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TECHNICAL REPORT

Future-Ready Water Systems: Climate-Smart Decision Support for Smart Water Allocation and Planning in India

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CGIAR Climate Action Program

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Front cover photo: SCADA + IoT–enabled water distribution system regulating real-time flows across the command area of the Darpanarayanpur Minor Irrigation Project, Odisha. (*photo:* D R Sena/IWMI)

Back cover photo: IWMI research team, along with scientists from ICAR–IIWM, during a field visit to the Darpanarayanpur Minor Irrigation Project (MIP) in Odisha. (*photo*: D R Sena/IWMI India)

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Contents

Summary

Ensuring reliable and efficient irrigation in the face of increasing climate variability is emerging as one of the most urgent challenges for South Asia's agricultural systems. Rising temperatures, erratic monsoon patterns, elevated evaporative demand, and shrinking natural storage buffers are placing unprecedented stress on minor irrigation systems, the backbone of rural food security and livelihoods. Traditional rotational irrigation practices, which rely on fixed schedules and experiential knowledge, are becoming increasingly inadequate for managing climate risks such as prolonged dry spells, delayed monsoons, and fluctuating inflows.

Darpanarayanpur Minor Irrigation Project (MIP) in Odisha represents a typical yet strategically important example of these challenges. The command area depends heavily on monsoon-fed ponds/mini-reservoirs and a small canal network to support predominantly rice-based farming. High interannual rainfall variability, limited storage, and continuous flooding practices of rice fields (PTRCF) make the system vulnerable to climate-induced water shortages. With recent canal automation upgrades and real-time hydrometeorological monitoring, the site provides an ideal living laboratory for developing and validating future-ready irrigation decision support tools.

To address these emerging pressures, this study applies the Climate-Informed Irrigation Decision Support System (CI-IDSS), a next-generation digital planning and irrigation scheduling platform developed by IWMI. CI-IDSS integrates Agricultural Production Systems sIMulator (APSIM) (Gaydon et al., 2017) process-based crop modeling, multi-GCM climate ensembles, real-time hydroclimatic data, and optimization algorithms to support both seasonal planning and dynamic water allocation. Advanced features under CI-IDSS enable automated APSIM simulations for large numbers of fields, scenario-based water-demand forecasting, and equitable water distribution across outlets using mathematical optimization.

A calibrated APSIM model of rice (*var. Swarna*) was used to assess the performance of conventional puddled transplanting under continuous flooding (PTRCF) and two climate-smart irrigation alternatives i.e., Alternate Wetting and Drying (PTRAWD) with 2-day (PTRAWD2) and 5-day (PTRAWD5) drying cycles. Calibration was conducted using detailed field observations from the Deras research farm, ensuring realistic representation of phenology, biomass growth, and soil-water dynamics. The calibrated models were then run with historical climate and future projections from 12 CMIP6 global climate models (GCMs) under the SSP245 and SSP585 scenarios, capturing a wide range of plausible hydroclimatic futures.

The multi-model ensemble analysis demonstrates that alternate wetting and drying (AWD) consistently reduces irrigation demand while maintaining stable actual evapotranspiration (AET) and biomass yields, even under high-emission climate scenarios. PTRAWD5 shows the highest resilience, with 10–12% lower median irrigation requirements and reduced exposure to high-demand extremes, whereas PTRCF displays strong sensitivity to future rainfall and evaporative variability. Kolmogorov–Smirnov tests further confirm that irrigation demand distributions shift significantly under climate change, especially for PTRCF, while AWD moderates these shifts and provides greater robustness across the GCM ensemble.

These findings indicate that climate-smart irrigation strategies such as AWD, supported by digital tools like CI-IDSS, can substantially enhance water productivity and reduce climate risks in smallholder irrigation systems. The preliminary CI-IDSS evaluation for Darpanarayanpur demonstrates a strong potential for integrating climate information, hydrology, and crop modeling into everyday irrigation decision-making, from pond/ reservoir release planning to outlet-level water distribution and crop diversification.

While this study presents encouraging insights, the results remain preliminary, as they are derived from model-based experiments and limited field observations of just one year. Scaling towards operational use will require multi-year field trials, real-time canal flow data, and farmer-level water-use monitoring to refine and validate the system. Nevertheless, the Darpanarayanpur pilot establishes a strong foundation for future-ready, climate-informed irrigation governance, and provides a scalable blueprint for similar irrigation commands across Odisha, the Ganga Basin, and other climate-sensitive regions to plan adaptive irrigation.

Introduction

Ensuring reliable water supply for agriculture is emerging as one of the most critical development challenges in South Asia, where rising temperatures, erratic monsoon rainfall, and increasing evapotranspiration are placing unprecedented pressure on already stressed irrigation systems (Ahmed et al., 2020). Minor Irrigation Projects (MIPs), which form the backbone of local food production and rural livelihoods, are particularly vulnerable because they rely on small tanks, ponds, and shallow groundwater sources whose storage reliability is highly climate-sensitive (Vanaja et al., 2019; Jain et al., 2025). Traditional irrigation decision-making in such systems is typically based on experience and fixed rotational schedules, making it poorly equipped to handle the increasing climate variability, seasonal dry spells, and inconsistent inflows associated with warming climates. In India, recent assessments show that the reliability of water infrastructure is declining as rainfall becomes more variable and drought flood cycles intensify (Jain et al., 2025).

Darpanarayanpur village in Odisha exemplifies these challenges. Located in a semi-humid monsoon environment, the area experiences high inter-annual rainfall variability, limited pond/reservoir storage capacity, and a strong dependence on paddy cultivation. Analysis of historical and CMIP6 future scenarios shows a clear trend of rising evapotranspiration demand and declining predictability of rainfall, both of which increase irrigation requirement and reduce the reliability of small reservoir systems.

Under these conditions, climate-smart irrigation strategies such as Alternate Wetting and Drying (AWD) become important, as they reduce water use while maintaining yield stability, findings supported both by global literature and by APSIM simulations (Gaydon et al., 2017; Biswas eta l., 2021) conducted for this study. AWD improves irrigation efficiency (Bouman et al., 2007; Carrijo et al., 2017) by enabling controlled soil wetting and drying cycles, and has been shown globally to sustain yields while reducing water inputs and methane emissions (Chu et al., 2015; Kumar and Rajitha, 2019; Fazlil Ilahi,et al., 2022; Bwire et al., 2023).

To address these emerging risks, modern irrigation systems require data-driven, adaptive, and forward-looking decision-support tools. The **Climate-Informed Irrigation Decision Support System (CI-IDSS)**, developed here by IWMI, represents a next-generation digital framework designed to bridge this gap. It integrates crop modeling (APSIM), climate projections, hydrological optimization, and remote sensing into a unified platform for planning and real-time irrigation management.

Recent advancements under CI-IDSS extend these capabilities to dynamic water allocation, spatially explicit modeling for thousands of plots, and automated simulation workflows that combine NASA POWER weather data, ISRIC soil grids, and Sentinel/MODIS indicators. Applied to the Darpanarayanpur command area of *Nayagarh* in Odisha state, CI-IDSS provides an evidence-based assessment of irrigation needs, water balance, crop performance, and climate-induced risks.

Overall, this study positions Darpanarayanpur as a representative case for developing future-ready, climate-smart irrigation systems. By combining biophysical modeling, climate ensemble analysis, and optimization, CI-IDSS offers a robust foundation for modernizing irrigation governance not only in Odisha but across the Ganges Basin and similar agro-ecological regions.

Darpanarayanpur, located in Eastern India's semi-humid monsoon region, faces increasing pressure on water resources due to high climate variability, frequent dry spells, and rising evaporative demand. Rice-based systems dominate the landscape and account for the majority of water consumption. Traditional irrigation planning relies heavily on experience-based decision-making, which is insufficient for future climate uncertainty. The need for climate-smart, data-driven water scheduling has become essential, especially in minor irrigation projects (MIPs) (OECD, 2024). CI-IDSS addresses these gaps by providing a future-ready digital planning framework integrating hydrology, crop modeling, remote sensing, and optimization.

To develop a future-ready, climate-informed irrigation management infrastructure that integrates GCM-supported water demand assessment, Robust bio-physical based crop water modeling, and diversification options such as direct seeded rice (DSR), AWD, and alternative cropping systems (Bouman et al., 2007; Joshi, 2016; Biswas et al., 2021; Kumar et al., 2022; Chaudhary et al., 2023; Johnson et al., 2024), to enhance water productivity and climate resilience across the command area. The system will be operationalized through an advanced Decision Support System (DSS) capable of (i) *forecasting plot-level and system-level water demand under multiple climate scenarios*, (ii) *supporting adaptive planning and crop diversification strategies, and* (iii) *enabling real-time, SCADA-linked water allocation and distribution to ensure equitable, efficient, and resilient irrigation management under variable future water supply conditions.*

Applied to the Darpanarayanpur Minor Irrigation Project (MIP), CI-IDSS offers a robust assessment tool for estimating irrigation demand, crop performance, water balance, and climate-induced risks under climate change scenarios.

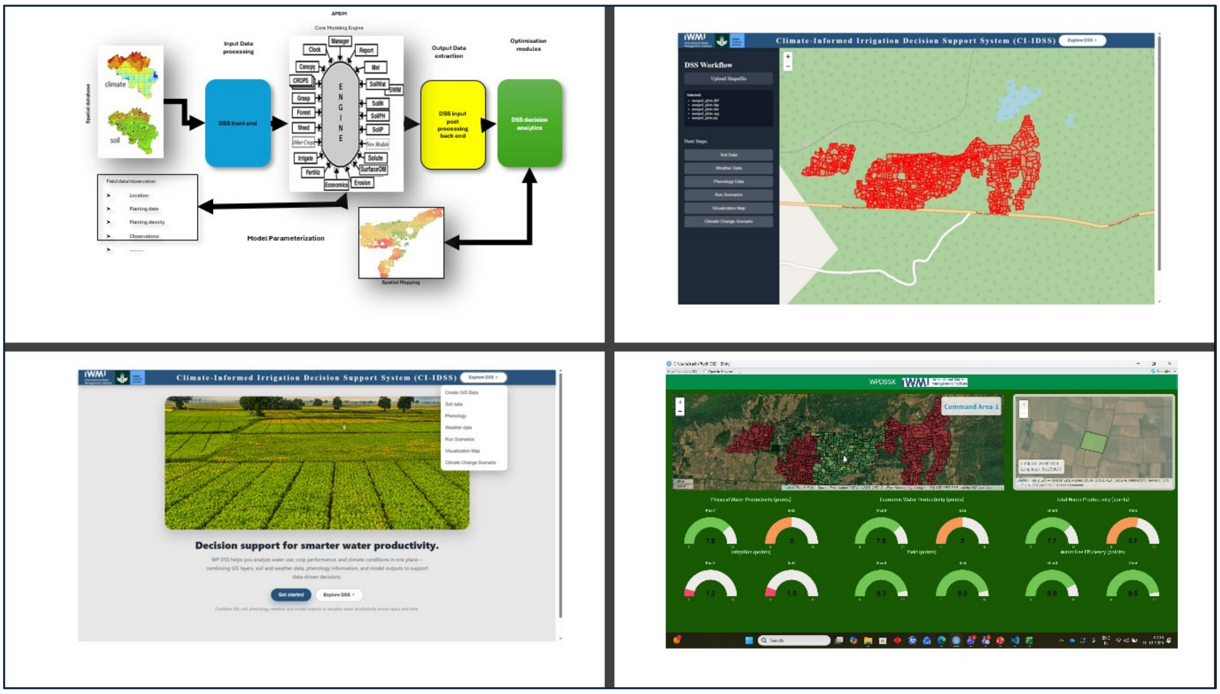
While system-level simulations indicate substantial increases in irrigation requirement and growing uncertainty in rainfall distribution, our preliminary varietal-focused investigation specifically evaluates the climate resilience of the widely cultivated Swarna rice variety under contrasting water-management regimes. APSIM simulations for *Swarna* under both puddled transplanted rice (PTR) and Alternate Wetting and Drying (AWD), demonstrate how varietal performance shifts under future climatic stressors and how water-saving practices can stabilize yields while reducing irrigation pressure. This varietal assessment is essential for identifying whether *Swarna* remains suitable as a recommended cultivar for the Darpanarayanpur command area, and how its adoption under AWD could enhance climate resilience relative to conventional PTR. These analyses illustrate how both varietal choice and irrigation practice influence system-wide resilience under projected climate futures.

Innovation Overview

The **Climate-Informed Irrigation Decision Support System (CI-IDSS)** process flow illustrates how the system transforms available water supply into optimized and resilient land-use outcomes at the command scale. Starting from the reservoir or diversion point, the DSS evaluates seasonal water availability using operational rule curves and translates this into feasible water distribution across the command's canal network. It then assesses the performance of the existing land-use pattern—capturing current irrigation demand, conveyance efficiency, and productivity levels—and compares it with alternative, diversified cropping configurations generated through scenario modeling. By aligning water availability, distribution capacity, and crop-water requirements, the DSS supports improvements in both irrigation efficiency and water productivity, enabling command managers to shift from traditional practices to scientifically optimized, climate-smart land-use strategies.

CI-IDSS Framework

The CI-IDSS framework (Figure 1) integrates spatial data, crop modeling, field observations, and decision analytics into a unified workflow for irrigation planning and water productivity enhancement. It begins with a spatial database consisting of climate, soil, and ancillary geospatial layers that define the biophysical environment of the command area. These datasets, along with field observations such as planting dates, planting density, crop type, and



WP DSS helps you analyze water use, crop performance, and climate conditions in one place—combining GIS layers, soil and weather data, phenology information, and model outputs to support data-driven decisions.

Combine GIS, soil, phenology, weather and model outputs to visualize water productivity across space and time.

yield measurements, feed into the DSS front end, where input data are processed, standardized, and organized for model simulations.

Figure 1. Schematic framework of Climate-Informed Irrigation Decision Support System.

Once pre-processed, the data is passed to the APSIM Core Modeling Engine, which forms the heart of the system. APSIM simulates crop growth, soil water balance, nutrient cycling, and hydrological processes using interconnected modules (e.g., SoilWat, SoilN, Canopy, Irrigate, SurfaceOM). Model parameterization is guided by field data and spatial mapping, ensuring that the simulations represent variations in soil type, climate, management practices, and cropping patterns across the command area.

The simulation output covering yield, crop water use, irrigation requirements, soil moisture, and related indicators are extracted through the DSS post-processing back end. These outputs are then passed to the DSS decision analytics module, which contains optimization routines, scheduling algorithms, and decision-support tools. This stage translates APSIM outputs into actionable insights such as optimized irrigation schedules, water allocation strategies, cropping system recommendations, and spatially disaggregated water productivity maps.

CI-IDSS consists of three integrated components that collectively form a comprehensive command-area decision-support ecosystem.

Component 1: Ex-Ante Scenario Analysis Engine

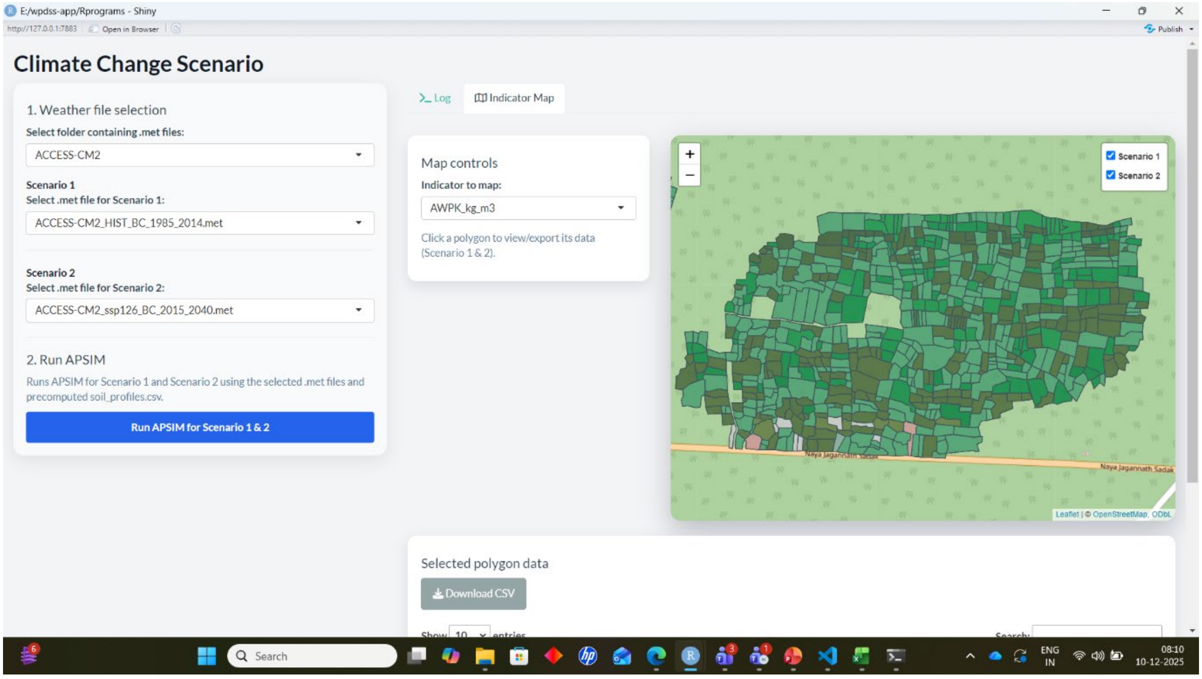
This component uses process-based crop modeling (APSIM) and open-source remote sensing data to simulate plot-level crop growth, soil-water balance, and irrigation requirements under different management and climate conditions.

Key capabilities include:

- Automated APSIM XML creation for entire spatial units i.e. command area field parcels connected to various outlets based on a user supplied database of cropping systems and remote sensing derived sowing time.
- Integration of ISRIC - World Soil Information, also known as the International Soil Reference and Information Centre- SoilGrids 2.0 global database (Poggio et al., 2021)(optional if data is unavailable), NASA POWER weather, sentinel-1A derived phenology.
- Simulation of cropping system alternatives (e.g., Direct Seeded Rice, Alternate wetting and drying, puddled transplanted rice), nutrient regimes (customized APSIM model interfaces accessed through database)
- Generation of indicators at field scale (cropping system as a whole and individual seasonal crop i.e. Kharif and Rabi) such as Physical water productivity, Economic water productivity, Water-use efficiency and Grain yield, biomass (Figure 1).

Component 2: Future Water Demand Pattern Compared to Historical Data

This module (Figure 2) evaluates how climate change shifts irrigation demand, crop stress, and water productivity across command areas.



E:/wpdss-app/Rprograms - Shiny

http://127.0.0.1:7883

Climate Change Scenario

1. Weather file selection

Select folder containing .met files: ACCESS-CM2

Scenario 1

Select .met file for Scenario 1: ACCESS-CM2_HIST_BC_1985_2014.met

Scenario 2

Select .met file for Scenario 2: ACCESS-CM2_ssp126_BC_2015_2040.met

2. Run APSIM

Runs APSIM for Scenario 1 and Scenario 2 using the selected .met files and precomputed soil_profiles.csv.

Map controls

Indicator to map: AWPK_kg_m3

Click a polygon to view/export its data (Scenario 1 & 2).

Selected polygon data

Figure 2. Climate Change Scenario module of the Climate-Informed Irrigation Decision Support System interface.

Key analytical functions:

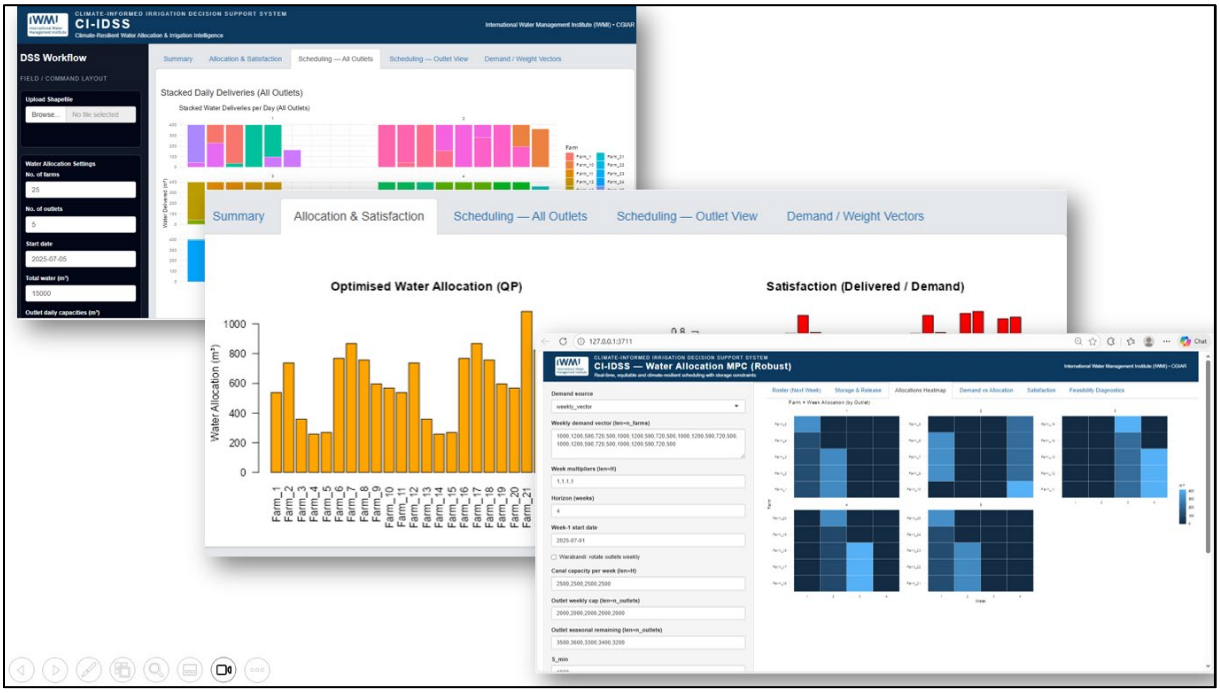
- Comparison of baseline vs. future climate scenarios to detect shifting crop-water demand windows.
- Identification of future irrigation hotspots in terms of demand under conditions of no stress or limiting supply.

Component 3: Dynamic Water Allocation and Irrigation Scheduling Module

This module (Figure 3) converts modeled water demand into real-time, actionable irrigation schedules using optimization and forecasting.

Key features:

- Quadratic Programming (QP) for equitable distribution of limited water.
- Model Predictive Control (MPC) for adaptive weekly or monthly scheduling.
- Outlet-wise and parcel-wise scheduling based on canal capacity and system constraints.
- Integration of remote sensing ET, NDVI/kNDVI (indices of Naturalized Differentiation vegetation Index), and stress indices for priority ranking.
- Output of irrigation calendars (dates + volumes) for each outlet.



Upload Shapefile: Browse... No file selected

Water Allocation Settings

No. of farms: 25

No. of outlets: 5

Start date: 2025-07-05

Total water (m³): 15000

Outlet daily capacities (m³)

Demand source: weekly_vector

Weekly demand vector (len=n_farms): 1000,1200,590,720,500,1000,1200,590,720,500,1000,1200,590,720,500,1000,1200,590,720,500,1000,1200,590,720,500

Week multipliers (len=H): 1,1,1,1

Horizon (weeks): 4

Week-1 start date: 2025-07-01

☐ Warabandi: rotate outlets weekly

Canal capacity per week (len=H): 2500,2500,2500,2500

Outlet weekly cap (len=n_outlets): 2000,2000,2000,2000,2000

Outlet seasonal remaining (len=n_outlets): 3500,3600,3300,3400,3200

S_min

Figure 3. Real-time water allocation module of the Climate-Informed Irrigation Decision Support System platform.

Study Area

Darpanarayanpur Minor Irrigation Project (MIP) is in Nayagarh District of Odisha state, within the semi-humid monsoon region of Eastern India. The command area covers approximately 285 ha, supported by a 650-ha catchment, and is part of a traditional tank–canal irrigation system central to the village’s rice-based farming economy. The region receives an average annual monsoon rainfall of 1200–1400 mm, though the distribution is highly erratic, leading to uncertainty in pond reservoir storage, canal flows, and irrigation reliability. Physio-graphically, the area contains loamy soils with shallow groundwater, making it suitable for paddy cultivation but sensitive to seasonal water deficits. Puddled Transplant Rice (PTR) is the dominant crop in the command during *Kharif* season, with limited diversification due to water constraints and traditional continuous flooding (CF) irrigation practices. Farmers depend heavily on the minor irrigation canal system, supplemented by small ponds and groundwater pumping, to meet critical crop water requirements during dry spells. The Darpanarayanpur canal network extends for 2.5 km, consisting of a head regulator, 11 solar-powered automatic gates, and five cross regulators, all installed as part of a recent canal automation initiative led by ICAR-IIWM in collaboration with hardware partners and the Odisha Department of Water Resources. An automatic weather station provides real-time climatic inputs to support irrigation advisory and operational control systems. IWMI provides support as a knowledge partner and research collaborator under Climate Action Science Program (CASP) and ICAR-IWMI joint work program for 2022-26.

Given the rising climate variability, increasing evapotranspiration, and inconsistent monsoon inflows, the system faces growing operational challenges. These trends necessitate climate-smart water management, dynamic scheduling, and improved allocation frameworks. Darpanarayanpur MIP was selected as a pilot site for developing and operationalizing an advanced Decision Support System (DSS) for real-time canal automation, integrating hydrodynamic modeling, crop water demand estimation, and SCADA-based gate control (Figure 4). The area provides an ideal test bed due to its manageable command size, established canal infrastructure, and high dependence on climate-sensitive rice irrigation systems. The study area represents a typical small-tank command system in coastal–inland Odisha where climate risks, infrastructure modernization, and data-driven irrigation planning converge, making it a strategic location for validating CI-IDSS and future-ready water management innovations.

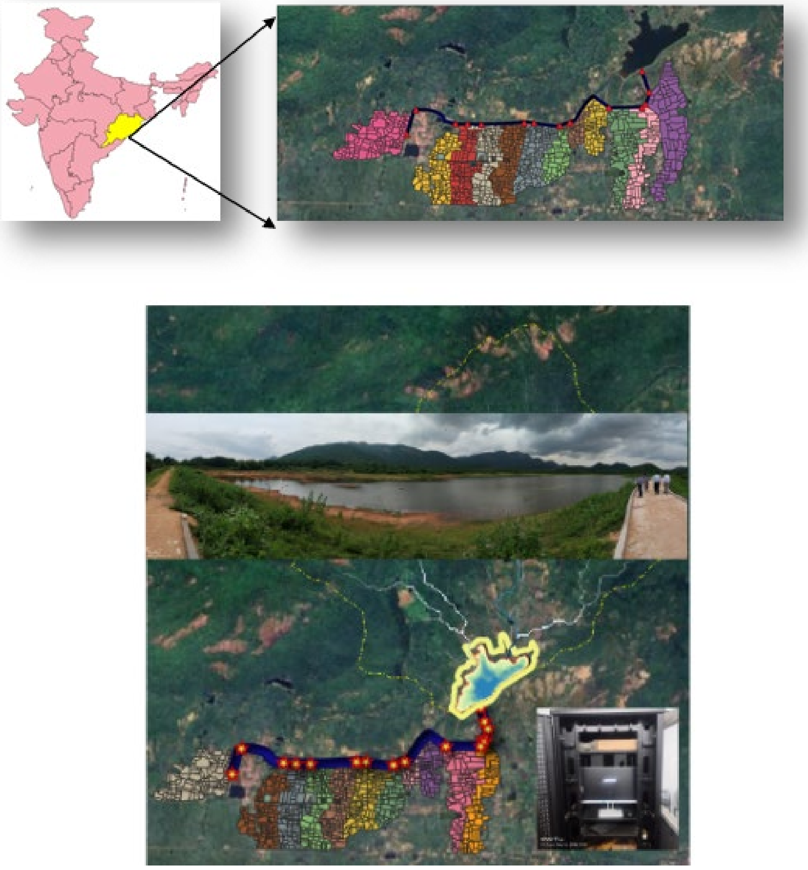


Figure 4. Darpanarayan command area of Naygarah district, Odisha)

This study evaluates water use, irrigation needs, and climate resilience for a popular rice variety *Swarna* under several irrigation treatments: PTRCF, DSR (both Dry and Wet) and AWD (Alternate Wetting & Drying)

Data and Methods

Historical and Future Climate Data

The selected ensemble of 12 Coupled Model Intercomparison Project Phase 6 (CMIP6) GCMs (Table 1) provides a robust and scientifically defensible basis for water-demand forecasting because it captures the full spread of plausible climate futures across model families, resolutions, and climate sensitivities. The set includes high-resolution models such as MPI-ESM1-2-HR and EC-Earth3, which better resolve monsoon dynamics and rainfall extremes, alongside conservative-sensitivity models such as INM-CM4-8/INM-CM5-0, ensuring balanced representation of warming trajectories. Models like MRI-ESM2-0 and ACCESS-ESM1-5 are proven for South Asian hydroclimate (Mishra et al., 2020), particularly monsoon rainfall, evapotranspiration, and dry-spell characteristics critical drivers of irrigation water demand. The ensemble also includes Earth System Models with explicit land–vegetation feedback (e.g., EC-Earth3-Veg, NorESM2-MM), which improves representation of surface fluxes relevant to crop water use. Together, this diverse mix of spatial resolutions, process representations, and climate sensitivities ensures robust median estimates, credible uncertainty bounds, and high confidence in projected irrigation requirements under SSP245 and SSP585 scenarios making the ensemble well suited for APSIM-based water-demand modeling and future-ready decision support.

Table 1. Details of CMIP6-GCMs Used for APSIM / DSS Water-Demand Simulations

Sl. No.	GCM Name (Folder)	Modelling Center / Institution	Country	Model Type / Family	Typical Resolution (Atmosphere)	Notes / Strengths
1	**ACCESS-ESM1-5**	CSIRO & Bureau of Meteorology	Australia	Earth System Model	~1° × 1°	Strong land–atmosphere coupling; widely used for Asia & monsoon projections
2	**BCC-CSM2-MR**	Beijing Climate Center	China	Coupled Climate System Model	~1.1°	Good for large-scale temperature/precipitation trends
3	**CanESM5**	Canadian Centre for Climate Modelling & Analysis (CCCma)	Canada	Earth System Model	~2.8°	Strong warming signal; widely used in global assessments
4	**EC-Earth3**	EC-Earth Consortium	Europe (EU)	Atmosphere–Ocean Coupled Model	~0.7°	High-performing model for monsoon and seasonal cycles
5	**EC-Earth3-Veg**	EC-Earth Consortium	Europe	Same as EC-Earth3 + dynamic vegetation	~0.7°	Includes vegetation feedbacks; useful for crop–climate studies
6	**INM-CM4-8**	Institute of Numerical Mathematics	Russia	Climate System Model	~2°	Conservative warming; often shows lower climate sensitivity
7	**INM-CM5-0**	Institute of Numerical Mathematics	Russia	Updated INM Model	~1.5°	Improved hydrological cycle representation vs INM-CM4-8
8	**MPI-ESM1-2-HR**	Max Planck Institute for Meteorology	Germany	Earth System Model (High Resolution)	~0.5°	High-resolution rainfall & monsoon representation; preferred for basin-scale hydrology
9	**MPI-ESM1-2-LR**	Max Planck Institute	Germany	Earth System Model (Low Resolution)	~1.8°	Good ensemble stability; widely used in CMIP6 benchmarking
10	**MRI-ESM2-0**	Meteorological Research Institute	Japan	Earth System Model	~1°	Strong performance for Asian monsoon rainfall and extremes

11	**NorESM2-LM**	Norwegian Climate Centre	Norway	Earth System Model (Low Resolution)	~2.5°	Good aerosol–cloud feedbacks; stable precipitation patterns
12	**NorESM2-MM**	Norwegian Climate Centre	Norway	Medium Resolution Earth System Model	~1.25°	Improved hydrology & monsoon representation vs LM version

Soil Data

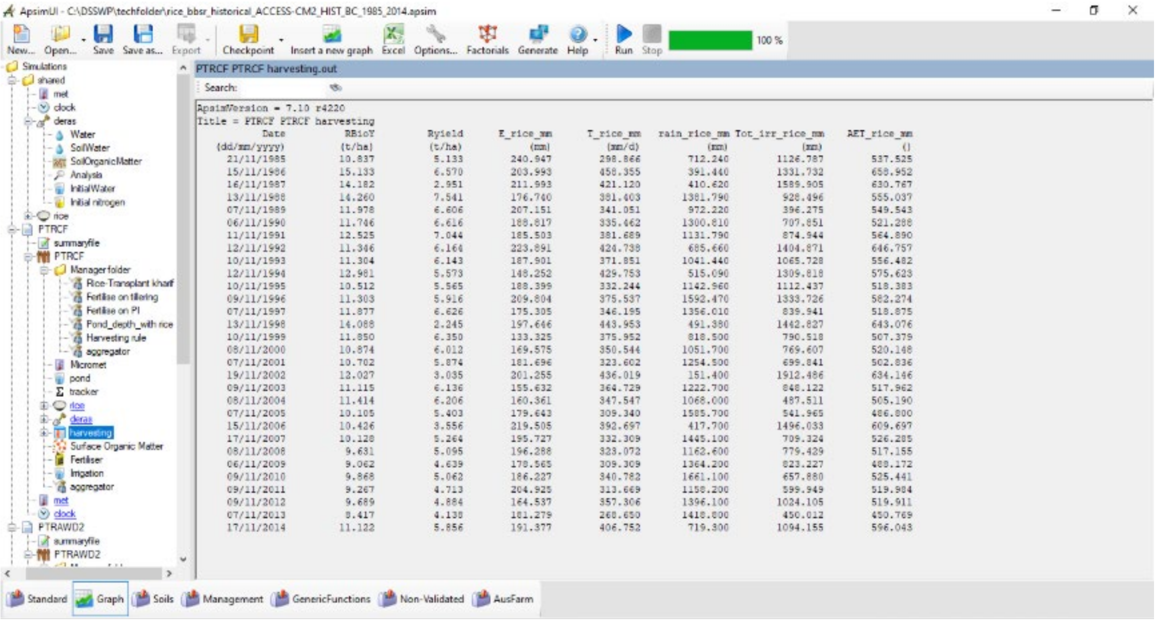
Soil information for each field was extracted from the, which provides harmonized, high-resolution (250 m) estimates of key soil physical and chemical properties. For every polygon, depth-wise attributes such as texture fractions, bulk density, soil organic carbon, and water-holding characteristics were retrieved and processed to generate APSIM-compatible soil profiles. These profiles were then ingested directly into the APSIM modelling framework to ensure consistent and spatially explicit representation of soil heterogeneity across the command area. Where available, user-supplied field soil data; such as laboratory measured soil moisture characteristics, local horizon descriptions, or field-surveyed soil depths, can replace or supplement the SoilGrids-derived inputs, enabling more accurate and site-specific simulation of crop growth and soil-water dynamics.

Retrieving Phenology Data Using Remote Sensing

Rice phenology across the command area was identified using a Sentinel-1 SAR time-series approach implemented through Google Earth Engine and processed in R. All IW-mode VV/VH observations within the transplanting season were extracted, speckle-filtered, and aggregated at the plot level. VH backscatter trajectories were smoothed and characteristic flooding–transplanting signals were detected using two complementary indicators: (i) a VH-minimum and subsequent sharp-rise feature, and (ii) an RVI-based emergence cue derived from multiple RVI formulations. These phenological markers were reconciled within agronomic date windows, and a final transplanting date for each plot was produced. The resulting plot-wise phenology layer was integrated with the command-area management dataset for downstream modelling and water-productivity analysis.

Parameterization of APSIM Model

APSIM rice modelling was carried out for the Deras research farm of IIWM, Bhubaneswar using two management treatments, PTRCF (puddled transplanted rice under continuous flooding) and PTRAWD to assess their comparative performance under current and future climate conditions (Figure 5).



```
ApsimVersion = 7.10 r4220
Title = PTRCF PTRCF harvesting
            Date           RBioY          Ryield       E_rice_mm       T_rice_mm    rain_rice_mm Tot_irr_rice_mm     AET_rice_mm
    (dd/mm/yyyy)          (t/ha)          (t/ha)            (mm)          (mm/d)            (mm)            (mm)              ()
      21/11/1985          10.837           5.133         240.947         298.866         712.240        1126.787         537.525
      15/11/1986          15.133           6.570         203.993         458.355         391.440        1331.732         658.952
      16/11/1987          14.182           2.951         211.993         421.120         410.620        1589.905         630.767
      13/11/1988          14.260           7.541         176.740         381.403        1381.790         928.496         555.037
      07/11/1989          11.978           6.606         207.151         341.051         972.220         396.275         549.543
      06/11/1990          11.746           6.616         188.817         335.462        1300.810         707.851         521.288
      11/11/1991          12.525           7.044         185.503         381.689        1131.790         874.944         564.890
      12/11/1992          11.346           6.164         223.891         424.738         685.660        1404.871         646.757
      10/11/1993          11.304           6.143         187.901         371.851        1041.440        1065.728         556.482
      12/11/1994          12.981           5.573         148.252         429.753         515.090        1309.818         575.623
      10/11/1995          10.512           5.565         188.399         332.244        1142.960        1112.437         518.383
      09/11/1996          11.303           5.916         209.804         375.537        1592.470        1333.726         582.274
      07/11/1997          11.877           6.626         175.305         346.195        1356.010         839.941         518.875
      13/11/1998          14.088           2.245         197.646         443.953         491.380        1442.827         643.076
      10/11/1999          11.850           6.350         133.325         375.952         818.500         790.518         507.379
      08/11/2000          10.874           6.012         169.575         350.544        1051.700         769.607         520.148
      07/11/2001          10.702           5.874         181.696         323.602        1254.500         699.841         502.836
      19/11/2002          12.027           3.035         201.255         436.019         151.400        1912.486         634.146
      09/11/2003          11.115           6.136         155.632         364.729        1222.700         848.122         517.962
      08/11/2004          11.414           6.206         160.361         347.547        1068.000         487.511         505.190
      07/11/2005          10.105           5.403         179.643         309.340        1585.700         541.965         486.800
      15/11/2006          10.426           3.556         219.505         392.697         417.700        1496.033         609.697
      17/11/2007          10.128           5.264         195.727         332.309        1445.100         709.324         526.285
      08/11/2008           9.631           5.095         196.288         323.072        1162.600         779.429         517.155
      06/11/2009           9.062           4.639         178.565         309.309        1364.200         823.227         488.172
      09/11/2010           9.868           5.062         186.227         340.782        1661.100         657.880         525.441
      09/11/2011           9.267           4.713         204.925         313.669        1158.200         599.949         519.984
      09/11/2012           9.689           4.884         164.537         357.306        1396.100        1024.105         519.911
      07/11/2013           8.417           4.138         181.279         268.650        1418.800         450.012         450.769
      17/11/2014          11.122           5.856         191.377         406.752         719.300        1094.155         596.043
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Figure 5. Agricultural Production Systems sIMulator (APSIM) Classic modelling interface used for rice simulations.

The model was first calibrated using Parameter ESTimation (PEST) focusing on key phenological and growth parameters for the widely cultivated *Swarna rice variety*, including thermal time requirements, leaf area development, biomass partitioning, and tillering dynamics (Doherty, 2025). Field observations from Deras were used to tightly constrain the model so that simulated phenology, biomass, and yield closely matched observed values across treatments.

Once calibration was completed for the two management systems with available field data—PTRCF and PTRAWD (2-day drying cycle), a comprehensive climate scenario analysis was undertaken using APSIM simulations driven by historical climate and future projections from all 12 CMIP6 GCMs (SSP245 and SSP585). Although field calibration was conducted only for PTRCF and PTRAWD-2, an additional PTRAWD-5 treatment was included in the evaluation phase to explore the performance of a more water-conservative AWD variant that is widely recommended in climate-smart irrigation literature. The calibrated PTRAWD2 parameters served as the baseline physiological representation of AWD behavior, with the extended drying interval (5 days) implemented through adjusted irrigation triggers rather than modified crop parameters ensuring methodological consistency. The performance of PTRCF, PTRAWD-2, and PTRAWD-5 was evaluated in terms of irrigation requirements, evapotranspiration, soil-water dynamics, and yield stability across the full ensemble of climate projections.

Preliminary Results

A controlled field experiment was conducted in 2022 at the ICAR–IIWM Deras Research Farm, Mendhasala (Odisha, eastern India), on Swarna, a widely cultivated rice variety in the region. Two irrigation management regimes were evaluated: puddled transplanted rice with continuous flooding (PTR-CF) and puddled transplanted rice under alternate wetting and drying with a two-day drying cycle (PTR-AWD). Data generated from this experiment formed the empirical basis for calibrating the APSIM rice model, allowing accurate representation of crop phenology, biomass accumulation, soil–water balance, and irrigation response under local agro-ecological conditions. Calibration diagnostics demonstrated strong agreement between observed and simulated variables, indicating robust model performance and stable parameterization. With this validated configuration, APSIM provides a reliable and comparative framework for assessing climate-change impacts and evaluating the resilience of alternative irrigation strategies. The preliminary results presented here reflect both the robustness of the field-calibrated model and its potential to guide climate-smart irrigation planning under future scenarios. The calibrated parameters related to crop phenology, soil-water dynamics, and atmospheric response have now been fully embedded within the APSIM configuration files. These calibrated profiles provide a robust foundation for extending simulations beyond the experimental plots, enabling the model to generate spatially explicit water-demand estimates across heterogeneous farm landscapes. By combining APSIM's calibrated crop parameters with field-specific soil properties, derived from ISRIC SoilGrids or user-supplied measurements, the modelling framework can reliably estimate irrigation requirements for diverse soil types and management conditions within the CI-IDSS framework across the command area.

Ensemble Analysis

All twelve CMIP6 GCMs were processed as an ensemble to generate robust climate signals for irrigation water demand modeling. For each variable; rainfall, temperature, PET, irrigation requirement, and AET daily and seasonal outputs were aggregated to compute ensemble median, P10, and P90 values. The median represents the most likely climate trajectory, while P10 and P90 capture the lower and upper bounds of uncertainty, providing a probabilistic range of future outcomes. This approach allows identification of both conservative and extreme climate scenarios that may impact crop water use.

Ensemble spread was also evaluated to quantify the inter-model variability, especially in monsoon rainfall intensity, dry spell length, and late-season evaporative demand—key drivers of irrigation scheduling. The ensemble distributions were statistically compared using Kolmogorov–Smirnov (KS) test to detect significant shifts between historical and future scenarios. These diagnostics enabled the selection of climate-resilient irrigation strategies by highlighting how different irrigation regimes (PTRCF, PTR-AWD2, PTR-AWD5) perform across the entire uncertainty envelope of future climate projections. The KS test results reveal distinct patterns in how climate change alters the distribution of key APSIM outputs across treatments. Comparisons between historical and SSP245 show that rice biomass yield (RBiOY) and AET distributions do not undergo statistically significant shifts for any treatment (all $p > 0.19$), indicating strong resilience of crop physiological performance under moderate warming. Rainfall distributions approach significance ($p \approx 0.064$), consistent with the modest widening of ensemble rainfall variability seen in the CDF plots. Irrigation requirement displays the clearest divergence: PTRCF shows a statistically significant shift ($KS = 0.143$, $p = 0.0012$), while PTRAWD2 shows a marginal shift ($p = 0.032$) and AWD5 remains non-significant ($p = 0.144$). This suggests that AWD practices partially buffer the system from climate-induced changes in irrigation demand.

Under historical vs. SSP585, the distributional shifts become more pronounced. Rainfall and irrigation demand show statistically significant changes for all treatments ($p < 0.01$ for rainfall; $p < 0.055$ for irrigation), with PTRCF again showing the strongest signal ($p = 0.0013$). Yield distributions exhibit mild sensitivity under SSP585, with AWD2 showing a significant shift ($p = 0.048$), whereas AWD5 and PTRCF remain stable. AET distributions remain statistically unchanged across all treatments (all $p > 0.56$), confirming that evaporative demand increases slightly but does not fundamentally alter seasonal AET variability.

The SSP245 vs. SSP585 comparison highlights that most variables experience no meaningful distributional shift, with all $p > 0.26$ except yield under AWD5 ($p = 0.934$) and irrigation under all treatments ($p > 0.93$). This indicates that the transition from moderate to high-end warming primarily amplifies the distributional changes already observed from historical to SSP245, rather than introducing new structural shifts.

Cumulative Probability Analysis

The CDFs show (Figure 6) clear ensemble spreads for all variables, illustrating uncertainty across the 12-GCM climate ensemble for historical, SSP245, and SSP585 scenarios. Historical distributions are consistently narrower, while SSP245 and SSP585 show widening bands, indicating increased climate variability and deepening uncertainty under warming.

Effect on Rice Yield

The APSIM–GCM ensemble analysis shows that grain yield (RYield) remains relatively stable across historical and future climate scenarios, with only marginal shifts in central tendency. Under historical conditions, median yields (P50) range from 5.33 t ha^{-1} (PTRCF) to 5.43 t ha^{-1} (PTRAWD2), and the upper tail (P90) reaches 6.43–6.49 t ha^{-1}, indicating strong yield potential under wet seasons. Under SSP245, median yields remain nearly unchanged, with PTRCF at 5.33 t ha^{-1}, PTRAWD2 at 5.40 t ha^{-1}, and PTRAWD5 at 5.34 t ha^{-1}, representing changes of less than ±1% from historical baselines. Under the more extreme SSP585, median yields show a slight tightening of the distribution: PTRCF declines to 5.26 t ha^{-1}, PTRAWD2 to 5.33 t ha^{-1}, and PTRAWD5 to 5.29 t ha^{-1}, corresponding to a modest 1–2.5% reduction relative to historical values.

The lower tail (P10), which is most sensitive to climate stress, shows only small changes: for PTRCF, P10 shifts from 4.36 to 4.33 t ha^{-1} (SSP245) and 4.38 t ha^{-1} (SSP585); for PTRAWD2, from 4.45 to 4.33–4.42 t ha^{-1}; and for PTRAWD5, from 4.39 to 4.28–4.39 t ha^{-1}. These changes denote < 2–3% variation in downside yield risk across scenarios. Importantly, the AWD treatments (PTRAWD2 and PTRAWD5) consistently maintain slightly higher P10 and P50 values than PTRCF under all scenarios, demonstrating improved resilience under warming and rainfall variability conditions. The upper tail (P90) remains robust across scenarios (6.30–6.49 t ha^{-1}), indicating that the climatic constraints of the future scenarios do not substantially limit high-yield potential.

Overall, the results confirm that median rice yield remains largely climate-resilient, while AWD practices offer marginal but systematic advantages in buffering yields against increased inter-annual variability under climate change.

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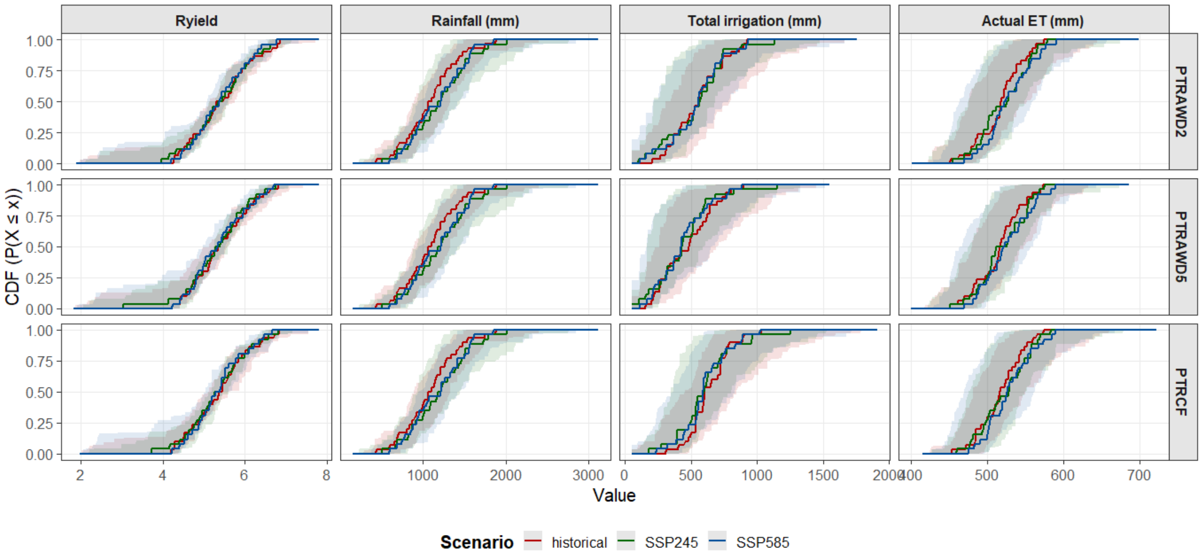

Figure 6. Treatment-wise cumulative distribution functions (CDFs) for rice yield (t/ha) (Ryield), crop season rainfall (mm) (rain_rice_mm), irrigation demand (mm) (Tot_irr_rice_mm), and actual evapotranspiration under historical and future climate scenarios (SSP245 and SSP585) (12 GCMs).

Effect on Rainfall During Cropping Season

The CDF analysis of crop season rainfall (rain_rice_mm) shows clear differences between historical and future climate scenarios, reflecting the projected intensification and variability of monsoon dynamics. Under historical conditions, rainfall exhibits a moderately wide distribution, (with P10 = 651 mm, median (P50) = 1094 mm, and P90 = 1586 mm) across all treatments. Since rainfall is exogenous to treatments, PTRCF, PTRAWD2, and PTRAWD5 share identical rainfall distributions.

Under SSP245, the lower tail remains similar (P10 ≈ 646 mm, a marginal <1% decrease), but the upper tail widens substantially, with P90 increasing to 1790 mm, an increase of ~13% compared to historical. The median also increases to 1139.7 mm, suggesting a modest shift toward wetter conditions, accompanied by an increase in interannual variability, as reflected in the broader ensemble bands seen in the CDF curves.

Under SSP585, rainfall intensifies further, with the lower tail rising to 705.6 mm (≈ +8% vs. historical) and the median reaching 1168.5 mm (≈ +7%). The upper tail (P90 ≈ 1773 mm) remains comparable to SSP245 but is ~12% higher than historical, indicating a greater likelihood of extreme rainfall events. These patterns are clearly reflected in the CDF plots, where SSP585 curves shift upward and leftward relative to historical values, accompanied by visibly wider uncertainty bands, signaling heightened interannual variability.

Overall, the CDF-based rainfall assessment confirms that future climates, particularly SSP585, are likely to deliver wetter conditions with significantly larger upper-tail extremes, increasing the frequency of high-rainfall years that may influence soil hydrology, irrigation demand reductions, and flood-risk factors within rice-based production systems.

Effect on Precipitation Excess Irrigation Requirement

The GCM-wise boxplots of irrigation requirement (Tot_irr_rice_mm) reveal (Figure 7) substantial inter-model variability across historical, SSP245, and SSP585 scenarios, with clear differences among irrigation treatments. For PTRCF, all GCMs show consistently higher irrigation demand, with median values generally exceeding 550–650 mm and upper extremes frequently surpassing 1,000 mm, particularly under historical and SSP245 conditions. PTRAWD2 exhibits a marked reduction in both median and upper-tail irrigation demand across nearly all GCMs, while PTRAWD5 demonstrates the largest shift toward lower water use, with several GCMs producing median irrigation requirements below 400 mm even under future climate scenarios. Notably, the spread (IQR and whiskers) remains wide for many models, especially CanESM5, EC-Earth3, MPI-ESM1-2-HR and MRI-ESM2-0, indicating high sensitivity of irrigation demand to model-specific rainfall and ET trajectories. Under SSP585, some GCMs (e.g., ACCESS-ESM1-5, NorESM2-MM) show reduced median irrigation demand due to enhanced rainfall projections, whereas others (e.g., CanESM5) retain large upper-tail values, reflecting the persistence of high-demand stress years even under wetter futures. Across all scenarios, AWD treatments consistently compress both the median and the interquartile range, demonstrating that AWD, particularly AWD5, reduces not only the expected irrigation requirement but also the climate-induced variability transmitted through inter-GCM uncertainty. This behavior underscores AWD’s robustness as a climate-smart irrigation strategy capable of moderating the extremes projected by individual climate models.

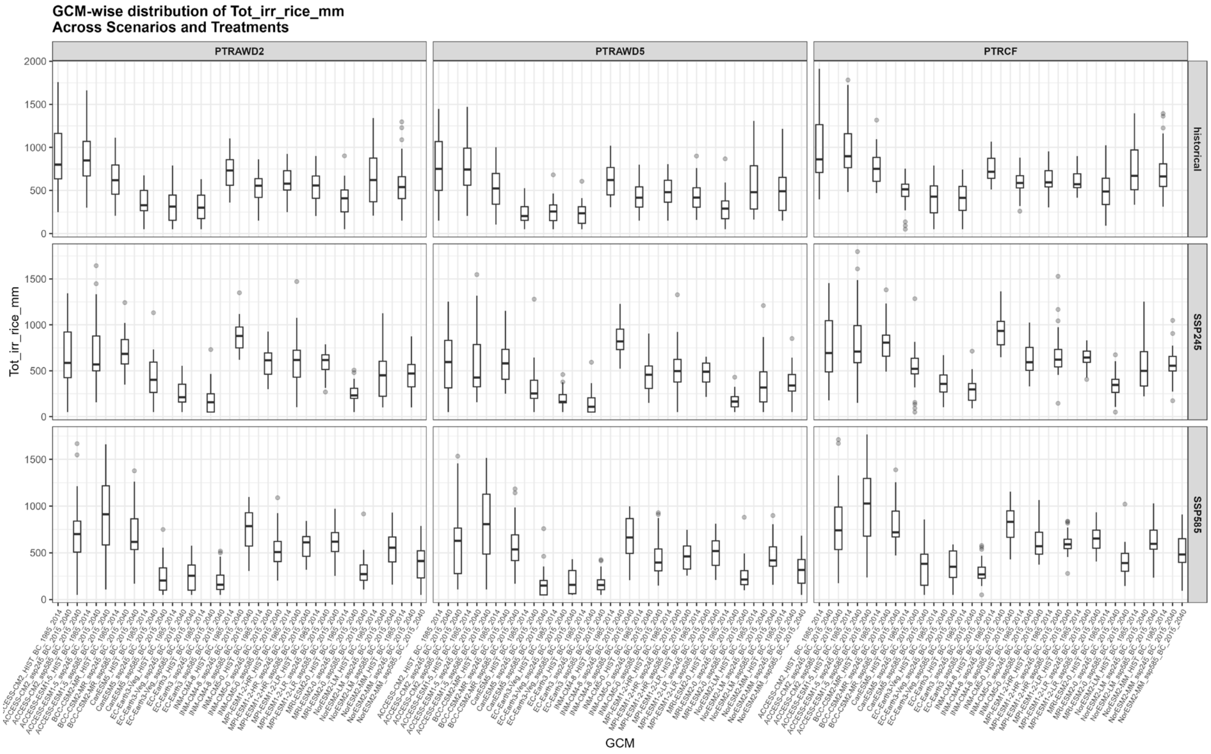

Figure 7. GCM-wise distribution of seasonal irrigation requirement (Tot_irr_rice_mm) for rice under contrasting management treatments and climate scenarios.

The irrigation CDFs show strong treatment differentiation. PTRCF consistently occupies the right-most (highest demand) position across scenarios. PTRAWD2 shifts the CDF leftwards, and PTRAWD5 shifts it even further, confirming systematic water savings. Under SSP245 and SSP585, CDF bands widen significantly, but PTRAWDx treatments maintain lower irrigation demand across all quantiles (P10–P90). AWD5 displays the smallest climate sensitivity, with only mild stretching of its CDF under SSP585. Across the 12-GCM ensemble, irrigation requirements exhibit clear shifts under future climates, with treatment-specific differences in both central tendency and variability (Figure 8).

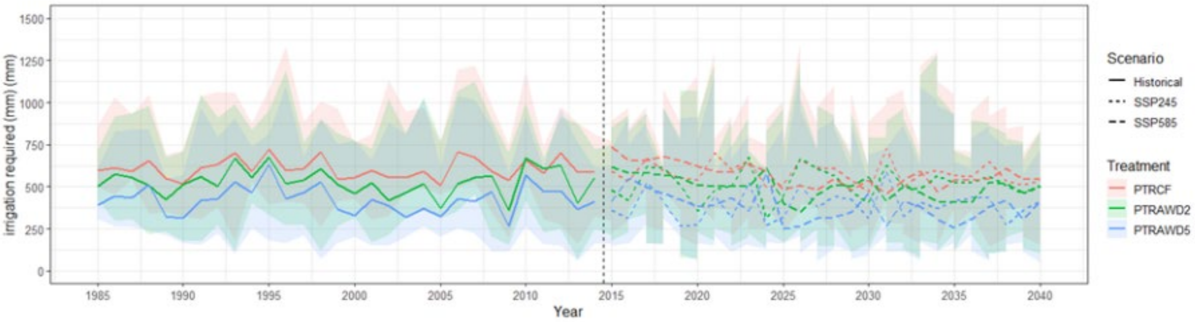

Figure 8. Ensemble median irrigation requirement (mm) for rice under three management treatments (PTRCF, PTRAWD2, PTRAWD5) across 12 GCMs for the period 1985–2040.

For PTRCF, the highest-demand system, median irrigation requirement decreases slightly from 596.6 mm (historical) to 578.1 mm under SSP245 and 559.1 mm under SSP585, reflecting the influence of increased median rainfall in several GCMs. AWD treatments show even stronger reductions i.e. median demand for PTRAWD2 declines from 529.6 mm to 504.4 mm (SSP245) and 501.4 mm (SSP585), while PTRAWD5 displays the largest savings, decreasing from 418.5 mm (historical) to 374.2 mm and 370.7 mm, representing 10–12% reductions. However, upper-tail behavior (P90) reveals that high-demand years persist even under future climates, with PTRCF reaching ~1000 mm, PTRAWD2 ~920–940 mm, and PTRAWD5 ~850–870 mm, indicating that climate variability continues to drive episodic irrigation stress. Overall, while median irrigation demand tends to decline under SSP245 and SSP585, the persistence of high-demand extremes underscores the importance of resilient water-saving systems, with AWD—particularly PTRAWD5, offering the most robust performance across the full climate uncertainty envelope.

Effect on Crop Water Use

AET CDFs (Fig.5.) remain narrow and tightly clustered for all treatments, indicating stable crop water use compared to rainfall and irrigation variability. A small right-shift under SSP585 reflects higher evaporative demand consistent with warming projections. Treatment effects on AET are minimal, becoming evident mainly through irrigation or soil-water availability rather than climate forcing. Across all treatments, AET exhibits relatively narrow distributions, indicating that crop water use remains comparatively stable even under changing climate forcings. For PTRAWD2, median AET (P50) shifts only slightly from 515.95 mm (historical) to 517.59 mm under SSP245 and 515.14 mm under SSP585, representing changes of less than ±1%. Similarly, PTRAWD5 shows a modest decline from 514.65 mm (historical) to 514.94 mm (SSP245) and 515.10 mm (SSP585), confirming that AWD does not substantially alter total seasonal AET despite reducing irrigation inputs. PTRCF displays the highest AET values, with medians increasing from 516.73 mm to 521.04 mm under SSP245 and 519.53 mm under

SSP585, reflecting a 1–2% rise in atmospheric evaporative demand under warming. Upper-tail (P90) AET also increases slightly across scenarios from ~574–577 mm historically to ~580–583 mm in SSP585, indicating more frequent high-AET years under stronger warming conditions. Overall, AET changes remain small (<3%), suggesting that climate-driven increases in evaporative demand are modest and that differences in irrigation requirement across treatments are driven primarily by soil–water dynamics and rainfall variability, rather than by changes in plant water use itself.

Treatment Resilience Across the CDF

PTRAWD5 shows the highest resilience, with the smallest upward shifts under SSP scenarios and the lowest irrigation probability across the entire CDF (Fig.5). PTRAWD2 performs comparably well, though with slightly higher median irrigation demand. PTRCF is the least resilient, with the broadest irrigation CDF under SSPs and greatest sensitivity to rainfall variability. The consistency of AWD yield CDFs with PTRCF indicates that **AWD reduces water risk without introducing yield risk**, even in high-uncertainty SSP ensembles.

Implications for Climate-Smart Irrigation

Ensemble CDFs demonstrate that irrigation demand variability will increase under future climates, but **AWD significantly dampens this variability**. The tight clustering of AET and yield CDFs across treatments suggests that management-driven irrigation savings do not compromise physiological crop water use or productivity. AWD treatments, especially PTRAWD5, offer robust adaptation benefits by minimizing exposure to high-demand tails of climate distribution.

AWD treatments reduce irrigation demand while maintaining yield stability, confirming global evidence (Bouman et al., 2007; Carrijo et al., 2017). Rising ET and reduced rainfall reliability under warming highlight the need for climate-adaptive irrigation scheduling. Multi-model GCM ensembles reveal growing uncertainty, highlighting the importance of risk-aware water budgeting. CI-IDSS provides a scalable tool to integrate climate information, hydrology, and optimization for smarter water management.

Policy Recommendations

The modelling evidence generated through APSIM–GCM integrations, together with field-calibrated irrigation strategies (PTRCF, PTRAWD2, PTRAWD5), provides a strong basis for informed water-management decisions across the minor irrigation systems under current and future climate scenarios. The following policy recommendations translate scientific insights into actionable interventions for short-, medium-, and long-term planning.

Short-Term Recommendations (1–2 Years)

- Implementing field-level AWD (Alternate Wetting and Drying) advisories across selected villages to demonstrate water savings and yield stability. The real-time soil-water data, rainfall forecasts, and APSIM-derived thresholds to guide farmers on safe drying periods, in conjunction with CI-IDSS.
- Refining water-release timing from village ponds and minor canals using climate-adjusted demand estimates. Introducing simple rule curves and daily/weekly allocation planning to improve equity and reduce conveyance losses.
- Rolling out the CI-IDSS at govt. owned reservoir SCADA system to support local decision-making. Upgrading skills of Panchayat technical staff and water user groups (Pani Panchayat in Odisha) to interpret irrigation demand forecasts, supply–demand gaps, and recommended release strategies. Greater transparency curbs elite capture and strengthens equitable water allocation.

Medium-Term Recommendations (3–5 Years)

- Produce dynamic cropping calendars aligned with future climate scenarios, integrating temperature thresholds, rainfall shifts, and water-availability projections. Promote DSR, short-duration cultivars, and drought-resilient varieties, where appropriate.
- Create digital twin platforms for minor irrigation projects, combining hydrodynamic canal models, real-time monitoring (SCADA, water levels, gate operations), and predictive analytics from GCM-driven APSIM simulations. Use these twins for scenario planning and operational optimization.
- Link solar pump operation schedules with CI-IDSS generated irrigation demand forecasts to minimize over-pumping and improve conjunctive water use. Introduce energy-water co-optimization to enhance cost efficiency and sustainability.

Long-Term Recommendations (5–10 Years)

- Encouraging diversification toward crops with lower water footprints, higher economic returns, and better adaptation under warming scenarios. Model-based suitability assessments will guide this transitions. CI-IDSS is designed to support state and national programs by enabling data-driven water allocation, multi-crop simulation, and climate scenario analysis. It is ready for scaling across Odisha to any other command areas.
- Expanding the CI-IDSS and digital-twin capabilities from village-level systems to basin-scale platforms that integrate hydrology, groundwater dynamics, reservoir operations, and agricultural water demand across entire river basins.
- Embed Water–Energy–Food (WEF) nexus metrics, such as water productivity, energy intensity, GHG footprint, and ecosystem flow requirements into state-level planning

frameworks. Use these indicators for strategic investments, climate-resilience plans, and irrigation modernization programs.

Conclusions

This study provides a preliminary yet comprehensive assessment of how climate-smart decision-support tools can transform irrigation management in minor irrigation systems such as Darpanarayanpur. By integrating APSIM-based crop simulations, multi-GCM climate ensembles, and optimized water-allocation logic within the CI-IDSS framework, we demonstrate the potential for a future-ready digital infrastructure capable of supporting adaptive irrigation scheduling, improved water productivity, and long-term climate resilience. The comparative performance of PTRCF and PTRAWDx treatments under historical and future climate scenarios highlights that AWD, particularly longer drying cycles, offers substantial irrigation savings with minimal impact on yields, making it a strong candidate for climate-smart rice management.

However, it is important to recognize that these findings are based on model-driven analyses, limited field observations, and initial allocations simulated under controlled conditions. As such, they represent an early-stage diagnostic rather than definitive operational recommendations. The next phase of work will involve systematic incorporation of multi-year field trials, high-resolution pond and canal operation data, and observed farmer-level water use patterns. This expanded evidence base will allow the CI-IDSS algorithms, allocation rules, and crop-model parameters to be refined, validated, and stress-tested under real operational constraints.

Moving forward, the combination of field-based calibration, improved hydrodynamic characterization of canals, and long-term monitoring of crop performance will be essential for transitioning this prototype into a fully operational decision-support system. Ultimately, this approach lays the foundation for a scalable and climate-informed irrigation management framework that can guide Panchayat-level decision-makers, canal operators, and state water agencies toward more resilient, equitable, and efficient water allocation systems in the decades ahead.

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