Ha.)
5.2	Culturable. – do --	:	801926 Acres. (324535 Ha.)
5.3	Cultivated in command (exceeding a bonded Dy. & Minors)	:	688906 Acres. (278796 Ha.)
5.4	Rice area including a bonded Dy. & Minors.	:	341514 Acres. (138208 Ha.)
5.5	Area proposed of Irrigation.		
	Kharief	:	(84986 Ha.) (141643 Ha.) 210000 Acres. 350000 Acres.
	Rabi	:	- -
	Existing	:	- (56657 Ha.) 140000 Acres.
6.	<u>ESTIMATED COST :</u>		
6.1	Estimated cost including overhead charges Unit-I	:	Rs. 4,30,77,465/-
6.2	Cost per acres of addition irrigation. Excluding cost of remodeling of Mahanadi Main Canal System.	:	Rs. 308/-
7.	<u>CANAL SYSTEM :</u>		
(A)	7.1 Length of Main Canal.	:	Dudhawa Sarona Canal 28 Km.
	7.2 Designed Irrigation proposed.	:	2875 Hact.
	7.3 New Canal. RBC	:	11 Km.
	7.4 Distributor & Minors.	:	18 Km.
	7.5 Full supply head Discharge.	:	100 Cusecs.
	7.6 Nos of Village to be served by canal system.	:	15 Nos. Village & through Mahanadi River.
(B)	7.7 Sluice.	:	4 Vents of 7½' x 9½' to discharge under Max. head of 2 ft.

(C)	7.8	Relief well.	:	72 Nos.
	7.9	Piezometers.	:	142 Nos.

C.G. MAJOR IRRIGATION PROJECT MRP COMPLEX
RAVISHANKAR SAGAR PROJECT
(MAHANADI RESERVOIR PROJECT PHASE-I)
SALIENT FEATURES

1.	State	:-	Chhattisgarh
2.	District	:-	Dhamtari
3.	Tahsil & Block	:-	Dhamtari
4.	Number of village affected	:-	55
5.	Location of project	:-	Ravishankar Sagar Dam Gangrel
6.	Year of starting the construction	:-	1973
7.	Year of completion	:-	1978
8.	Year of commissioning of dam	:-	1979
9.	Catchments Area	:-	3670 Sq.Km.
10.	Topo Sheet No.	:-	64H/10
	: Longitude	:-	81 ⁰ -34'
	:Latitude	:-	20 ⁰ -37'
11	Mean Annual Rain Fall		
	Dhamtari: Maximum	:-	1910 mm.
	: Minimum	:-	792 mm.
12.	Mean Mansoon Yield	:-	1282 mm.
13.	Mansoon Yield (75% dependable)	:-	1557 Mcum.
14.	Gross storage capacity	:-	910.50 Mcum.
15.	Dead storage capacity	:-	143.60 Mcum.
16.	Live storage capacity	:-	767.00 Mcum.
17.	River Bed Level	:-	322.47 M
18.	sill level of Sluice feeder canal	:-	336.21 M.
19.	Pen stock level U/s of power dam	:-	331.19 M.
20.	Top bund level	:-	353.00 M.
21.	Maximum water level	:-	350.70 m.
22.	Full Reservoir level	:-	348.70 M.
23.	Water spread area	:-	FRL-9540 hac
			MWL-10674 hac
24.	Length of Dam	:-	1830 M.(Earthen-1245m , Gravity-455m , Rockfill-130m)
25.	Crest level	:-	338.70M
26.	Minimum Drawdown Level	:-	336.00 M

27.	Top width of Dam	:-	7.50 M.		
28.	Width of spill channel	:-	252.50 M.		
29.	Design flood through spillway	:-	17230 Cumecs		
30.	Maximum flood passed	:-	8609.46 Cumecs (date- 29/07/1991)		
31.	DAM	:-	Main Earth	Saddle	Rock fill
31.0	EARTH DAM/ROCK FILL DAM				
	Type	:-	Homogeneous	Homogeneous	Rock fill
31.1	Length		1245.75 m.	1050.00 m.	130.00
31.2		:-	(4085.24)	(3444.00)	(426.00)
	Top width		7.50 m	3.00 m	7.50 m
31.3			(24.60')	(9.84')	(24.60')
	Top of Dam R.L.	:-	353.00 m	352.80 m	353.00 m
31.4			(1158.14)	(1157.18)	(1158.14)
	Maximum height above	:-			
31.5	Stripped level		33.50 m.	9.00 m.	10.00 m
i/			(100.04)	(29.52')	(32.8')
	Diaphram/ open cut off		47.00 m.	12.3 m.	13.00 m.
ii/	foundation grade.		(154.16')	(40.34')	(42.64')
32.	SPILL WAY BRIDGE				
32.1	Type	:-	Prestressed RCC girder bridge with RCC deck slab		
32.2	Design load	:-	Class A.A. loading		
32.3	Clear width of road way	:-	5.5 M. (18.04'ft)		
32.4	Deck level	:-	353.00 M.(1158.14 ft)		
33.	METAL WORKS				
33.1	Radial Crest Gates	:-	14 Nos. 15 M x 10 M.(50x33)		
33.2	Stop log gates		2 Sets each comprising of the one non-interchangeable bottom piece of size 15 M x 2.112 M.(49.2'x6.92') &4 Nos. interchangeable pieces of size 15 M. x2.112M (49.2' x6.92')		
33.3			1 Nos. 90/25 Tones Capacity		
33.4	Gantry crane	:-			
	Feeder canal Regulator (Vertical lift	:-	4 Nos. 1.8 M (5.8' x 3.04')		

33.5	gates)		
	Penstock service and stop log gates	:-	proposed to provide 4 Nos. service gate of size 2.09 m. x 3.69(6.85'x 12.12') & a stop log gate of size 2.682 m. x 2.525 m. (8.79'x 8.28')

34. FEEDER CANAL

34.1	Length	:-	42 Km.(26.25 Miles)
34.2	Head Discharge	:-	19.83 cumecs (700.26)

35. POWER

35.1	No. & size of unit to be installed	:-	4 No. propeller standard turbines of 2.5 MW capacity
35.2	Type of turbine	:-	propeller standard type turbine
35.3	Installed Capacity	:-	2.5 x 4 M.W.=10 M.W.

36. SIDE SLOPES

U/S	:-	1:1.96, 1:2.45, 1:3.43, 1:3.43
D/S	:-	1:1.96 ,2:2.20, 1:3.18

Sub Divisional Officer
W.M. Sub Dn. No. 09
Gangrel

Executive Engineer
WM Division Rudri
Code No. 38

C.G. MAJOR IRRIGATION PROJECT MRP COMPLEX

NEW RUDRI BARRAGE

SALIENT FEATURE

1. LOCATION

1.1 State	:-	Chhattisgarh
1.2 District	:-	Dhamtari
1.3 Tahsil	:-	Dhamtari
1.4 Village	:-	Rudri
1.5 Distance from District HQ	:-	5 Km.
1.6 Latitude	:-	20°-39'40"
1.7 Longitude	:-	81°-33'56"

2. DETAILS OF TRANSITION-CANAL :-

2.1 Bed-Width	-	32.00 m.
2.2 Bed-Level	-	317.810 m.
2.3 Side-Slopes	-	2:1
2.4 Full Supply depth	A	- At Discharge 293.30 Cumecs- 4.05 m.
	B	- At Discharge 391.06 Cumecs- 4.95 m.
2.5 Designed discharge of canal	-	391.06 Cumecs
2.6 Free board	-	0.91 m.
2.7 Bed-Grade	-	1:4500
2.8 Crest-Level of Head Regulator	-	320.250
2.9 Perimeter at	F.S.D.	- 4.05 m. -50.11 m.
	F.S.D.	- 4.95 m. – 54.14 m.

3. DETAILS OF BARRAGE AND PRINCIPLE LEVELS

3.1 Maximum pond level	-	323.200
3.2 Capacity of NRB at full pond level	-	4.4475 m.cum
3.3 Max. discharge passed through one HR gate	-	3384 cusecs
3.4 Max. discharge passed through one spill way gate at level	-	323.20=5874 cusecs
3.5 Average River bed level	-	319.000
3.6 Max. flood discharge released in River (on date 09.07.01)	-	219659 cusecs
3.7 Crest level of under sluice	-	318.000
3.8 Crest level of Spillway gate	-	320.200
3.9 Crest level of H.R. gate	-	320.25 m.
3.10 Total length of Barrage	-	464 m.
3.11 Total Nos. of HR gate & size 5 Nos.	-	10x2.95 m.
3.12 Total Nos. under sluice gate & size 3 Nos.	-	18x5.35 m.
3.13 Total Nos. spill way gate & size 20 Nos.	-	18x3.15 m.
3.14 Max. water level during flood	-	327.800

ANNEXURE-II: PHOTOGRAPHS



(A) Sindhur Reservoir.



(B) Murrumsilli Reservoir

ANNEXURE-II: PHOTOGRAPHS



(C) Dudhawa Reservoir



(D) Ravishankar Sagar Reservoir



(E) Rudri Barrage



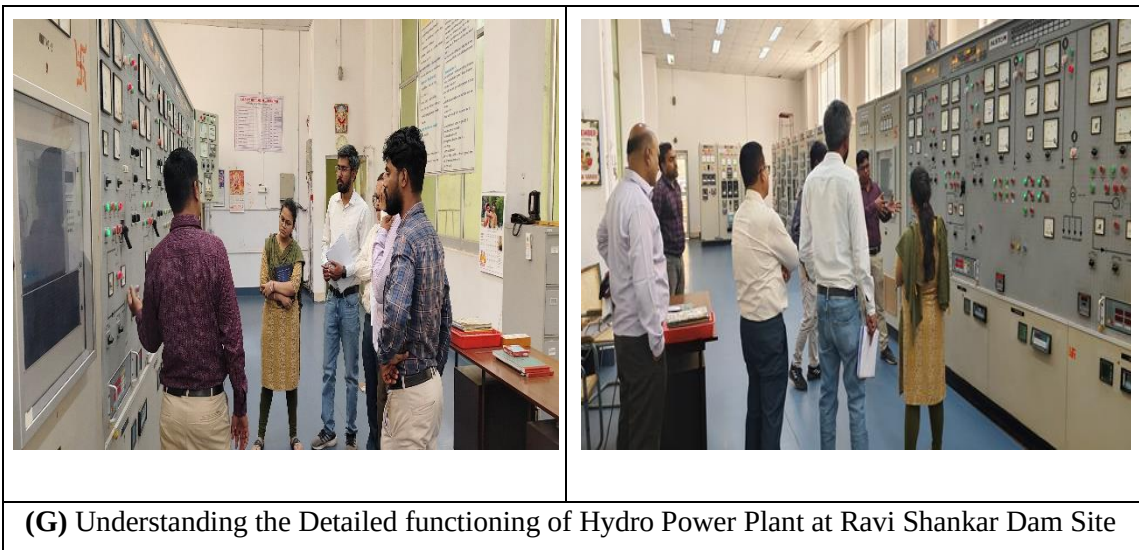
(F) Data Collection from Dam division Dhamtari.



(E) Identification of Dam location.



(F) Verification of site's data



(G) Understanding the Detailed functioning of Hydro Power Plant at Ravi Shankar Dam Site

Study Group

Director	: Dr. M.K. Geol Scientist-G
Coordinator	: Dr. Anil Kumar Lohani, Scientist-G
NIH Regional Centre Bhopal	
Principal Investigator	: Dr. Rahul Kumar Jaiswal, Scientist-F
Co-Principal Investigators	: Dr. Ravi V Galkate, Scientist-F
	: Dr. T Thomas, Scientist-F
	: Mrs. Shashi P Indwar, Scientist-D
	: Sri Shohrat Ali, JRF
	: Mrs. Varnika, JRF
NIH Roorkee	
Co-Principal Investigators	: Dr. Anil Kumar Lohani, Scientist-G
	: Dr. M.K. Goel, Scientist-G
	: Dr. Vishal Singh, Scientist-C
	Dr. Deepti Rani, RA
Water Resources Department, Govt. of Chhattisgarh	
Principal Investigator	: Mr. Jayant Bisen, Deputy Director
Co-Principal Investigators	: Mr. Vikas Kumar Dubey A.E
	: Ms. Ananya Gupta A.E
	: Mr. Prince Awadhiya Sub Engineer
	: Dr. Surnendra C Chandina Astd. Professor (IGKV Raipur)

APPENDIX-A Project summary

Table A.1: Summary

Project objectives			
Objectives as per project document		Revised objective	Reasons for revision
i. Estimation of revised capacities of the reservoirs and revised demand with future projection. ii. Development of long-term hydrological series for the reservoirs using a water balance approach. iii. Development of a model for the short-term/long-term integrated operation of the reservoirs in the Mahanadi Reservoir Project Complex. iv. Optimization of reservoir operation for maximization of benefits from the Mahanadi Reservoir Project Complex.		-	-
Manpower deployed (against sanctioned manpower)			
Sanctioned		Deployed	
Designation	Person months	Designation	Person months
JRF	Sh. Shivendra Jaiswal May 2022 to July 2023 (15 months)	JRF	Smt. Varnika July 2022 to September 2024 (27 months)
JRF	Sh. Shohrat Ali October 2023 to September 2024 (12 months)		
Field Assistant	-	-	-
Infrastructure/ equipment			
Planned (as per project proposal)		Developed/ procured	Reasons for deviation
Laptop		-	-
Remote sensing data			
Field work			
Planned (as per project proposal)		Completed	Reasons for deviation
		-	-
Workshop/ Capacity building/ technology transfer			
Planned (as per project proposal)		Organized	Reasons for deviation

	-	-
Study area		
Planned	Extended	
Mahanadi Reservoir Project (MRP)	-	
New data generated in the project		
Planned (as per project proposal)	Achievement	Reasons for deviation
-	-	-
Envisaged contribution of the project		
Planned (as per project proposal)	Contribution made	Reasons for deviation
Development of Rule Curve for all Reservoirs (Sondhur, Dudhawa, Murumsilli & Ravishankar Sagar Reservoirs) for optimal management of resources	Rule curves for all the dams were developed	-
Assessment of impact of climate change on crop water requirement, water availability, etc.	The climate change impact in near century periods was assessed	-
Development of rule curves under climate change	Rule curves under climate change scenarios were developed	-
Application of indigenously developed reservoir operation software NIH RESyP for complex project	Applied successfully	-
How research outcome benefited the end user department and society		
Planned (as per project proposal)	Benefit derived	Reasons for deviation
- The rule curves developed for the reservoirs of MRP will be helpful to optimally operate theses reservoirs in integrated manner - Assessment of climate change on climatic variables, crop water, water availability, etc. - The rule curves for integrated operation of reservoirs of MRP under climate change scenarios - Development of new technique (OTSU based) for assessment of sediment in reservoirs	- Rule curves for integrated operation - Useful in planning resources under climate change - Useful to WR department to operate reservoirs under climate change - WR Department can use this technique for quick assessment of sediment -	- - -

Farmers/end users can get knowledge of impact of climate change.				-	
End-of-project deliverables					
Planned (as per project proposal)		Achieved		Reasons for deviation	
Rule curves for integrated operation of reservoirs in MRP		Yes		-	
Outsourcing (>1 lakh)/ consultancy (All)					
Consultant (name and qualifications), organization / outsource agency		Work assigned	Estimated cost Rs		Actual cost Rs
-		-	-		-
Financial achievement (Rs in Lakh)					
Central India Hydrology Regional Centre, National Institute of Hydrology, Bhopal					
S No	Head	Approved budget	Approved revised budget	Final expenditure	Reasons for deviation
1	Remuneration/Emoluments for Manpower etc.	18.40	18.40	15.71	
2	Travelling Expenditure	06.00	06.00	2.21	
3	Infrastructure/Equipment	09.50	09.50	0.14	
4	Experimental Charges/Field work/Consumables	04.00	04.00	0.06	
5	Capacity building/Technology transfer	02.00	02.00	-	
6	Contingency	02.10	02.10	0.02	
7	Outsourcing/ consultancy	04.00	04.00	-	
	Total	46.00	46.00	18.14	
Water Resource Department Govt. of Chhattisgarh, Raipur					
S No	Head	Approved budget	Approved revised budget	Final expenditure	Reasons for deviation

1	Remuneration/Emoluments for Manpower etc.	-	-	-	-
2	Travelling Expenditure	04.00	-	-	-
3	Infrastructure/Equipment	-	-	-	-
4	Experimental Charges/Field work/Consumables	01.50	-	-	-
5	Capacity building/Technology transfer	04.00	-	-	-
6	Contingency	00.50	-	-	-
7	Outsourcing/ consultancy	-	-	-	-
	Total	10.00	-	-	-

Table A.2: Quantitative outcome

i. Research papers published/ submitted				
S No	Research paper (National/ International Journal/ conferences/ symposium/ workshop/ seminar)			Impact Factor for Journal
1.	Jaiswal, R.K., Dhruw, G., Jain, S., Galkate, R.V., Lohani, A.K., Verma, A. (2023) Efficient segmentation algorithm for estimation of revised reservoir capacities in google Earth engine, Water Resour Manage, 37, 3795-3812, https://doi.org/10.1007/s11269-023-03511-2			3.9
2.	Jaiswal, R.K., Lohani A.K., Galkate, R.V. (2022) Rainfall and Agro Related Climate Extremes for Water Requirement in Paddy Grown Mahanadi Basin of India, Agricultural Research, https://doi.org/10.1007/s40003-022-00629-4			1.5
3.	Jaiswal, R.K., Lohani, A.K. (2023) A framework to assess the dynamics of climate extremes on irrigation water requirement using machine learning techniques, Journal of Earth System Science, https://doi.org/10.1007/s12040-022-02044-3			2.0
Reports/Monographs/Internal publications brought out				
S. No.	Reports/Monographs/Internal publications			
1.	Yearly and quarterly progress Reports on PDS			
ii. New techniques/models/ software/ knowledge developed, if any				
• OTSU based technique for assessment of reservoir sediment. • MIKE 11 NAM model has been developed for generation of long term hydrological series. • Application of NIH ReSyP software for complex reservoir system. • Rule curves for integrated reservoir operation of reservoirs of MRP. • Assessment of impact of climate change on crop water requirement, water availability, power generation, etc. • Rule curves for integrated reservoir operation of reservoirs of MRP under climate change				
iii. Web site/ application developed				
Name	Web address	Server location	Launch date	Details of information

				available	
	-	-	-	-	
iv. Patents filed/awarded, if any					
Workshop/ conferences/ seminars/capacity building programs organized					
S. No.	Topic	Dates, duration, No. of participants	Report published (Y/N)		
v. Stake holders feedback and action taken on constructive feedback					
S No.	Feedback received	Action taken			
Stakeholder meet (Topic and date)					
vi. Field observations obtained, thematic maps generated (water quality and salinity, isotope, soil moisture, stage and discharge, sediment, water level, River cross sections, geophysical/ resistivity survey, hydrogeological investigations etc.)					
S No	Parameter, frequency, period, groundwater/ River/ tank/ hand pump/ spring	Number (planned)	Numbers (measured)		
	-	-	-		
vii. Field installations (piezometers, River stage/ discharge, soil moisture etc.)					
S. No	Name, make/ model	Unit price, total price, quantity	Date of installation	% utilization	Remarks regarding maintenance / breakdown
viii. Equipment/ software purchased					
a. Equipment purchased					
S. No	Name, make/ model	Unit price, total price, quantity	Date of installation	% utilization	Remarks regarding maintenance / breakdown
	-	-	-	-	-
	-	-	-	-	-
b. Software purchased					
S. No	Name, version, license	Unit price, total price, quantity	Date of installation	% utilization	Remarks regarding maintenance / breakdown
ix. Plans for utilizing the equipment facilities in future					
S. No.	Installation/ equipment	Planned future use			
x. Data dissemination policy for data generated in the project					
xi. Number of post-graduate/doctoral candidates completed their courses (Please give a list of such candidates)					
Post-graduate student					
1. M.Tech thesis of Snehil Scholar No: 20210752 of IGKV, Raipur (2021-23) titled "Assessment of Climate Change Impact on Irrigation Water Requirement in the Command of Ravi Shankar Sagar Reservoir of Chhattisgarh State"					
2. M.Tech thesis of Preeti Verma Scholar No: 20220504 of IGKV, Raipur (2022-24) titled "Assessment of water availability in Ravishankar Sagar Reservoir under climate change Scenario"					

3. M.Tech thesis of Yashwant Joshi Scholar No: 20220508 of IGKV, Raipur (2022-24) titled “Estimation of Probable Maximum Precipitation for Upper Mahanadi Basin Under Projected Climatic Scenario”

Ph.D. Student

1. Gunja Dhruw, Research Scholar of Indira Gandhi Krishi Vishwaviyalaya, Raipur titled “Studies on Reservoir Operation under Climate Change pattern for Ravishankar Sagar Reservoir using Mike Hydro Basin Model”– Ongoing
2. Bhupendra Dhankar, Research Scholar of Indira Gandhi Krishi Vishwaviyalaya, Raipur titled “Development of Framework for Flood Risk Assessment and Management of Downstream area of Ravishankar Sagar Reservoir under Climate Change Scenario”-Ongoing

xii. Foreign deputation/visit of PI/Co-PIs/students, if any

A.3 Activity chart

Include activity chart/ modified activity chart, and reasons for modification of activity chart.

Appendix B Supplementary results

Provide supplementary results here, if any

Integrated Reservoir Operation Studies for Mahanadi Reservoir Project Complex in Chhattisgarh

PDS No	SP-56/2021-2022/NIH(CIHRC)
Duration of the project	2 Years
Lead Organization	National Institute of Hydrology Central India Hydrology Regional Centre, Bhopal
Study Team from Lead Organization	
PI	Dr. Rahul Kumar Jaiswal, Scientist-F, NIH-Bhopal
Co-PI (RC Bhopal)	Mr. Ravi V. Galkate, Scientist-F
	Mrs. Shashi P. Indwar, Scientist-D
Co-PI (NIH Roorkee)	Dr. Anil Kumar Lohani, Scientist-G
	Dr. M. K. Goel Scientist-G
	Dr. Vishal Singh, Scientist-C
	Mr. Sumit Saini, Research Scientist
	Ms. Dipti Rani, RA
Partner Organization	Water Resources Department, Govt. of Chhattisgarh
Study Team from Partner Organizations	
PI	Mr. Jayant Bisen, Deputy Director
Co-PI	Mr. Vikas Kumar Dubey, Assistant Engineer Ms. Ananya Gupta, Assistant Engineer
	Mr. Prince Awadhiya, Sub Engineer
	Dr. Surnedra Chandina Astt. Professor (IGKV Raipur)
Total Cost of Project (Rs)	Rs, 56 Lakh
Lead Organization:	Rs. 46 Lakh
Partner Organization:	Rs. 10 Lakh

