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Regional Variability in Climate Change Impacts on Agricultural Reservoir Water Balance and Tailored Adaptation Strategies under SSP Scenarios in South Korea

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Abstract

In this study, the impact of climate change on the main water balance factors of agricultural reservoirs was examined using Shared Socioeconomic Pathways (SSPs). Trends in reservoir inflow, net irrigation water requirement, and required storage were analyzed for the past 40 years (1981–2020) and projected for the future (2031–2070) using a multi-model ensemble (MME) of 18 GCMs. The results indicate that while reservoir inflow exhibited a consistent increasing trend across all study regions due to projected precipitation rises, the responses of net irrigation water requirements and required storage were highly variable by region. Based on these divergent trends, the study regions were classified into four distinct types. For each type, tailored adaptation strategies were proposed, ranging from demand-side management (e.g., precision irrigation) to infrastructure-led adaptation (e.g., increasing storage capacity). These findings emphasize that climate change adaptation for agricultural water management must transcend uniform approaches and instead focus on region-specific strategies that address localized hydrological vulnerabilities.

Keywords: Climate change; Agricultural reservoir; Trend analysis; Mann–Kendall test; Agricultural water management

1. Introduction

Climate change refers to statistically significant shifts in historical climate patterns and poses a critical threat to global sustainable development (Parry et al. 2007; Alemu and Dioha 2020; Dioha and Kumar 2020; Milentijević et al. 2022). To mitigate climate change impacts, many agricultural nations emphasize the importance of understanding regional climate trends and developing proactive response strategies (Rimi et al. 2009; Panda and Sahu 2019; Sarkar and Maity 2024). To this end, many nations have established adaptation policies at the national level; however, there is an increasing need to downscale these broad frameworks for local-scale implementation.

Agriculture depends strongly on climate and is directly impacted by extreme weather events (Kishore et al. 2016; FAO 2023). Many researchers have focused on assessing agricultural productivity under climate variability by examining climatic factors, such as temperature and precipitation (Ademe et al. 2020; Mugabe et al. 2024; Raoufi et al. 2024; Yuan et al. 2024). The increasing frequency and intensity of weather events—such as rising temperatures and precipitation variability—threaten sustainable agriculture by declining productivity, worsening water imbalances, and damaging agriculture infrastructure (Park et al. 2014; Hristov et al. 2020; Jeong H-K and Han 2022; Sanou et al. 2023). Consequently, securing effective agricultural water management strategies is increasingly recognized as vital for mitigating the impacts of climatic extremes (Nurkhaida and Rejekiningrum 2021).

In South Korea, agricultural reservoirs serve as the core infrastructure for agricultural water management, storing surplus inflow during non-irrigation periods and supplying it during irrigation periods (Kim et al. 2022). However, most reservoirs were designed based on historical climate and cultivation data, which makes them highly vulnerable to the variability of recent water supply and demand patterns (Kim S et al. 2021; Kim S-J et al. 2022). Particularly, the required storage capacity calculated based on historical data may fail to ensure a stable water supply, making it critical to re-evaluate the water balance relationship—comprising reservoir inflow, net irrigation water requirement, and required storage—using the latest climate change scenarios. Recently, the Shared Socioeconomic Pathways (SSPs) have emerged as the most advanced framework for such assessments, integrating socioeconomic transitions with climatic forcing (Masson-Delmotte et al. 2021).

This study aims to propose regional response strategies based on long-term trends in the main water balance factors of agricultural reservoirs. To achieve this, the latest SSP scenarios were utilized to quantify reservoir inflow, net irrigation water requirement, and required storage. The statistical significance and magnitude of long-term shifts in these three factors were evaluated by comparing two distinct periods: the historical (1981–

2020) and the future (2031–2070). Based on these results, the study areas were classified into four distinct types, for which specific response strategies were proposed. These findings are expected to provide a scientific basis for developing region-specific agricultural infrastructure reinforcement and agricultural water management strategies to enhance climate resilience.

2. Materials and methods

2.1. Study Area and Selection of Representative Reservoirs

South Korea manages 17,047 agricultural reservoirs, categorized by managing authority: 13,620 are overseen by local governments and 3,427 by the Korea Rural Community Corporation (KRC). Among these, 536 reservoirs are classified as large-scale reservoirs with an effective storage capacity exceeding 1 million tons (MAFRA 2024). To reflect the distinct water supply and demand characteristics of each region, South Korea (excluding Jeju Island) was divided into eight major administrative provinces, and one representative reservoir was selected from each. From these 536 large-scale facilities, reservoirs with over 40 years of continuous meteorological records and automated water level monitoring systems were prioritized. Subsequently, the reservoir with the largest benefitted area in each province was finally selected, as these reservoirs exert the most significant influence on regional agricultural water supply and demand. By applying these criteria, eight reservoirs were finally selected for this study (Table 1, Fig. 1).

Table 1. Agricultural reservoir and meteorological data information used in this study

Region	Agricultural reservoirs				Meteorological Stations (Nearby)
	Name	Total Storage (×1000 m^3)	Effective Storage Capacity (×1000 m^3)	Benefitted Area (ha)	
U1: Gyeonggi-do	Yongseol	3,020.0	2,932.4	401.6	Icheon
U2: Gangwon-do	Sacheon	2,106.7	2,106.6	344.9	Gangneung
M1: Chungcheongnam-do	Cheonjang	2,882.0	2,877.5	551.0	Buyeo
M2: Chungcheongbuk-do	Samgi	2,811.2	2,811.2	410.0	Cheongju
M3: Gyeongsangbuk-do	Daewon	2,947.0	2,880.0	448.8	Gumi
L1: Jeollabuk-do	Gungsan	2,210.0	2,210.0	260.0	Buyeo
L2: Jeollanam-do	Wolnam	2,226.6	2,225.0	500.7	Jangheung

L3: Gyeongsangnam-do	Muggye	2,467.5	2,458.0	334.5	Sancheong

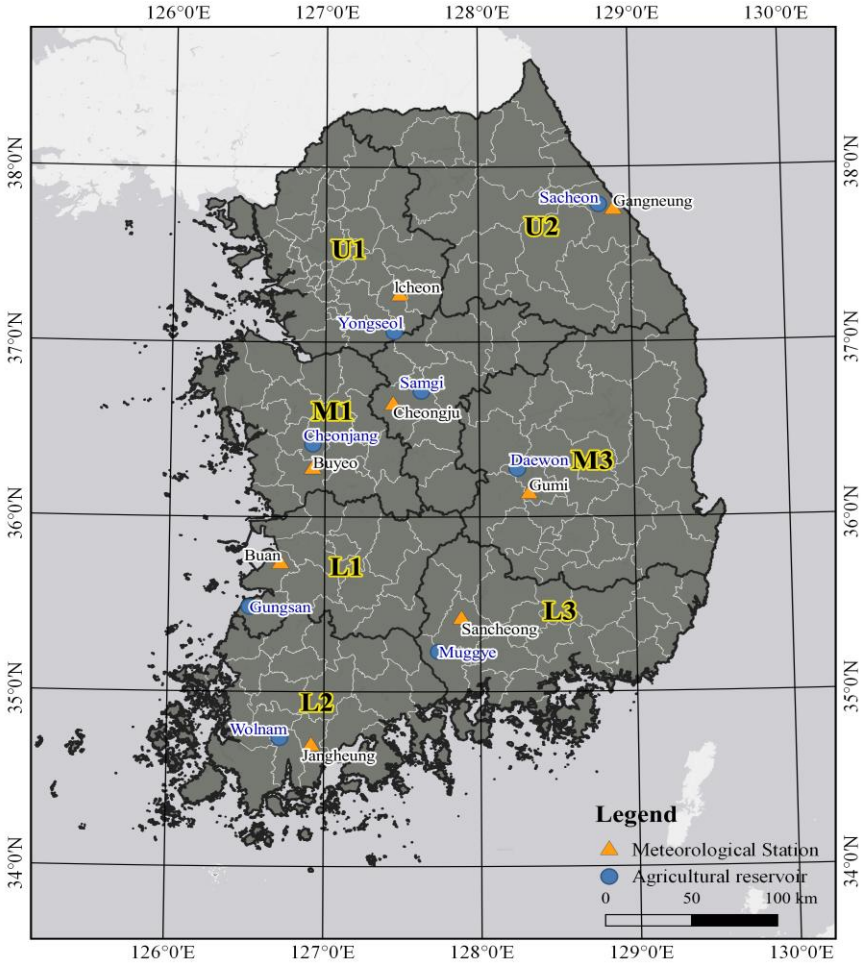


Fig. 1 The eight regions corresponding to provinces U1 (Gyeonggi), U2 (Gangwon), M1 (Chungcheongnam), M2 (Chungcheongbuk), M3 (Gyeongsangbuk), L1 (Jeollabuk), L2 (Jeollanam), and L3 (Gyeongsangnam)

2.2. Climate data source

Climate change scenarios provide essential data for assessing future climate impacts and developing strategies to mitigate potential damage. The IPCC Sixth Assessment Report adopted SSPs as standard greenhouse-gas pathways, incorporating radiative forcing levels and various socioeconomic factors projected for the year 2100 (Masson-Delmotte et al. 2021; Kim J-U et al. 2023).

Aligned with international research trends, the Rural Development Administration (RDA) of South Korea collects global SSP scenario data provided through the Coupled Model Intercomparison Project Phase 6 (CMIP6). This dataset, based on 18 global climate models, has been refined using the SQM downscaling method

and certified by the Korea Meteorological Administration (KMA) as the standard climate change scenario for South Korea. The high-resolution (1 km) climate change scenario data include daily records for five meteorological variables: minimum temperature, maximum temperature, precipitation, wind speed, and solar radiation. These data are distributed by observation station and grid (RDA 2022; Hur et al. 2024). The analysis conducted in this study utilized 40 years (1981–2020) of observed weather data from the KMA and 40-year future projections (2031–2070) under the SSP2-4.5 (moderate) and SSP5-8.5 (high-emission) scenarios produced by the RDA (Table 2).

Table 2. Past climate data and future climate change scenarios used in this study

Period	Climate Data	Number of Meteorological Stations	Meteorological variables	Source
Past (1981–2020)	Observed	8	Daily minimum temperature, Daily maximum temperature, Precipitation, Wind speed, Solar radiation	KMA[a]
Future (2031–2070)	Climate change scenarios (SSP2-4.5 and SSP2-8.5)			RDA[b]

[a]KMA = Korea Meteorological Administration, [b]RDA = Rural Development Administration.

2.3. Analysis of water balance factors for agricultural reservoirs

This study focuses on three water balance factors: reservoir inflow, net irrigation water requirement, and required storage. These factors are defined as key elements in the 2023 revised Design Standards for Agricultural Production Infrastructure for Farmland Irrigation (KDS 67 40 00) and serve as the most critical design parameters in Rural Water Development Projects and Farmland Improvement Projects. To perform the hydrological and hydraulic analyses, the KRC Hydraulics & Hydrology Analysis System (K-HAS) was utilized, as it is the specialized software package developed for and used in the actual design process of agricultural reservoirs.

The reservoir water balance is analyzed using a continuity equation (Eq. 1), which integrates inflow data from the Daily Irrigation Reservoir Operation Model (DIROM) and net irrigation water requirements calculated via the Penman equation:

$$S_{(t)} = S_{(t-1)} + \mathrm{IN}_{(t)} + \mathrm{GI}_{(t)} + \mathrm{SP}_{(t)} - \left(R_{(t)} + O_{(t)} + E_{(t)} + \mathrm{GD}_{(t)} + \mathrm{WD}_{(t)}\right), \quad (1)$$

where S represents the reservoir storage, IN is inflow, GI is groundwater inflow, SP is surface precipitation, R is outflow (irrigation water requirement), O is overflow from the spillway, E is evaporation from the surface, GD is

underground infiltration, and WD is embankment infiltration. The subscripts (t) and ($t-1$) represent day t and day $t-1$, respectively.

The required storage is defined as the annual maximum storage volume derived from this continuous daily simulation. Groundwater inflow and underground and embankment infiltration, being either unmeasurable or negligible, were excluded from the analysis. Furthermore, as most agricultural reservoirs are equipped with natural overflow-type spillways, any storage exceeding the spillway height was assumed to overflow.

Inflow was estimated as daily runoff derived from daily precipitation using a runoff estimation model that simulates inflow and outflow in irrigation reservoirs (Eq. 2):

$$Q_{ij} = \sum_{i=1}^{n} \sum_{j=1}^{m} (\mathrm{ST}_{i,t} - H_{ij}) A_{ij,} \quad (2)$$

where Q_{ij} represents the total runoff (mm) on day t, i is the tank number, j is the number of outlets for tank i, ST_i is the water depth (mm) in tank i, H_{ij} is the height (mm) of the j-th outlet of tank i, and A_{ij} is the cross-sectional area of the outlet (dimensionless).

Simultaneously, the net irrigation water requirement (WR) was calculated as the sum of evapotranspiration and deep percolation, minus effective rainfall (Eq. 3):

$$\mathrm{WR}_{(t)} = \left(\mathrm{ET}_{n(t)} + D_{(t)}\right) - \mathrm{ER}_{(t)}, \quad (3)$$

where ET_n is the actual crop evapotranspiration (mm), D is percolation depth (mm), ER is effective rainfall (mm), and the subscript (t) represents day t.

Effective rainfall was determined using a water balance equation that considers daily changes in ponding depth in paddy fields (Eq. 4), applying a maximum ponding depth (PD_{max}) of 80 mm and minimum maintained ponding depth (PD_{min}) of 20 mm.

$$\mathrm{PD}_{(t)} = \mathrm{PD}_{(t-1)} + \mathrm{ER}_{(t)} + \mathrm{IR}_{(t)} - \mathrm{CU}_{(t)}, \quad (4)$$

where PD is the ponding depth (mm), ER is effective rainfall (mm), IR is irrigation (mm), and CU is crop consumptive use (sum of actual evapotranspiration and deep percolation, mm).

The cropping season was defined as April 17 to September 11 for central regions and April 27 to September 21 for southern regions, with crop coefficients adjusted according to regional conditions and crop growth stages (Table 3). Precipitation below 5 mm/day was considered ineffective rainfall. Data on channel water delivery losses, deep percolation, and watershed areas were based on values provided by the Ministry of Agriculture, Food and Rural Affairs (MARFA 2014).

142 **Table 3.** Crop coefficients for calculating actual crop evapotranspiration based on the Penman equation

Region	4L[a]	5E	5M	5L	6E	6M	6L	7E	7M	7L	8E	8M	8L	9E	9M
Central	0.56	0.56	0.56	0.75	0.95	1.06	1.09	1.17	1.39	1.53	1.58	1.47	1.42	1.32	1.32
Southern	0.56	0.56	0.56	0.56	0.75	0.95	1.06	1.09	1.17	1.39	1.53	1.58	1.47	1.42	1.32

[a]E is the early part of the month (1–10 days), M is the mid part of the month (11–20 days), and L is the late part of the month (21–31 days).

143

144 ## 2.4. Trend analysis

145 In this study, the Mann–Kendall test was employed for trend analysis. Recommended by the World Meteorological
146 Organization (WMO), the Mann–Kendall test is widely used to detect trends in climatic time series data
147 (Uranchimeg et al. 2015; Jin et al. 2021). As a non-parametric method, it does not require the data to follow a
148 specific distribution and can identify both linear and nonlinear trends, making it robust against outliers and missing
149 values (Xavier et al. 2020). The null hypothesis of the Mann–Kendall test states that no trend exists in the time
150 series data. The test statistic S ranges between −1 and +1, indicating the presence and direction of a trend (Kendall
151 1975; Djaman et al. 2017; Agbo et al. 2023; Arfasa et al. 2024).

152 The test statistic S is calculated as

153 $$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}\left(x_j - x_i\right), \quad (5)$$

154 where x_j and x_i are sequential time series values, n represents the amount of time series data, and $\operatorname{sgn}(x_j - x_i)$ is the
155 sign function, defined as

156 $$\operatorname{sgn}\left(x_j - x_i\right) = \begin{cases} +1 \text{ if} \left(x_j - x_i\right) > 0 \\ 0 \text{ if} \left(x_j - x_i\right) = 0 \\ -1 \text{ if} \left(x_j - x_i\right) < 0 \end{cases}. \quad (6)$$

157 For $n > 10$, the test statistic Z approximately follows a standard normal distribution and is given as

158 $$Z = \begin{cases} \frac{S-1}{\sigma} & \text{if} S > 0 \\ 0 & \text{if} S = 0 \\ \frac{S+1}{\sigma} & \text{if} S < 0 \end{cases}, \quad (7)$$

159 where σ is the variance of statistic S.

160 Ultimately, the decision to accept or reject the null hypothesis is based on a comparison of the calculated
161 Z-value with the critical value at the chosen significance level. In this study, a trend was considered statistically
162 significant if the Z-value exceeded ±1.96 at the 5% significance level ($p \leq 0.05$).

163

164 ## 3. Results

165 ### 3.1. Trend in annual inflow

166 The multi-model ensemble (MME) enhances the reliability of climate change projections by integrating the
167 strengths of multiple GCMs while reducing the influence of individual model weaknesses (Noor et al. 2019). To
168 minimize uncertainties associated with single models, an MME based on 18 GCMs suitable for agricultural water
169 analysis was used in this study. Trend analysis of inflow for agricultural reservoirs revealed statistically significant
170 increasing trends across all eight regions (Table 4). Notably, the SSP5-8.5 scenario exhibited a more pronounced
171 increasing trend compared to SSP2-4.5. The annual average inflow showed the smallest increase (839.9 mm) in
172 the M3 region and the largest increase (4966.9 mm) in the U2 region, relative to historical values. Among the 18
173 GCMs analyzed, the CanESM5 and MIROC-ES2L models consistently projected increasing trends across all
174 regions and scenarios (Table 5). In contrast, the INM-CM5-0 model did not show any significant trends in any
175 region or scenario.

176

177 **Table 4.** Summary of descriptive statistics and Mann–Kendall trend test for reservoir inflow

Region[a]	Mean (mm/yr)			Mann–Kendall trend test[b]							
	Past	Future		SSP2-4.5				SSP5-8.5			
		SSP2-4.5	SSP5-8.5	*Z*	*T*	*P*	*S*	*Z*	*T*	*P*	*S*
U1	6,071.7	7,203.2	7,430.1	3.82	0.29	<0.000	Increasing	4.42	0.34	<0.000	Increasing
U2	22,705.8	26,693.7	27,672.7	3.08	0.23	<0.002	Increasing	3.74	0.28	<0.000	Increasing
M1	10,668.1	12,739.5	13,257.1	3.39	0.26	<0.001	Increasing	4.35	0.33	<0.000	Increasing
M2	8,574.8	9,918.2	10,250.1	2.86	0.22	<0.004	Increasing	3.76	0.29	<0.000	Increasing
M3	7,374.9	8,214.8	8,454.8	2.41	0.18	<0.016	Increasing	3.19	0.24	<0.001	Increasing
L1	23,099.8	26,642.5	27,741.0	3.54	0.27	<0.000	Increasing	4.48	0.34	<0.000	Increasing
L2	9,011.3	10,456.6	10,785.1	3.44	0.26	<0.001	Increasing	4.03	0.31	<0.000	Increasing
L3	24,196.6	27,245.9	27,830.0	2.12	0.16	<0.034	Increasing	2.60	0.20	<0.009	Increasing

[a]U1 is Gyeonggi-do, U2 is Gangwon-do, M1 is Chungcheongnam-do, M2 is Chungcheongbuk-do, M3 is Gyeongsangbuk-do, L1 is Jeollabuk-do, L2 is Jeollanam-do, and L3 is Gyeongsangnam-do.

[b]*Z* is the normalized test statistic, *T* is Kendall's tau, *P* is the *p*-value of the significance test (two-tailed), and *S* is the direction of tendency (increasing, decreasing, or no trend).

Table 5. Trend analysis of reservoir inflow for 18 GCMs and ensemble data

	SSP2-4.5								SSP5-8.5							
	U1	**U2**	**M1**	**M2**	**M3**	**L1**	**L2**	**L3**	**U1**	**U2**	**M1**	**M2**	**M3**	**L1**	**L2**	**L3**
ACCESS-CM2	2.54	4.23	2.60	2.73	2.49	2.48	1.77	2.31	2.57	3.71	2.51	2.49	2.60	2.28	2.49	2.36
ACCESS-ESM1-5	2.58	1.69	1.50	1.65	1.58	1.35	0.00	−0.40	2.78	2.56	2.19	2.02	2.08	1.93	0.13	−0.23
CanESM5	4.81	4.23	4.47	4.96	3.49	4.55	4.54	4.49	4.72	3.96	4.47	4.78	4.73	4.62	4.69	4.57
CNRM-CM6-1	3.02	2.25	2.85	2.79	2.41	2.82	1.12	1.98	3.02	1.78	2.14	2.68	1.28	2.02	1.76	0.78
CNRM-ESM2-1	1.89	1.57	2.92	1.96	2.07	2.95	2.40	1.65	1.19	1.52	3.45	1.21	2.84	3.33	3.10	2.40
EC-Earth3	0.83	0.88	0.75	0.60	0.63	0.65	1.79	−0.15	2.53	1.03	1.67	1.96	1.43	1.86	−0.25	0.09
GFDL-ESM4	1.09	2.68	1.00	0.98	2.67	1.97	1.94	2.55	1.54	3.78	1.68	1.76	3.43	2.92	2.80	3.04
INM-CM4-8	−1.21	−1.13	0.27	−1.13	−0.53	1.01	1.28	−0.43	−0.42	0.03	2.72	−0.43	−0.07	2.34	2.41	−0.36
INM-CM5-0	−0.50	0.60	1.70	−0.62	−0.16	1.10	1.15	0.69	−0.38	−1.03	1.00	−0.34	0.05	0.53	0.58	1.52
IPSL-CM6A-LR	2.46	2.01	2.31	2.50	2.62	1.72	1.31	1.47	3.35	1.98	3.05	3.39	3.64	2.25	1.93	2.09
KACE-1-0-G	0.52	−0.16	0.37	0.23	0.60	−0.40	0.21	0.25	2.39	2.36	2.00	2.14	2.01	0.98	1.28	1.49
MIROC-ES2L	3.49	3.14	2.69	3.42	2.53	2.67	2.95	2.66	4.22	3.30	3.11	3.95	2.18	3.11	3.34	2.97
MIROC6	0.74	1.62	1.03	0.42	1.03	0.81	1.98	0.54	0.70	1.40	0.23	0.47	0.55	0.23	1.80	0.03
MPI-ESM1-2-HR	1.24	1.33	1.08	1.15	2.48	0.94	2.04	2.30	2.23	2.85	2.10	2.41	1.87	2.24	1.43	0.82
MPI-ESM1-2-LR	1.99	2.70	1.72	1.65	1.97	1.72	1.28	0.88	3.97	2.38	3.69	4.09	4.01	3.60	3.22	2.96
MRI-ESM2-0	2.62	0.72	2.34	2.14	0.86	2.00	1.66	0.44	2.70	1.38	2.16	2.27	1.52	1.84	1.20	0.84
NorESM2-LM	2.56	3.30	2.22	2.56	2.52	2.49	2.63	2.37	1.86	2.76	1.72	1.97	1.96	1.72	2.01	1.48
UKESM1-0-LL	2.75	−0.59	2.48	2.38	−0.10	1.28	2.25	−0.41	2.52	1.45	2.45	2.40	0.76	1.58	2.57	0.35
Ensemble	**3.82**	**3.08**	**3.39**	**2.86**	**2.41**	**3.54**	**3.44**	**2.12**	**4.42**	**3.74**	**4.35**	**3.76**	**3.19**	**4.48**	**4.03**	**2.60**

3.2. Trend in annual net irrigation water requirement

Net irrigation water requirement refers to the amount of water required in the field during the crop growth period and is directly related to agricultural water demand. The analysis revealed no statistically significant trends in any region except U2 under the SSP2-4.5 scenario (Table 6). Under the SSP5-8.5 scenario, increasing trends were observed in the U2, L2, and L3 regions, whereas the remaining five regions showed no distinct trends. In the U2 region, the annual average net irrigation water requirement increased by 3.1 mm/yr under the SSP2-4.5 scenario and 11.1 mm/yr under the SSP5-8.5 scenario compared to historical values. Although the increase was smaller than in the U1, L2, and L3 regions, it exhibited the most statistically significant increasing trend. Results from individual GCMs varied: some models showed increasing trends (e.g., ACCESS-ESM1-5, INM-CM4-8), whereas

others projected decreasing trends (e.g., CanESM5). Overall, however, no consistent or significant trend was detected (Table 7). Notably, the CNRM-CM6-1, MRI-ESM2-0, and NorESM2-LM models showed no trends across all regions and scenarios.

Table 6. Summary of descriptive statistics and Mann–Kendall trend test for net irrigation water requirement

Region[a]	Mean (mm/yr)			Mann–Kendall trend test[b]							
	Past	Future		SSP2-4.5				SSP5-8.5			
		SSP2-4.5	SSP5-8.5	*Z*	*T*	*P*	*S*	*Z*	*T*	*P*	*S*
U1	605.4	609.7	613.2	1.33	0.10	<0.185	no trend	1.30	0.10	<0.193	no trend
U2	786.9	790.0	798.0	2.38	0.18	<0.017	increasing	3.17	0.24	<0.002	increasing
M1	673.6	650.6	653.7	0.15	0.01	<0.884	no trend	0.51	0.04	<0.609	no trend
M2	818.7	796.8	801.7	−0.07	−0.01	<0.944	no trend	0.42	0.03	<0.675	no trend
M3	637.4	607.7	613.9	0.18	0.01	<0.858	no trend	0.86	0.07	<0.390	no trend
L1	649.0	600.7	601.2	−0.28	−0.02	<0.781	no trend	0.38	0.03	<0.705	no trend
L2	463.5	488.5	494.4	1.72	0.13	<0.085	no trend	2.55	0.19	<0.011	increasing
L3	539.2	554.9	564.7	1.45	0.11	<0.147	no trend	2.85	0.22	<0.004	increasing

[a]U1 is Gyeonggi-do, U2 is Gangwon-do, M1 is Chungcheongnam-do, M2 is Chungcheongbuk-do, M3 is Gyeongsangbuk-do, L1 is Jeollabuk-do, L2 is Jeollanam-do, and L3 is Gyeongsangnam-do.

[b]*Z* is the normalized test statistic, *T* is Kendall's tau, *P* is the *p*-value of the significance test (two-tailed), and *S* is the direction of tendency (increasing, decreasing, or no trend).

Table 7. Trend analysis of net irrigation water requirement for 18 GCMs and ensemble data

	SSP2-4.5								SSP5-8.5							
	U1	U2	M1	M2	M3	L1	L2	L3	U1	U2	M1	M2	M3	L1	L2	L3
ACCESS-CM2	2.30	1.93	2.09	1.47	0.35	0.54	0.67	1.37	2.55	1.82	2.23	2.16	0.72	1.23	2.06	1.79
ACCESS-ESM1-5	1.78	4.02	1.80	1.70	1.30	0.93	4.15	4.00	1.54	2.92	2.77	2.69	2.55	2.02	4.47	4.30
CanESM5	−2.96	−2.54	−3.14	−3.59	−3.23	−3.71	−2.06	−2.13	−2.03	−1.94	−2.16	−2.44	−3.15	−2.85	−0.99	−1.28
CNRM-CM6-1	−0.79	−0.58	−0.88	−1.33	−1.12	−1.41	0.62	−0.47	0.59	0.44	0.28	−0.21	−0.41	−0.55	0.08	0.51
CNRM-ESM2-1	−0.93	−0.70	−2.33	−1.25	−2.41	−3.06	−0.44	−1.57	0.15	0.66	−1.75	−0.15	−1.92	−2.47	−1.00	−0.75
EC-Earth3	−0.27	1.16	1.23	−0.16	0.20	0.21	2.26	1.96	−0.88	1.14	1.52	−0.83	−0.67	−0.64	2.06	1.52
GFDL-ESM4	1.02	0.48	0.14	0.22	−1.26	−1.16	0.36	−0.31	0.43	0.49	−0.25	0.41	−1.56	−2.01	−0.26	−0.47
INM-CM4-8	3.34	2.56	0.54	2.99	2.13	−0.54	1.04	3.38	3.70	2.89	−2.18	2.87	2.18	−1.52	0.56	3.39
INM-CM5-0	1.74	1.87	−0.30	0.90	0.62	−0.29	1.22	2.11	2.46	2.91	−0.49	1.60	0.61	−1.23	0.74	2.03

IPSL-CM6A-LR	−1.73	2.38	−2.66	−1.99	−2.87	−1.03	0.77	0.16	−1.76	3.88	−2.52	−1.92	−2.80	-0.69	0.31	0.60
KACE-1-0-G	1.31	3.93	1.25	0.86	1.71	1.30	3.29	2.41	1.13	3.78	0.71	0.57	0.47	−0.40	3.03	1.34
MIROC-ES2L	0.10	1.01	−0.11	−0.74	−0.13	−0.80	1.06	0.76	−0.93	1.26	1.72	−1.68	1.71	0.69	2.49	2.31
MIROC6	1.02	1.25	−0.05	0.58	−0.35	−1.03	1.26	0.33	1.42	1.95	1.27	1.11	0.91	0.38	2.21	1.86
MPI-ESM1-2-HR	−0.26	−1.64	−1.67	−1.14	−2.71	−2.56	−1.25	−1.48	−0.45	−1.98	−0.96	−1.21	−1.47	−1.62	−0.19	0.04
MPI-ESM1-2-LR	−0.25	−0.78	−0.82	−0.52	−1.08	−1.52	−0.01	−0.19	−2.60	−0.94	−2.87	−2.88	−3.02	−3.39	−0.87	−1.26
MRI-ESM2-0	0.77	0.15	−0.58	−1.15	−0.36	−0.79	0.74	0.71	1.68	1.52	−0.44	−0.49	−0.28	−0.20	1.72	1.23
NorESM2-LM	0.43	0.16	0.04	−0.08	−0.53	−0.97	0.74	0.63	1.17	0.98	0.68	0.94	0.22	0.13	1.50	1.38
UKESM1-0-LL	0.58	2.93	0.63	0.10	2.31	1.18	2.30	2.87	0.74	3.69	0.55	0.34	2.42	0.74	2.84	3.57
Ensemble	**1.33**	**2.38**	**0.15**	**−0.07**	**0.18**	**−0.28**	**1.72**	**1.45**	**1.30**	**3.17**	**0.51**	**0.42**	**0.86**	**0.38**	**2.55**	**2.85**

3.3. Trend in annual required storage

The required storage in agricultural reservoirs refers to the volume that must be secured at a given time, calculated as the difference between the full storage capacity and the actual volume in the reservoir at that time. In this study, it was defined as the annual maximum required storage volume. The analysis revealed that all models except INM-CM4-8 and ACCESS-ESM1-5 exhibited no significant trends (Table 9). However, MME results confirmed increasing trends in six out of eight regions, excluding M1 and L1 (Table 8). Generally, the SSP5-8.5 scenario, which involves higher radiative forcing and greater temperature increases, showed more pronounced increasing trends compared to the SSP2-4.5 scenario (Masson-Delmotte et al. 2021). However, in the U1 and M2 regions, more distinct increasing trends were observed under the SSP2-4.5 scenario.

Table 8. Summary of descriptive statistics and Mann–Kendall trend test for required storage

Region[a]	Mean (mm/yr)			Mann–Kendall trend test[b]							
	Past	Future		SSP2-4.5				SSP5-8.5			
		SSP2-4.5	SSP5-8.5	*Z*	*T*	*P*	*S*	*Z*	*T*	*P*	*S*
U1	1,293.4	1,327.6	1,345.2	2.80	0.21	<0.005	increasing	2.21	0.17	<0.027	increasing
U2	886.3	929.9	967.3	2.11	0.16	<0.034	increasing	2.19	0.17	<0.029	increasing
M1	1,899.7	1,808.7	1,871.8	1.04	0.08	<0.297	no trend	0.95	0.07	<0.341	no trend
M2	1,766.7	1,725.9	1,763.9	2.21	0.17	<0.027	increasing	2.18	0.17	<0.029	increasing
M3	1,319.3	1,376.3	1,440.4	2.95	0.23	<0.003	increasing	3.30	0.25	<0.001	increasing
L1	464.0	390.9	406.6	0.14	0.01	<0.891	no trend	−0.11	−0.01	<0.911	no trend
L2	1,344.0	1,381.2	1,455.2	2.09	0.16	<0.037	increasing	3.11	0.24	<0.002	increasing

L3	496.2	529.0	554.4	2.07	0.16	<0.038	increasing	2.81	0.21	<0.005	increasing

[a]U1 is Gyeonggi-do, U2 is Gangwon-do, M1 is Chungcheongnam-do, M2 is Chungcheongbuk-do, M3 is Gyeongsangbuk-do, L1 is Jeollabuk-do, L2 is Jeollanam-do, and L3 is Gyeongsangnam-do.

[b]*Z* is the normalized test statistic, *T* is Kendall's tau, *P* is the *p*-value of the significance test (two-tailed), and *S* is the direction of tendency (increasing, decreasing, or no trend).

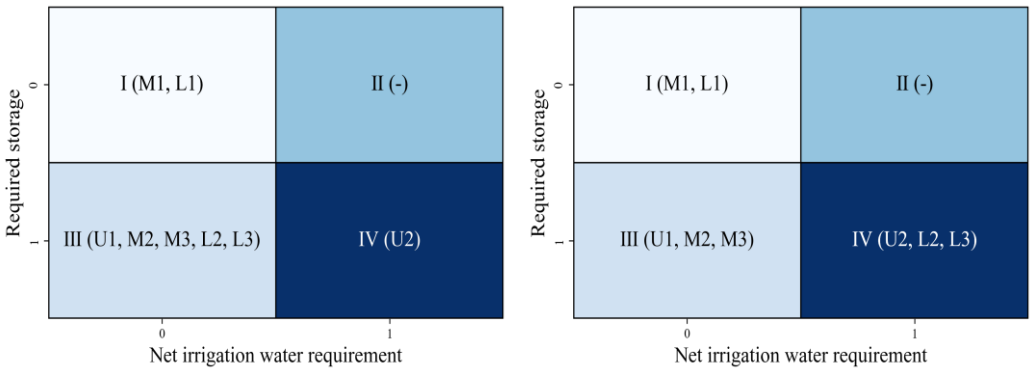
Table 9. Trend analysis of required storage for 18 GCMs and ensemble data

	SSP2-4.5								**SSP5-8.5**							
	U1	**U2**	**M1**	**M2**	**M3**	**L1**	**L2**	**L3**	**U1**	**U2**	**M1**	**M2**	**M3**	**L1**	**L2**	**L3**
ACCESS-CM2	1.14	0.87	1.58	0.55	0.89	−0.84	−0.25	0.01	1.52	−0.08	2.24	1.54	2.36	−0.19	1.62	0.91
ACCESS-ESM1-5	1.36	3.01	0.59	1.67	0.98	−0.14	3.88	2.69	1.08	2.99	2.64	2.84	2.86	1.68	4.01	3.55
CanESM5	−1.49	−1.92	−1.70	−2.07	−0.92	−2.17	−2.17	−1.08	−0.19	−1.49	−0.54	−0.62	−1.38	−1.45	−1.03	−0.18
CNRM-CM6-1	0.03	−0.54	−0.60	−0.72	0.15	−1.38	0.26	−0.40	0.85	0.96	−0.21	0.41	0.44	−0.69	−1.09	0.33
CNRM-ESM2-1	−1.23	−1.13	−1.77	−1.22	−0.99	−2.35	−1.97	−1.23	−0.26	0.52	−2.51	−0.44	−0.15	−2.52	−1.67	−0.98
EC-Earth3	−0.55	−0.16	1.32	−0.40	1.23	−0.92	1.08	0.85	−0.45	0.32	2.02	−0.18	0.65	−1.34	1.91	0.09
GFDL-ESM4	1.20	0.56	−0.04	0.18	−0.12	−1.92	−0.93	−0.84	0.29	−0.23	−0.75	−0.29	−0.79	−1.94	−1.75	−0.99
INM-CM4-8	3.31	3.40	0.95	3.61	3.54	0.06	0.73	3.93	3.59	2.94	−0.79	3.60	3.39	0.91	1.47	4.84
INM-CM5-0	2.21	2.17	0.95	1.98	1.52	0.79	0.59	2.94	2.47	2.75	0.79	2.51	2.51	1.25	0.74	2.80
IPSL-CM6A-LR	−1.35	2.10	−2.98	−2.00	−2.52	−1.46	−0.70	−0.45	−1.24	2.50	−2.18	−1.25	−1.61	−0.95	−0.74	0.34
KACE-1-0-G	0.97	2.32	1.29	0.90	2.25	0.60	2.31	1.60	0.95	2.71	0.97	0.63	0.43	−1.45	1.25	0.45
MIROC-ES2L	0.08	1.66	0.98	−0.58	1.28	0.81	1.03	1.92	0.17	2.55	0.56	−0.59	1.57	1.14	0.65	2.53
MIROC6	0.84	1.47	−0.14	0.59	0.18	−1.11	0.02	0.56	1.54	1.77	1.52	1.81	2.48	0.03	1.92	1.43
MPI-ESM1-2-HR	0.64	−0.30	−1.48	0.13	−1.60	−1.57	−1.46	0.00	−0.22	−1.07	−0.32	−0.66	−0.40	−0.54	−0.30	0.59
MPI-ESM1-2-LR	0.01	−0.32	−0.10	0.01	0.34	−1.09	−0.81	−0.90	−2.06	−0.62	−1.76	−2.14	−1.41	−2.62	−1.62	−1.33
MRI-ESM2-0	−0.38	−0.85	−1.13	−1.35	−0.39	−1.82	0.11	−0.33	0.97	0.53	−0.67	−0.64	0.38	−1.83	1.76	−0.27
NorESM2-LM	0.73	0.48	0.70	0.93	1.20	−0.59	0.22	0.55	1.14	0.82	1.40	1.21	1.65	0.93	1.52	2.23
UKESM1-0-LL	0.66	0.85	0.25	0.33	2.62	0.57	0.27	2.27	−0.15	1.31	−0.25	−0.15	2.52	0.55	1.38	2.81
Ensemble	**2.80**	**2.11**	**1.04**	**2.21**	**2.95**	**0.14**	**2.09**	**2.07**	**2.21**	**2.19**	**0.95**	**2.18**	**3.30**	**−0.11**	**3.11**	**2.81**

3.4. Regional classification of climate change impacts on agricultural reservoirs

The design and management of agricultural reservoirs affected by climate change require region-specific approaches (Moon et al. 2020). In this study, regions were classified on the basis of the statistical significance of trends in net irrigation water requirements and required storage (Fig. 2). Regions showing statistically significant trends were assigned a value of 1, whereas those without significant trends were assigned a value of 0.

Quadrant I includes regions where neither net irrigation water requirements nor required storage exhibited significant trends. In these areas, maintaining the existing agricultural water management system is essential, with a focus on enhancing operational reliability through preventive maintenance and the optimization of aging infrastructure. Quadrant II includes regions where net irrigation water requirements exhibited increasing trends, but required storage did not. These regions are primarily affected by increased evapotranspiration, necessitating a focus on demand-side management. Recommended strategies include adopting precision irrigation technologies and implementing water-saving education programs for farmers. Quadrant III includes regions where required storage exhibited increasing trends, but net irrigation water requirements remained stable. This pattern suggests that intensified precipitation variability significantly impacts storage stability despite stable crop water demand. In response to this supply-side volatility, strategies such as reservoir dredging and expansion, emergency water-supply planning, and the construction of new reservoirs should be considered. Quadrant IV includes regions where both net irrigation water requirements and required storage exhibited increasing trends, necessitating the most comprehensive response. Regions such as U2, L2, and L3 fall into this category under both the SSP2-4.5 and SSP5-8.5 scenarios, with clear upward trends identified in the time series data (Fig. 3). To accommodate future increases in both water demand and supply, integrated water management strategies are essential. These should include reservoir expansion and modernization, the implementation of AI-based monitoring systems, the construction of flood control infrastructure, and the development of efficient water distribution and reuse systems.



(a) SSP2-4.5 scenario (b) SSP5-8.5 scenario

Fig. 2 Confusion matrix of net irrigation water requirement and required storage across regions U1 (Gyeonggi), U2 (Gangwon), M1 (Chungcheongnam), M2 (Chungcheongbuk), M3 (Gyeongsangbuk), L1 (Jeollabuk), L2 (Jeollanam), and L3 (Gyeongsangnam)

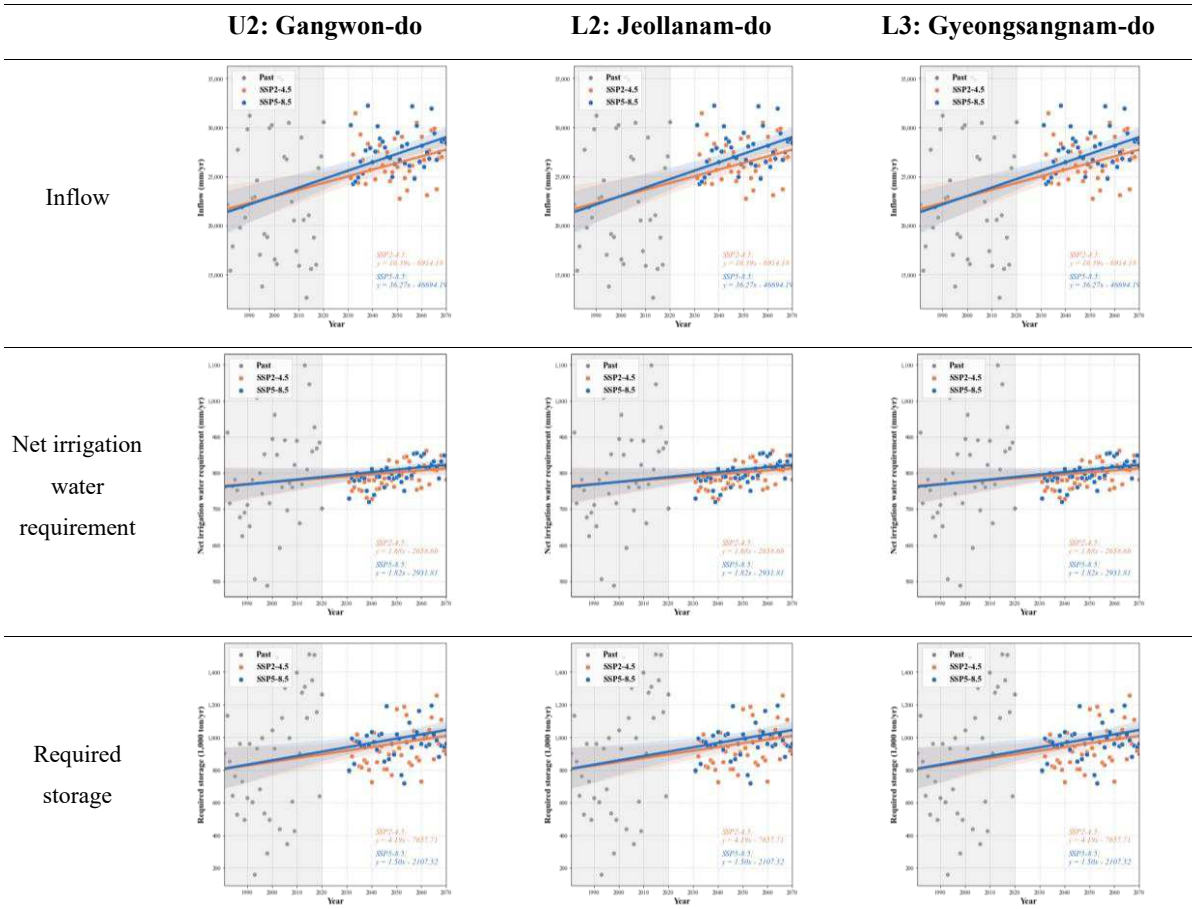


Fig. 3 Time series changes in net irrigation water requirement and required storage in increasing regions under climate change

4. Discussion

In this study, the impact of climate change on the main water balance factors of agricultural reservoirs was examined using SSPs, a set of newly developed climate change scenarios. Trends in inflow, net irrigation water requirement, and required storage were analyzed over the past 40 years (1981–2020) and projected for the next 40 years (2031–2070).

The analysis revealed a statistically significant increase in reservoir inflow across all regions, closely associated with the projected increase in precipitation under future climate-change scenarios (NIMS 2020; Sung et al. 2023). Given that precipitation patterns play a crucial role in water resource management, particularly in the operation of agricultural reservoirs (Lee et al. 2020), these changes have important implications. The observed increase in inflow aligns with projections from existing climate change models (NIMS 2020; Cho J-P et al. 2020; Kim ST et al. 2023; Kim JH et al. 2023). These findings highlight the need for future agricultural water

management policies to adapt to increasing inflow. Expanding reservoir capacity or enhancing operational strategies may be necessary to accommodate rising inflow volumes (Cho Y et al. 2020). Additionally, measures should be implemented to mitigate the heightened risk of flooding associated with more frequent heavy rainfall (Heo et al. 2022).

The net irrigation water requirement showed no significant trends except in the U2 region. Typically, rising temperatures increase evapotranspiration, leading to higher demand. However, in this study, the increase in net irrigation water requirements was found to be minimal, primarily because the simultaneous increase in precipitation enhanced effective rainfall, thereby offsetting the potential rise in irrigation demand. As Yoo et al. (2012) noted, while greater precipitation can reduce demand, seasonal variability and shifts in rainfall intensity remain critical factors that can limit actual effective rainfall availability. These findings indicate that climate change impacts on agricultural water demand must be evaluated through the complex interplay between rising temperatures and shifting seasonal precipitation distributions. Regarding required storage, although no significant trends were observed in individual GCM models, the MME approach provided more robust and statistically significant results by accounting for the inherent uncertainties of individual models (Kundzewicz et al. 2018). The more pronounced increasing trends under the SSP5-8.5 scenario indicate that, as climate change intensifies, the storage requirement is likely to increase, highlighting the direct impact of rising temperatures and changing precipitation on agricultural water demand. However, the more distinct increasing trends under SSP2-4.5 in certain regions (e.g., U1 and M2) indicate that the complex interactions between regional characteristics and climate variability must be considered.

Finally, the results of the regional classification have important implications for future policy. Moon et al. (2020) emphasized that understanding regional characteristics is essential for providing scientific evidence to support local government responses. This classification highlights the importance of developing region-specific response strategies. In regions without significant trends (Quadrant I), the focus should be on enhancing the climate resilience of existing infrastructure through preventive maintenance. In contrast, regions in Quadrant IV require the most comprehensive countermeasures, addressing both water supply stability and flood control infrastructure (Noh et al. 2023).

In summary, agricultural water management in the era of climate change is a multifaceted challenge that demands a comprehensive approach grounded in regional hydrological characteristics. The proposed classification can enhance the effectiveness of adaptation policies by enabling the prioritized allocation of limited resources to

high-risk regions. Future research should build on these regional classifications to develop more targeted response strategies and conduct integrated analyses that incorporate socioeconomic factors and changes in agricultural structures within each region. Additionally, designing adaptive management strategies that address uncertainties in climate change scenarios will remain a critical focus area.

5. Conclusions

As global awareness of climate change increases, the need for reliable adaptation strategies continues to grow. In particular, the production, analysis, and dissemination of accurate future climate projections are becoming increasingly important (Sung et al. 2023). These projections are essential for policymakers and stakeholders to develop and implement effective climate change adaptation strategies. By utilizing this information, countries and regions can better prepare for the anticipated impacts of climate change, address vulnerabilities, and explore potential opportunities (Zhao and Boll 2022).

In this study, the impact of climate change on the core water balance factors of agricultural reservoirs was analyzed, highlighting their complexity and significant regional variability. The findings demonstrate that increased precipitation does not necessarily guarantee enhanced water security, as the interplay between supply and demand varies across regions. To address these challenges, this study proposed a regional classification system that enables policies to be tailored to specific hydrological characteristics and available resources. A long-term, adaptive approach is essential for establishing sustainable agricultural water management systems.

The results of this study provide important foundational data for improving the design and management of agricultural reservoirs in response to climate change. Future research should expand the scope of analysis to include a broader range of reservoirs and further investigate how shifts in seasonal precipitation patterns and the increasing frequency of extreme weather events affect agricultural water demand and required storage capacity. Such continuous evaluation will be critical for enhancing the climate resilience of agricultural infrastructure and ensuring stable food production in a changing environment.

Glossary

Multi-Model Ensemble (MME): A method that combines multiple climate models to reduce uncertainties and improve the reliability of climate projections.

Net Irrigation Water Requirement: The total amount of water required for crops during the growing season, considering evapotranspiration and effective rainfall.

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