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Projected impacts of climate change on global irrigation water withdrawals

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ABSTRACT

Investigating processes causing water resource depletion risks is key to understanding past, present, and future excessive irrigation water withdrawal. Quantitative spatiotemporal analysis of the factors driving excessive irrigation water withdrawal is currently inadequate. Although multiple drivers typically contribute to this risk, we studied, for the first time, whether and how Actual Irrigation Water Withdrawals (AIWW) could affect global future water resources projection. Here, we used AIWW datasets from five CMIP6 climate models based on two Shared Socioeconomic Scenarios (SSP370 and 585) and a global hydrological model (H08) to compare the historical (1981–2014) with the future periods: 2041–2070 and 2071–2100. Results show that the temporal AIWW average variations have shown a statistically significant increase during 1981–2014 ($p<0.05$ and $R^2 = 0.98$) ranging from 101.82 to 136.24 mm yr^{-1} (mean = 120.5 mm yr^{-1}). Under SSP370 and SSP585, the global spatial AIWW average during 2041–2070 and 2071–2100 are 142.55 and 145.55, and 144.91 and 149.74 mm yr^{-1}, respectively. Under SSP370 and SSP585, the average AIWW changes for 2041–2070 and 2071–2100 are projected to be 96.71, 97.55, 103.52, and 106.98 %, respectively. Under SSP370 and 585, the average global AIWW anomaly changes for 2041–2070 and 2071–2100 are also projected to be −96.86, −106.29, −97.72, and −111.48 %, respectively. Higher AIWW increases are mainly concentrated in India, South China, parts of the United States, parts of Europe, and parts of South African and Latin American countries. Substantiated with population increase, and higher food demand, an increased AIWW will further aggravate globally. Thus, exploring future AIWW changes is a key step forward that requires greater attention in irrigation research interventions helpful to inform societies to reduce future risks of water resource depletion. Adaptation policies targeting the future use of water for irrigation are crucial to lessen water resource depletion risk, suggesting the need for large-scale policy interventions.

1. Introduction

Water is an essential natural resource for consumptive and non-consumptive uses that require sufficient quantity and quality at the right place and time (Foley et al., 2011; Zhang et al., 2022). Societies demand water to achieve better living standards (Foley et al., 2011). As a result, humans have boosted water infrastructures to maximize their benefits. For example, in the Anthropocene, the world's food production is dependent on water for irrigation. Thus, irrigation consumes more water than any other human activity amounting to 1277 km^3y^{-1} (Siebert et al., 2010). Studies show that irrigation accounts for 70 % of global water withdrawals and 90 % of consumptive water use globally

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(FAO, 2015, 2017; Siebert et al., 2010; Zhou et al., 2020). It also contributes nearly 40 % of crop production and covers 16 % of agricultural land globally (Leng and Tang, 2014; Zhang et al., 2022). The global agricultural land area equipped for irrigation has increased from 111 million ha in 1950–306 million ha in 2005 because of the rapid growth in worldwide population and Gross Domestic Product (GDP) (Siebert et al., 2015). These indicate that there has been a tremendous increase in irrigation water used in the twentieth century. As the water for irrigation purposes is also drawn from groundwater resources, groundwater is subjected to excessive withdrawals and overexploitation globally.

Excessive water resource extraction for irrigation is the main cause of ground and surface water depletion that might lead to hydrological droughts. With continued water demand for irrigation, there is an increase in unsustainable use of water resources which societies rely on. Actual Irrigation Water Withdrawal (AIWW), aimed for irrigation purposes, is the volume of water extracted from rivers, lakes, and aquifers (Frenken and Gillet, 2012), which is currently drawing greater attention in the global water use system suggesting the need for in-depth study. As the proportion of irrigation areas continues to expand and water extractions for irrigation increases, understanding if and how AIWW responds to environmental change has become more pressing. Moreover, the AIWW has been an important part of a water use system in the global environment but understanding its current and future spatiotemporal patterns is lacking across many regions. Notably, this is more pronounced in countries purely dependent on agriculture. Recognizing the issue and studying the extent of the AIWW processes is vital for the societies suggesting the need for detailed investigation.

Research on the future projections of worldwide irrigation water withdrawal in the context of climate change has advanced significantly, with recent studies employing sophisticated climate models and scenarios to predict water needs under varying conditions (Eekhout et al., 2024; Javansalehi and Shourian, 2024; Tian et al., 2023). These studies incorporate factors such as changing precipitation patterns, temperature increases, and shifts in crop types and growing seasons to estimate future water demands. Unlike earlier research, which often relied on static models or limited geographic scopes, this study used high-resolution data and ensemble simulations to provide more accurate and global projections. These advancements offer several distinguishing features and provide a clearer understanding of the spatial and temporal variability in water needs. This comprehensive approach enhances the ability to develop targeted strategies for sustainable water management and adaptation to climate change impacts.

While irrigation contributes to achieving food security it is compromising the sustainability of the water resources. Yet future water withdrawal for irrigation is expected but how much and how isn't adequately known globally at spatial and temporal scales. Assessing the impact of AIWW requires an accurate estimation of water effectively withdrawn for irrigation purposes. Thus, an accurate understanding of the irrigation system is required to capture the volume of water withdrawn for irrigation effectively. Thus, emphasizing novel research areas that bring scientists and policymakers together to focus on future AIWW research works is crucial. As the AIWW is directly linked to human interventions, this study also shows how the expansion of global irrigation areas is aggravated by anthropogenic effects. This study is therefore undertaken to investigate the following pressing research questions. 1) when and how is AIWW changing spatiotemporally? and 2) what are the key AIWW global impacts on water resources and its underlying causes and interactions in the worldwide context? The changes in the impacts of AIWW over the historical period (1981–2014) and the future (2041–2070 and 2071–2100) were investigated across many regions globally.

2. Materials and methods

2.1. Global climate models, scenarios, datasets, and study periods

This study is undertaken on global terrestrial lands aimed at capturing global trends in AIWW projections. To study the spatiotemporal impact of AIWW during the 21st century, multi-model climate forcing data were used from Global Climate Models (GCMs) of the ISIMIP (The Inter-Sectoral Impact Model Intercomparison Project; https://www.isimip.org/) (Warszawski et al., 2014). These models are among the different global climate models participating in the CMIP6 (Coupled Model Intercomparison Project Phase 6; https://www.wcrp-climate.org/wgcm-cmip/wgcm-cmip6 (Eyring et al., 2016; O'Neill et al., 2016). These 5 GCMs; GFDL-ESM4 (Dunne et al., 2020), IPSL-CM6A-LR (Boucher et al., 2020), MPI-ESM1–2-HR (Giorgetta et al., 2013), MRI-ESM2 (Yukimoto et al., 2019), and UKESM1–0-Ll (Sellar et al., 2019) were used in this study (Table 1) and were applied in previous studies to assess the spatiotemporal impact of AIWW in the global context during the 21st century (Eyring et al., 2016; O'Neill et al., 2016). These datasets are bias-corrected and are available at 0.5-degree resolution downloaded from the ISIMIP3b ensemble member. These ensemble models aim to assess the impacts of climate change across a range of sectors, such as water, agriculture, health, and biodiversity, using a consistent framework. This provides consistent and comparable assessments of climate change impacts across a wide range of sectors using standardized climate forcing data and simulation protocol. Thus, an ensemble mean of the five models was used for analysis.

The Shared Socioeconomic Pathways (SSPs) of water (Graham et al., 2018) selected for this study are SSP370 and SSP585 (Kriegler et al., 2014; Riahi et al., 2017). The SSP375 and SSP585 represent upper levels of the climate scenarios with radiative forcing of 7 W/m^2 and 8.5 W/m^2 by the year 2100, respectively (O'Neill et al., 2016). These scenarios are selected to represent the current and future assumptions of an increase in population thereby food consumption via irrigation where irrigation water utilizes groundwater sources (Graham et al., 2018; He et al., 2021; O'Neill et al., 2016; Taylor et al., 2012). The study period has two parts, historical simulations (1981–2014) and future projections (2041–2100). Data was analyzed in historical (base period = 1981–2014 i.e., 35 years) and future (projected) during the mid-21st century (2041–2070) and late 21st century (2071–2100).

2.2. The H08 global hydrological model

H08 is a grid-cell based global hydrological model applied to quantify the sources of water used by humans (Hanasaki et al., 2018). H08 spatially covers the whole globe at a resolution of $0.5^\circ \times 0.5^\circ$ to assess the

Table 1
List of GCMs (Global Climate Models) used in this study.

GCMs	Institute	Simulation round	Data type	Sector	References
GFDL-ESM4	Geophysical Fluid Dynamics Laboratory (GFDL)	ISIMIP3b	Output	Global water	(Dunne et al., 2020)
PSL-CM6A-LR	Institute Pierre-Simon Laplace (IPSL)	ISIMIP3b	Output	Global water	(Boucher et al., 2020)
MPI-ESM1–2-HR	Max Planck Institute Earth System Model	ISIMIP3b	Output	Global water	(Giorgetta et al., 2013)
MRI-ESM2	Meteorological Research Institute (MRI)	ISIMIP3b	Output	Global water	(Yukimoto et al., 2019)
UKESM1–0-LL	Met Office Hadley Centre	ISIMIP3b	Output	Global water	(Sellar et al., 2019)

geographical heterogeneity of hydrology and water use. It is one of the global hydrology models that is used as an impact model to simulate the ISIMIP3b protocol global water sector outputs. By tuning H08 hydrological parameters based on the study of Yoshida et al. (2022), the GCM models were trained to produce global water component outputs for the ISIMIP3b protocols. As a result, the AIWW simulated outputs of the H08 hydrological model forced by the five climate models are used in this study as provided by Hanasaki et al. (2018) and Yoshida et al. (2022).

The H08 global hydrological model simulates future global actual irrigation withdrawal based on several key assumptions. It balances water supply from surface and groundwater sources with agricultural demand, considering crop-specific irrigation requirements and using the Penman-Monteith equation for evapotranspiration. The model projects future irrigation needs based on land use change scenarios and climate change impacts, integrating data from global climate models (GCMs). It also accounts for the potential depletion of groundwater in regions where surface water is insufficient. These assumptions, supported by various studies, allow the H08 model to provide detailed assessments of irrigation demands under changing environmental conditions (Hanasaki et al., 2008).

In the H08 global hydrological model, water requirements for crops are estimated based on crop-specific factors such as potential evapotranspiration (PET) and crop coefficients (Kc). The model calculates crop water requirements (CWR) by combining these factors and also considers soil moisture availability to determine actual irrigation needs. Major crops like wheat, maize, rice, and soybeans are included, and use crop-specific parameters like crop growth stages, rooting depth, and phenology to simulate the water requirements for each crop with the model differentiating between irrigated and rain-fed agriculture. The H08 model also accounts for double cropping cycles by simulating each crop cycle separately and adjusting water demand according to seasonality. These features make the model effective for simulating actual irrigation withdrawal under different scenarios.

As the AIWW is the volume of water extracted from water sources such as rivers, lakes, or groundwater for irrigation purposes, the irrigation efficiency and the total water withdrawn are the key parameters in the estimation of the AIWW. The irrigation water requirement is a key parameter to estimate the irrigation water withdrawal, which is highly influenced by the irrigated area and crop types. In the H08 model, the estimation of irrigation water withdrawal involves the total areas of irrigated land, crop water requirements, and the efficiency of the irrigation system in delivering water to the crops (Siebert et al., 2010, 2015). Thus, the H08 model considers irrigation water withdrawal used to irrigate crops in the irrigated area of each grid cell (Hanasaki et al., 2018; Yoshida et al., 2022). To meet the growing demands for food, land use activities are likely to in the future (Hurtt et al., 2020). As projected land use and hence irrigation area for the future was used as input for the H08 hydrological model, it has played its main role in the simulation of the AIWW (https://www.isimip.org/impactmodels/details/52/).

2.3. Temporal analysis

2.3.1. Mann-Kendall analysis across timescales

In this study, time series analysis for the historical and future periods was undertaken to understand the trends. Thus, the well-known Mann-Kendall analysis technique for such trends analyzes the timeseries AIWW datasets. The Mann-Kendall analysis is a statistical test to evaluate trends by assessing whether the AIWW data values are increasing or decreasing over a specific period. It is also helpful to examine whether the trend in either direction is statistically significant or not in the timeseries. Thus, in the Mann-Kendall test, the nonparametric method is applied for trend analysis (Salehi et al., 2019).

2.3.2. Uncertainty Analysis of the timeseries datasets

Future climate projections and analysis are subject to different sources of uncertainties. An ensemble-based experiment was applied to minimize these possible uncertainties, and the AIWW ensemble was calculated from the mean of the five GCMs used in this study (see Table 1). Considering the minimum value of the AIWW across the five GCMs as lower and maximum value as the upper bound of the uncertainty range, the uncertainty in the GCM projections was drawn for the period between 1981 and 2100 for each SSP scenario (SSPs 370 and 585). The mean of the five models was used to show the average trends of the future AIWW useful to detect possible uncertainty ranges of the GCMs.

2.4. Spatial analysis for long-term percentage and anomaly changes

In this study, the percentage change is estimated by subtracting the historical spatial data from future spatial datasets, dividing the difference by historical spatial data, and multiplying the result by 100. This is essential to see whether the AIWW is increasing or decreasing over time. On the other hand, the anomalies were estimated as the difference between the long-term average value of each AIWW point/pixel as it deviates from individual pixel values (Eq 2). In other words, anomalies are the differences between the amount of AIWW used in a particular year and the long-term average amount of AIWW throughout the study years.

To calculate the average anomaly of AIWW across the time steps for each grid (pixel):

$$Anomaly_{i,j,t} = AIWW_{i,j,t} - \overline{X}_{i,j} \tag{1}$$

where$Anomaly_{i,j,t}$ is the anomaly at grid point (i, j) and time t. $AIWW_{i,j,t}$ is the AIWW at grid point (i, j) and time t. $\overline{X}_{i,j}$ is the long-term mean of AIWW at grid point (i, j).

To calculate the long-term mean of the AIWW at each grid point (i, j), i.e., $\overline{X}_{i,j}$ the following formula is used:

$$\overline{X}_{i,j} = \frac{1}{n}\sum\nolimits_{t=1}^{n} AIWW_{i,j,t} \tag{2}$$

where n is the total number of time steps.

Finally, the average AIWW anomaly across the time steps for each grid (pixel) can be calculated as

$$AvgAnomaly_{i,j} = \frac{1}{n}\sum\nolimits_{t=1}^{n} Anomaly_{i,j,t} \tag{3}$$

where is the *AvgAnomaly* is the average anomaly of AIWW.

The anomaly percentage changes were estimated in a similar approach used to estimate the percentage of AIWW changes. Anomalies were used to track changes in AIWW over time globally as they show disparities from the long-term mean of AIWW. The AIWW is mainly limited in the northern hemisphere countries including parts of Canada and large parts of Russia as they are primarily non-irrigation areas. The AIWW in the dryland areas of North African countries, northern Australia, and northern Brazil of the southern hemisphere also were similarly limited.

3. Results

3.1. Spatial and temporal variations of historical AIWW (1981–2014)

Understanding historical AIWW is crucial for estimating future water withdrawals for irrigation. Fig. 1(a) reveals the spatial average variations of the AIWW from 1981 to 2014. The spatial average for the AIWW is 120.5 mm yr^{-1} during the 35 years of the historical period (1981–2014). Higher AIWW is mainly concentrated in India, East China, parts of the United States, parts of Europe, and parts of South African and Latin American countries. In these regions, the AIWW is estimated to be greater than 100 mm yr^{-1} (Fig. 1). However, due to fewer irrigation practices, the AIWW is mainly lower in the northern hemisphere countries including Canada and Russia. North African countries,

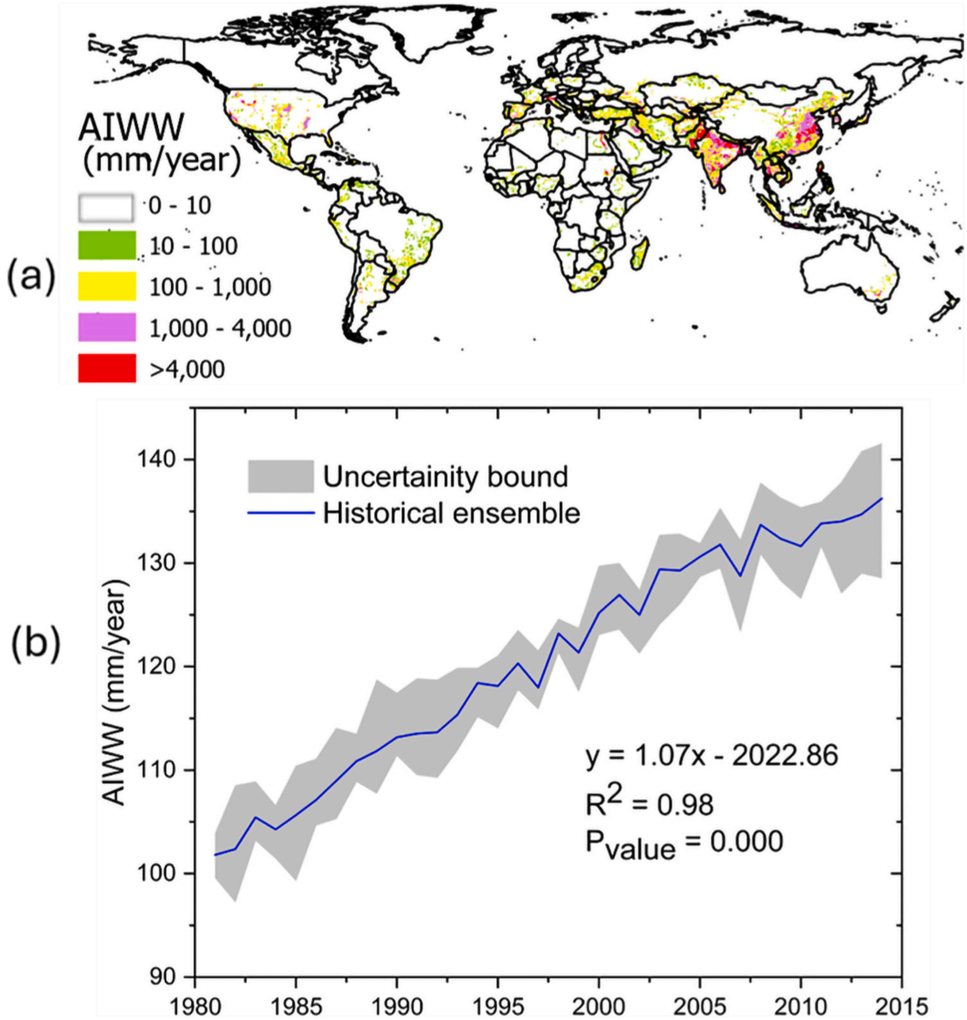

Fig. 1. Spatial (a) and temporal (b) variations of historical AIWW (1981–2014). The gray-filled range in (b) corresponds to the uncertainty bound using the minimum (lower bound) and maximum (upper bound) of the GCMs. The x-axis represents time in years. The mean is calculated using the AIWW values from the H08 model driven by the forcing of the GCMs given in Table 1.

northern Australia, and northern Brazil experience lower AIWWs amounting to less than 0.1 mm yr^{-1}.

Fig. 1(b) indicates the temporal variations of AIWW during the historical period from 1981 to 2014. As revealed in Fig. 1(b), the temporal AIWW trend has shown a statistically significant increasing trend ($P < 0.05$) from 1981 to 2014. Thus, the global annual average AIWW has increased significantly from 101.82 in 1981–136.24 mm yr^{-1} in 2014 globally.

3.2. Spatial and temporal variations of future AIWW

3.2.1. Spatial variations of future AIWW (2041–2100)

Understanding future AIWW is necessary for better irrigation planning in an increasing population and climate change context. Fig. 2 presents the spatial average of AIWW variations in the future during 2041–2100 split into 30-year periods (2041–2070 and 2071–2100) for both SSP370 and 585. The spatial average AIWW values under SSP370 during 2041–2070 and 2071–2100 are projected to be 142.55 and 144.91 mm yr^{-1}, respectively. Similarly, under SSP585 the spatial average AIWW values are projected to be 145.55 and 149.74 mm yr^{-1} during 2041–2070 and 2071–2100, respectively. Higher AIWW is mainly concentrated in India, South China, parts of the United States, parts of Europe, and parts of South African and South American countries. In these regions, the AIWW is estimated to be greater than 100 mm yr^{-1} (Fig. 2). However, the AIWW is mainly less in the northern hemisphere countries including Canada and Russia, North African countries, northern Australia, and northern Brazil. These regions experience lower AIWWs amounting to less than 0.1 mm yr^{-1}.

3.2.2. Temporal variations of future AIWW

Fig. 3 presents the temporal variation of AIWW during the period 2041–2070 and 2071–2100 for both SSP370 and 585. The temporal AIWW trend has shown that there is an increasing trend during each 30-year future period for both SSPs. All these trends are statistically significant ($P = 0.05$) increasing across the timescales. There is a higher R^2 (0.73) for SSP585 during 2041–2070, while the R^2 values of the remaining SSPs are relatively smaller suggesting data were not significantly explained by the model and as a result, its effect is lower. Globally for the SSP370 and SSP585 the temporal average AIWW have increased from 141.44 and 143.03 in 2041–142.81 and 148.2 mm yr^{-1} in 2070, respectively. Similarly, the temporal AIWW increased globally from 144.65 and 148.46 in 2071–147.37 and 151.73 mm yr^{-1} in 2100 for the SSP 370 and 585, respectively.

The AIWW timeseries and their uncertainty bound along the GCMs ensemble are presented in Fig. 3. These suggest that the projected timeseries of AIWW for SSP370 and 585 scenarios during the period 1981–2100 showed increasing AIWW conditions globally with uncertainties varying across the time scales and SSPs.

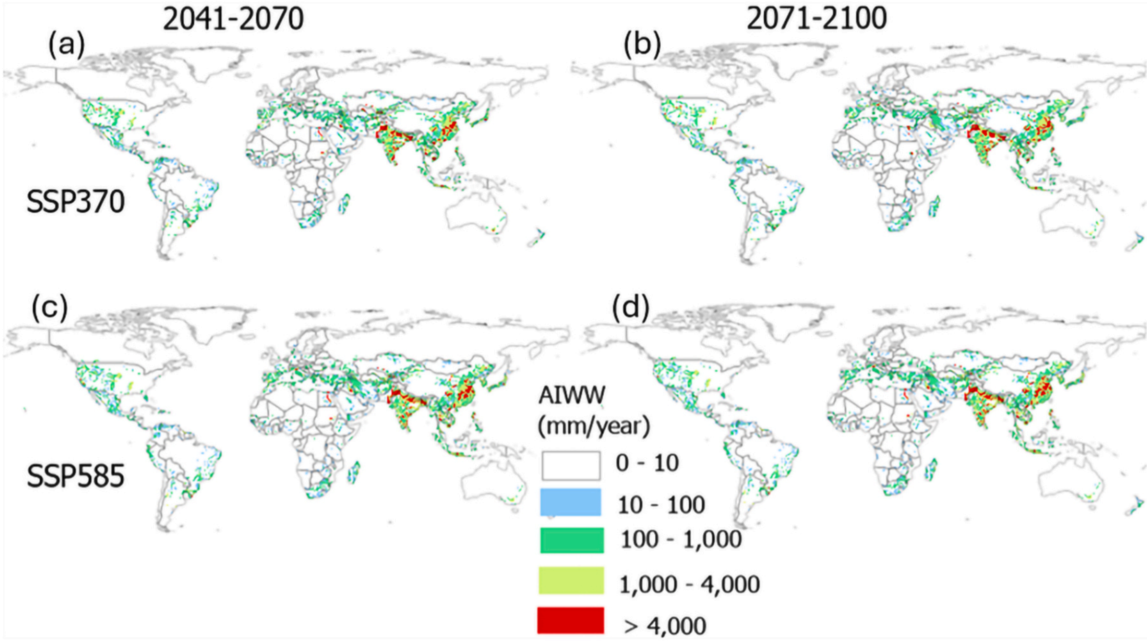

Fig. 2. Future average AIWW spatial variations for the period from 2041 to 2100 for both SSP370 and 585. (a), Average AIWW (mm/year) during 2041–2070 for SSP370, (b) average AIWW (mm/year) during 2071–2100 for SSP 370, (c), average AIWW (mm/year) during 2041–2070 for SSP585, and (d) average AIWW (mm/year) during 2071–2100 for SSP 585.

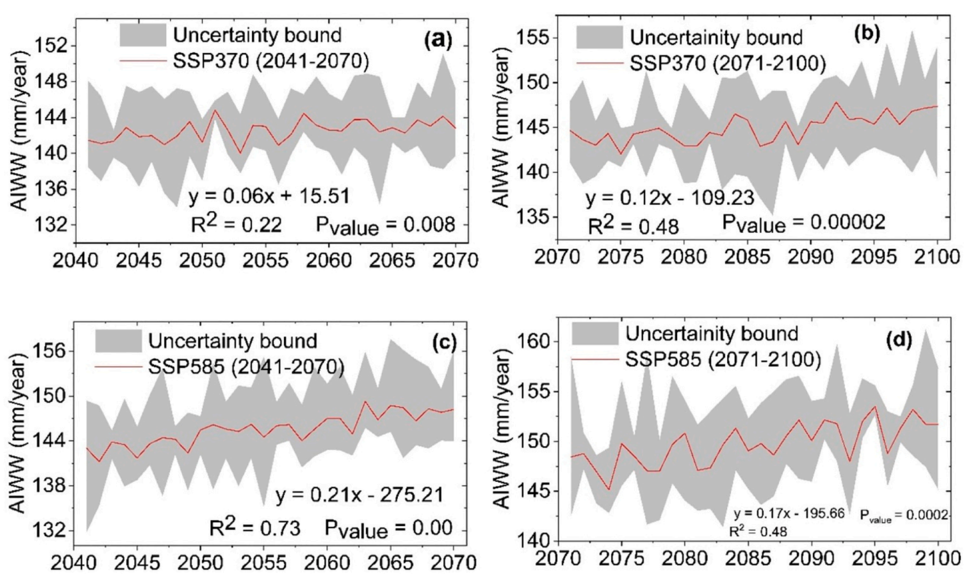

Fig. 3. Future temporal AIWW variations for 2041–2100 for both SSP370 and 585. (a), AIWW (mm/year) during 2041–2070 for SSP370, (b) AIWW (mm/year) during 2071–2100 for SSP 370, (c), AIWW (mm/year) during 2041–2070 for SSP585, and (d) AIWW (mm/year) during 2071–2100 for SSP 585. The gray-filled range corresponds to the uncertainty bound using the minimum (lower bound) and maximum (upper bound) values from the H08 model driven by the forcing of GCMs. The x-axis represents time in years. The ensemble mean was calculated using the AIWW values of the GCMs given in Table 1.

3.3. Projected spatial changes in future AIWW

The spatial changes in AIWW under SSP370 for the periods of 2041–2070 and 2071–2100 are projected to be 96.71 and 103.52 % higher than the historical period, respectively (Fig. 4). Similarly, under SSP 585, the average AIWW changes are projected to increase by 97.55 and 106.98 % in 2041–2070 and 2071–2100, respectively. In large areas of India, South China, the United States, Europe, South Africa, and Madagascar, the spatial annual average AIWW ranges from 0 % to 50 %. Higher AIWW spatial changes are mainly concentrated in parts of India, South China, the United States, Europe, South Africa, and Latin American countries. In these regions, the AIWW change has shown greater than 100 % (Fig. 4). However, the AIWW has shown negative changes mainly in the northern hemisphere and partly in the southern hemisphere. Large parts of Europe such as Spain, parts of the United States, and Japan experience negative AIWW changes suggesting the AIWW is likely to decrease in the future period of 2041–2100 for both scenarios. These changes are mainly derived from the land surface hydrology, river routing, reservoir operation, crop growth, environmental flow, and water abstraction in simulating the H08 (Hanasaki et al., 2018). The hydrological parameters and water use are due to increased population and subsequently possible increase in irrigated agriculture

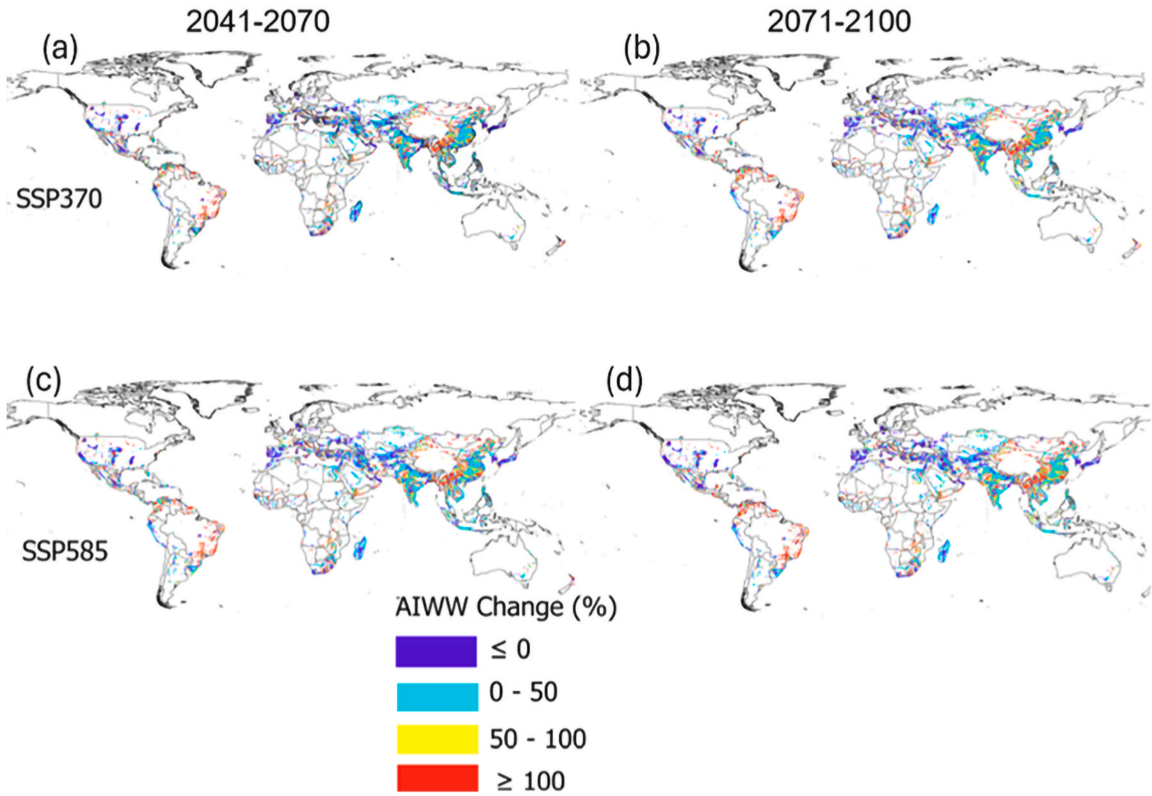

Fig. 4. Projected future AIWW spatial changes for the period 2041–2100 compared with that during 1981–2014 for both SSP370 and SSP585. (a), AIWW change (%) during 2041–2070 for SSP370, (b) AIWW change (%) during 2071–2100 for SSP 370, (c), AIWW change (%) during 2041–2070 for SSP585, and (d) AIWW change (%) during 2071–2100 for SSP 585.

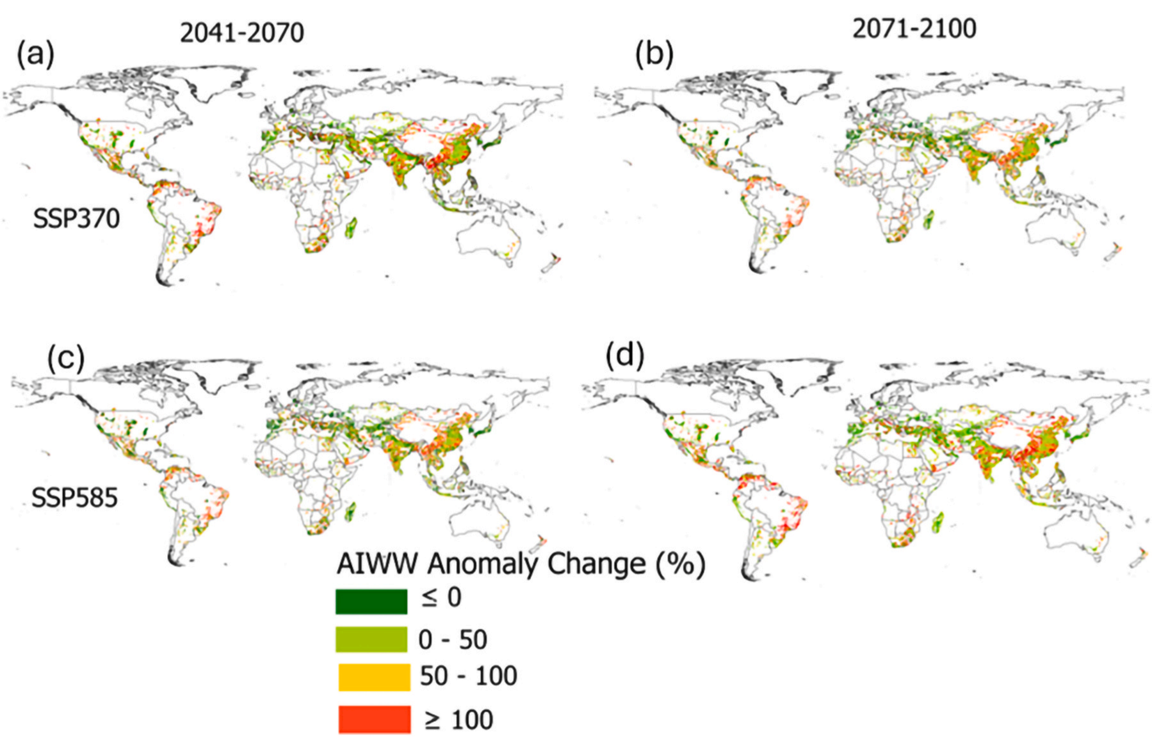

Fig. 5. Projected AIWW Anomaly changes for the period 2041–2100 compared with that during 1981–2014 for both SSP370 and SSP585. (a), AIWW Anomaly change (%) during 2041–2070 for SSP370, (b) AIWW Anomaly change (%) during 2071–2100 for SSP 370, (c), AIWW Anomaly change (%) during 2041–2070 for SSP585, and (d) AIWW Anomaly change (%) during 2071–2100 for SSP 585.

for crop production (Hurtt et al., 2020). Therefore, this increase in AIWW is mainly driven due to increased future irrigation areas and its intensification.

3.4. Projected AIWW Anomaly change

Irrigation anomalies are used to identify areas that are at risk of water shortages or water surpluses in the future. The spatial average SSP370 AIWW anomaly changes for 2041–2070 and 2071–2100 were estimated to be −96.86 and −97.72 % globally, respectively (Fig. 5). For the SSP585, the spatial AIWW anomaly changes were estimated at −106.29 and −111.48 % globally, respectively. Higher AIWW anomaly changes are mainly concentrated in south Brazil, Colombia, parts of south China, and parts of the southern United States. Lower spatial anomaly changes have been shown in parts of Europe, parts of South Africa, Madagascar, Malaysia, Indonesia, and Japan. In these regions, the AIWW has shown negative changes (Fig. 5) suggesting that AIWW will likely decrease.

4. Discussion

4.1. Global impacts of irrigation water withdrawal on groundwater resources

Irrigation has expanded and intensified rapidly over the 20th century with the increased exploitation of groundwater resources especially accelerated after the 1950 (Rodell et al., 2009; Scanlon et al., 2012; Wada et al., 2010). Groundwater is a key water source for irrigation in regions where frequent water stress and large aquifer systems exist (Wada et al., 2010). It is also the main source of AIWW globally, especially in the developed world for irrigation purposes. A study by Jasechko et al. (2024) explained that groundwater levels from 170,000 wells and 1693 aquifers reveal the global extent of groundwater decline. Döll et al. (2014) also explained that the rate of global groundwater depletion doubled during 1960–2000. Groundwater was also depleted significantly at a rate of 20.4 km^3 $year^{-1}$ in China during 1965–2016 (Huang et al., 2023).

Groundwater depletes when natural groundwater recharge is surpassed by groundwater abstraction. These lead to overexploitation of groundwater substantiated by both increased population and climate change impacts. Guermazi et al. (2018) indicated that anthropogenic pressures have a higher influence on groundwater resources. This indicates that anthropogenic activities and climate change even bring much higher impacts on irrigation water withdrawals from groundwater sources. These collectively suggest that the increase in water withdrawals accelerates the decline in groundwater levels worldwide. Thus, access to groundwater withdrawal for irrigation should be more efficiently managed to prevent the depletion of the aquifer (Guermazi et al., 2018).

These increasing trends of groundwater depletion are a result of the expansion of irrigation, which accounts for 70 % of global groundwater withdrawals (Jasechko et al., 2024). Conversely, there has been a worldwide increase in the AIWW due to the expansion of irrigated agriculture. Scanlon et al. (2012) indicated that 60 % of irrigation relies on groundwater in the United States suggesting aquifer overexploitation can significantly impact crop production. As a result, the groundwater in the United States has been severely depleted, with 40 % of at least 85, 000 wells hitting all-time lows in the last 10 years (The New York Times, 2023). These indicate that groundwater depletion is severely affecting several states, such as Utah, California, and Texas, where climate change is further amplifying the threat to these states' drinking water and food supply (The New York Times, 2023).

4.2. Climate change impacts on irrigation water withdrawals

Results demonstrate that AIWW is likely to increase during the 21st century in all the SSP scenarios considered in this study. This study is consistent with the many studies worldwide. Warziniack et al. (2022) indicated that total consumptive water use will increase by as much as 235 % under the worst-case scenario. These suggest that climate change impacts on agriculture is an overwhelming factor as compared to socioeconomic changes. Obembe et al. (2023) also further indicated that irrigation water withdrawals are expected to increase in the 21st century. Similarly, according to Wada et al. (2013), GCM ensemble projections generally show an increasing trend in future irrigation water withdrawal especially under the highest greenhouse gas emission scenario. These suggest that the increase in irrigation water withdrawal varies substantially on the levels of global warming and associated precipitation changes.

In addition, The GCM forcing and global hydrological models' simulation may lead to uncertainties. This study used an ensemble to reduce possible uncertainties due to the model's reliability in representing water withdrawals under existing climate conditions. According to Wada et al. (2013), uncertainties arising from global climate models (GCMs) are large and likely to show a substantial increase starting from the midcentury. Soares et al. (2022) suggested uncertainties can be minimized through greater awareness of sources of uncertainty and greater efforts to develop more sophisticated assessment tools. According to Puy et al. (2022), the computation of irrigation water withdrawal estimates currently ignores uncertainties leading to miscalculating the volumes of water withdrawn for irrigation that jeopardizes sustainable water management.

By the end of the century, irrigated lands in most of the developed countries will likely decrease. According to McDonald and Girvetz (2013), the irrigation system in the US is challenged by increased irrigation area and irrigation rates due to climate change. According to Elliott et al. (2014) the northern/eastern United States, parts of South America, much of Europe, and Southeast Asia are likely to show an increase in irrigation. This is consistent with our results which AIWW change will likely show an increase in most of these areas. Conversely, the irrigation water consumption in the newly emerging and developing countries will increase in irrigation rate and its area coverage. Freshwater limitations in some irrigated regions such as the western United States, China, and West, South, and Central Asia could necessitate the reversion from irrigated lands to rainfed agriculture by the end of the century (Elliott et al., 2014) which agrees with our results on the AIWW anomaly changes.

4.3. Future driving causes of irrigation water withdrawal

Over the past 100 years global water demand has increased by 600 % (Boretti and Rosa, 2019). In the 20th century water use has grown twice the rate of population increase (FAO, 2015, 2017). Boretti and Rosa (2019) explained that nearly 6 billion people will suffer from water scarcity due to increasing water demand, and reduction of water resources by 2050 driven by dramatic population and economic growth.

In the last 30 years, global food production has grown by more than 100 % (FAO, 2017) and this is mainly due to an increased use of irrigation water from groundwater sources. Most of this population growth is expected in developing countries in Africa and Asia. FAO has estimated that about 60 % additional food will be required to fulfill the food requirements of a growing global population by 2050 (FAO, 2015, 2017) and might double this by the end of the 21st century. Irrigated food production will increase by more than 50 % by 2050 (FAO, 2015, 2017), suggesting that irrigation practices are likely to improve thereby yields increase. This increment will demand more arable land and intensification of irrigated agriculture for increased production. Thus, as the population increases there is a possibility of increasing demand for improved living standards. This will likely worsen the water withdrawals from the groundwater sources. These are likely to aggravate due to emerging economies from the developing countries substantiated by increased population growth concurrently with an increase in food production and improved living standards.

Finally, the limitations of the study are worth mentioning. The use of global hydrological models calibrated with discharge data from large catchments to estimate irrigation water withdrawal introduces key limitations. These include a mismatch in scale, as global models may not capture the fine-scale variability and specific conditions of smaller irrigation areas. Parameters generalized for large catchments may not accurately represent the localized processes and soil characteristics of smaller catchments. Moreover, coarse spatial resolution in global models can overlook critical details of small-scale irrigation practices, leading to inaccuracies. These factors contribute to uncertainties in estimating water withdrawals for irrigation purposes.

5. Conclusion

Investigating excessive water withdrawal risks due to increased irrigation water is essential in human-dominated environments globally. Here, using Shared Socioeconomic scenarios, the historical, present, and future irrigation water withdrawals have been quantified using spatial and temporal analysis. For this, the long-term AIWW was subjected to analysis for the impacts of climate change on global AIWW, and as a result, the following findings are obtained from this study.

1. The AIWW spatial average is increased by 120.5 mm yr^{-1} significantly ($p<0.05$) with $R^2 = 0.98$ during the 1981–2014 historical period. Thus, the AIWW temporal average has increased significantly from 101.82 in 1981 to 136.24 mm yr^{-1} in 2014 globally with uncertainties varying across the time scales and SSPs.
2. The AIWW spatial average under SSP370 scenarios during 2041–2070 and 2071–2100 are 142.55 and 149.74 mm yr^{-1}, respectively. Similarly, the AIWW spatial average under SSP585 is 145.55 and 149.74 mm yr^{-1} during 2041–2070 and 2071–2100, respectively.
3. Globally for the SSP370 and SSP585 the average temporal AIWW has significantly increased from 141.44 and 143.03 in 2041 to 142.81 and 148.2 mm yr^{-1} in 2070, respectively. Similarly, the global temporal AIWW significantly increased on average from 144.65 and 148.46 in 2071–147.37 and 151.73 mm yr^{-1} in 2100 for the SSP 370 and 585, respectively with uncertainties varying across the time scales and SSPs.
4. The spatial average AIWW changes under SSP370 during 2041–2070 and 2071–2100 were estimated to be 96.71 and 103.52 % globally, respectively. For the SSP 585, the global spatial average AIWW changes were also 97.55 and 106.98 %, respectively.
5. The spatial average AIWW anomaly changes under SSP370 for 2041–2070 and 2071–2100 were estimated to be −96.86 and −97.72 % globally, respectively. Under SSP585, the spatial average AIWW changes were estimated at −106.29 and −111.48 % globally, respectively.
6. Higher AIWW are mainly concentrated in India, South China, parts of the United States, parts of Europe, and parts of South African and Latin American countries. With a future increase in population, food demand, and improved living standards, higher AIWW pressures from rapidly developing countries are inevitable.

Exploring future AIWW changes is a key step forward that requires greater attention in future irrigation and water security research for intervention. Thus, identifying the processes underlying higher AIWW-causing mechanisms that could inform societies to reduce groundwater risks is important. Adaptation policies targeting the future use of water for irrigation are crucial to lessen groundwater depletion risk, suggesting the need for large-scale policy interventions.

CRediT authorship contribution statement

Binod Baniya: Writing – review & editing. **Li He:** Writing – review & editing, Project administration, Funding acquisition. **Yongdong Wang:** Writing – review & editing. **Solomon Hailu Gebrechorkos:** Writing – review & editing, Visualization, Validation, Data curation. **Qiuhong Tang:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Gebremedhin Gebremeskel Haile:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Kidane Welde Reda:** Writing – review & editing, Validation, Methodology.

Declaration of Competing Interest

The authors declare that there are no competing interests.

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Data Availability

The data used is described in the paper

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