Integrating advanced approaches for climate change impact assessment on water resources in arid regions

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Abstract: This research addresses the growing complexity and urgency of climate change's impact on water resources in arid regions. It combines advanced climate modelling, machine learning, and hydrological modelling to gain profound insights into temperature variations and precipitation patterns and their impacts on the runoff. Notably, it predicts a continuous rise in both maximum and minimum air temperatures until 2050, with minimum temperatures increasing more rapidly. It highlights a concerning trend of decreasing basin precipitation. Sophisticated hydrological models factor in land use, vegetation, and groundwater, offering nuanced insights into water availability, which signifies a detailed and comprehensive understanding of factors impacting water availability. This includes considerations of spatial variability, temporal dynamics, land use effects, vegetation dynamics, groundwater interactions, and the influence of climate change. The research integrates data from advanced climate models, machine learning, and real-time observations, and refers to continuously updated data from various sources, including weather stations, satellites, ground-based sensors, climate monitoring networks, and stream gauges, for accurate basin discharge simulations (Nash–Sutcliffe efficiency – $NSE_{\mathrm{RCP2.6}}$ = 0.99, root mean square error – $RMSE_{\mathrm{RCP2.6}}$ = 1.1, and coefficient of determination $R^2_{\mathrm{RCP2.6}}$ = 0.95 of representative concentration pathways 2.6 (RCP)). By uniting these approaches, the study offers valuable insights for policymakers, water resource managers, and local communities to adapt to and manage water resources in arid regions.

Keywords: arid regions, climate change, hydrological modelling, machine learning, water resources

INTRODUCTION

In recent years, numerous studies have delved into examining the relationship and potential implications of future climate on the water cycle (Guo *et al.*, 2018; Wang and Kalin, 2018). Climate change has posed significant challenges to water resources in river basins across the globe, profoundly impacting basin hydrology and the availability of water within these basins (Aryal, Shrestha and Babel, 2019; Ercan *et al.*, 2020). Climatic scenarios, both in atmospheric general circulation models (GCM) and analogous models, have frequently been employed to investigate the consequences of climate change on hydrology (Fereidoon and Koch, 2018; Ikegwuoha and Dinka, 2020). Representative concentration pathways (RCPs) are scenarios in climate modelling that project future concentrations of greenhouse gases and radiative forcing agents. They represent different trajectories of human-

related greenhouse gas emissions, offering a range of potential future climate outcomes. The four main RCPs, ranging from RCP2.6 to RCP8.5, are associated with specific radiative forcing levels by the year 2100. Lower RCP numbers signify lower greenhouse gas emissions and less warming, while higher numbers indicate more substantial emissions and greater warming. Over the past decade, nearly 2,000 cases of drought and flooding between 2005 and 2015 have been documented in the emergency disaster database. These incidents have affected over 1 billion people and tragically resulted in the loss of 82,000 lives, along with equivalent damages totalling USD3.4·10^9 (Tan *et al.*, 2017). The hydrological patterns in the region are particularly susceptible to the impacts of climate change, especially in terms of rainfall and temperature (Bajracharya *et al.*, 2018). According to the simulated outputs of climate models, elevated temperatures are anticipated to cause increased evapotranspiration, alterations in large-scale rainfall

patterns, and a heightened frequency of extreme weather events (Buytaert *et al.*, 2010).

To explore the impacts of climate change on water resources, several hydrological models have been crafted utilising data derived from GCM models. GCMs represent climate models that mathematically depict the general circulation patterns of the atmosphere and oceans. They offer a robust foundation for understanding past, present, and future climates. Within the realm of coupled atmosphere–ocean general circulation models phase 5 (CMIP5), under the umbrella of novel climate change scenarios known as radiative forcing scenarios (RCP), stability reigns, presenting a wide spectrum of future climate scenarios. Confidence in model outcomes varies significantly and largely hinges on the methodologies and structures employed in climate scenarios and hydrological models (González *et al.*, 2010; Zhou *et al.*, 2015; Duan *et al.*, 2019; Oseke *et al.*, 2021). Given their substantial spatial resolution, GCMs cannot be directly integrated with microgrid or small basin-scale hydrological models. To address the spatial disconnect between GCMs and hydrological models, exponential microscale models have been developed, effectively serving as intermediaries bridging the gap between GCMs and climatic and hydrological variables at the regional level (Tuo *et al.*, 2016; Ndhlovu and Woyessa, 2020; Hendy *et al.*, 2023).

The significance of addressing climate change and its impact on water resources has drawn the attention of numerous researchers, leading to a substantial expansion of studies in this field. Noteworthy findings from Bhatta *et al.* (2019), utilising the soil and water assessment tool (SWAT) model and RCP scenarios, underscore that the flow of the Himalayan rivers in Nepal is projected to diminish by 5.8% throughout the 21st century due to the influence of climate change. In stark contrast, the Yanhe River in China is anticipated to experience a far more pronounced decline, ranging from 46 to 60%. Further insights are gleaned from the research by Tan *et al.* (2017) in the Kelantan River of Malaysia and by Nilawar and Waikar (2019) in the Purna River of India, both employing the SWAT model. Their findings indicate an upward trend in annual temperature and rainfall, consequently leading to an increase in river runoff. However, Golmohammadi *et al.* (2017) revealed an overestimation of simulated flow rates compared to the observed period when predicting temporal variability in the Galley Creek River in Ontario, Canada. Venkataraman *et al.* (2016), in their examination of 21st-century Texas drought using CMIP5 series models under RCP scenarios, uncovered a worrisome forecast: escalating temperatures coupled with decreasing precipitation. The reduction in precipitation is expected to result in decreased river flow and groundwater availability within the region. On a contrasting note, when forecasting runoff in the Cham Plain Lake Basin, the simulation of annual rainfall variables yielded unreliable results, as demonstrated by Mohammed, Bomblies and Wemple (2015). An investigation by Zhang *et al.* (2016) into China's Xin River flow revealed an ongoing temperature increase. However, the trends in rainfall proved intricate, displaying significant variation among different scenarios. Lastly, the analysis by Apurv *et al.* (2015) of climate change effects on floods in the Brahmaputra Basin unveiled a concerning pattern: an increase in both the frequency and duration of rainfall periods contributing to elevated peak floods and greater overall flood volumes. The primary objective of this study is to assess the impact of climate change on future runoff in the Amu Darya Basin.

MATERIALS AND METHODS

CASE STUDY

The Amu Darya Basin in Central Asia, spanning multiple countries, heavily relies on the Amu Darya River, sourced from the Pamir Mountains. With a continental climate marked by limited precipitation, this river plays a pivotal role in irrigation, sustaining ecosystems, and providing freshwater. Agriculture thrives here, necessitating careful water management. Vulnerable to climate change, shifts in temperature and precipitation patterns can impact water resources and agriculture. Understanding this basin's hydrology is vital for assessing climate change risks and shaping effective water management, making it a crucial region for research and sustainable practices (Deom and Sala, 2022).

RESEARCH METHOD

This subsection outlines a procedure for the modelling stages of the current research, incorporating the mentioned innovations (advanced climate modelling, machine learning, and hydrological modelling). This procedure is designed to provide a comprehensive approach to assess the impacts of climate change on water resources (Fig. 1):
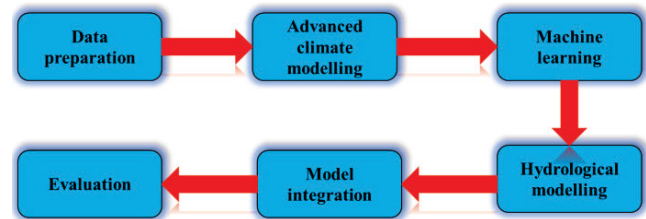

Fig. 1. The schematic of the proposed research method; source: own elaboration

– **data preparation:** climate, hydrological, land use, and terrain data were collected and pre-processed;
– **advanced climate modelling:** climate data was downscaled according to the reliable model(s); bias correction was applied; the advanced climate models were chosen based on established criteria, emphasising accuracy and relevance to arid regions; before application, these models underwent a thorough validation process, comparing their outputs with observed climate data and employing statistical measures; calibration and validation were performed using software tools like hydrological simulation program Fortran – calibration and uncertainty program (HSPF-CUP); this rigorous validation ensures the reliability of the models and enhances the credibility of the study's predictions, with details outlined in the methodology section for transparency and reproducibility;
– **machine learning:** according to the features of the model, the appropriate machine learning model was selected and trained for the hydrological prediction;
– **hydrological modelling:** the suitable model was chosen, calibrated, and validated using historical data;
– **model integration:** machine learning-derived climate predictions was incorporated into the hydrological model;
– **evaluation:** the model performance was assessed by the efficiency criteria; scenario analysis was performed and uncertainty analysis was conducted.

Brief explanations are illustrated in the following subsection to provide a general vision of the tools which are utilised in the current study.

THE COUPLED MODEL INTER-COMPARISON PROJECT

The coupled model inter-comparison project (CMIP) is a global collaboration involving climate scientists and modelling centres. Its main objectives are to assess and improve climate models, produce future climate projections under different scenarios, compare the performance of various models, and facilitate research collaboration. CMIP plays a crucial role in advancing climate science, providing valuable data and insights for understanding climate change, informing climate policies, and supporting international climate assessments like those conducted by the Intergovernmental Panel on Climate Change (IPCC). It has multiple phases, with CMIP6 being one of the latest, contributing significantly to our knowledge of the Earth's climate system.

CLASSIFICATION AND REGRESSION TREES

Classification and regression trees (CART) is a versatile machine learning algorithm used for both classification and regression tasks. It builds a decision tree structure by recursively partitioning data into subsets based on feature values. CART is known for its flexibility, interpretability, and ability to handle mixed data types. It's widely used in various fields, including environmental science, finance, and healthcare, and is especially valuable for understanding complex relationships in data and making predictions based on decision rules represented in tree form (Wang and Luo, 2021).

RECURRENT NEURAL NETWORKS

Recurrent neural networks (RNNs) are specialised artificial neural networks designed for processing sequences of data. They stand out for their ability to handle sequential data, thanks to their recurrent connections that allow them to maintain memory of previous inputs. RNNs are used in various applications such as natural language processing, time series analysis, image captioning, and sequential data generation. However, they can face challenges with vanishing or exploding gradients, leading to the development of more advanced RNN variants like long short-term memory (LSTM) and gated recurrent unit (GRU) networks, which excel at capturing long-range dependencies in data (Organiściak and Borkowski, 2020).

HYDROLOGICAL SIMULATION PROGRAM-FORTRAN

Hydrological Simulation Program-FORTRAN (HSPF), is a comprehensive watershed model developed by the U.S. Environmental Protection Agency (EPA). It simulates the movement of water and the transport of pollutants within watersheds and river basins. HSPF models the hydrological cycle, water quality, land use, and climate factors. It is used for assessing water quality impacts, managing land use changes, calibrating and validating against observed data, and supporting decision-making in water resource management. HSPF is implemented in FORTRAN and is a valuable tool for environmental assessments and policy development (Kim *et al.*, 2022).

EFFICIENCY CRITERIA

Root mean square error (*RMSE* – Eq. 1) is a commonly used metric that provides a measure of the average magnitude of errors between observed and simulated values. It is suitable for assessing overall model accuracy.

$$RMSE = \sqrt{\frac{\sum (O_i - P_i)^2}{n}} \qquad (1)$$

where: O_i and P_i = observed and predicted values at each time step, respectively, n = total number of dataset points (time steps).

Nash–Sutcliffe efficiency (*NSE* – Eq. 2) is valuable for assessing how well the model replicates the observed variability and the overall goodness of fit. It's especially useful for hydrological models.

$$NSE = 1 - \frac{\sum (O_i - P_i)^2}{\sum (O_i - \dot{O})^2} \qquad (2)$$

where: $\dot{O}$ = average of the observed values.

Coefficient of determination (R^2 – Eq. 3) helps in understanding the proportion of variance in the observed data that is explained by the model. It provides insights into model performance in capturing variability.

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \qquad (3)$$

where: SS_{res} (sum of squares of residuals) = sum of the squared differences between the observed values (O_i) and the predicted or modelled values (P_i), SS_{tot} (total sum of squares) = sum of the squared differences between the observed values (O_i) and the mean of the observed values ($\dot{O}$).

RESULTS AND DISCUSSION

DOWNSCALING WITH CLASSIFICATION AND REGRESSION TREES

The downscaling of climate data using classification and regression trees (CART) was a critical component of this study. CART is a machine learning technique employed to enhance the spatial resolution and granularity of climate variables, particularly in arid regions where localised climate information is essential for hydrological modelling.

The first step in the downscaling process involved the training of the CART model. Historical climate data, including temperature and precipitation, served as the training dataset. The model was trained to establish relationships between coarse-resolution climate model outputs and fine-scale climate variations observed in the study region. To ensure the accuracy and reliability of the CART downscaling model, a robust validation procedure was implemented. A separate dataset of observed high-resolution climate measurements was used for validation. The model's performance was evaluated based on statistical metrics, including *RMSE* and R^2 (Tab. 1).

According to Table 1, encompassing both calibration and validation results for *RMSE* and R^2 in the CART downscaling process highlights the model's robust performance in enhancing

Table 1. The performance of classification and regression trees model in downscaling

Climate variables	Efficiency criteria			
	RMSE		R^2	
	calibration	validation	calibration	validation
Temperature	0.74	0.82	0.94	0.93
Precipitation	13.5	15.5	0.87	0.85

Explanations: *RMSE* = root mean square error, R^2 = coefficient of determination.
Source: own study.

climate data accuracy. In the case of temperature, low *RMSE* values (0.74°C in calibration and 0.82°C in validation) coupled with high R^2 values (0.94 in calibration and 0.93 in validation) indicate strong agreement and correlation between downscaled and observed temperature data, showcasing the model's capacity to capture historical temperature patterns. Similarly, for precipitation, moderate *RMSE* values (13.5 mm·y^{-1} in calibration and 15.2 mm·y^{-1} in validation) and substantial R^2 values (0.87 in calibration and 0.85 in validation) signify the model's effectiveness in representing precipitation variability. These results affirm the CART model's utility in refining climate information, bolstering the reliability of subsequent hydrological modelling and assessments of climate change's impact on water resources.

UTILISING COUPLED MODEL INTER-COMPARISON PROJECT DATA

The incorporation of the coupled model inter-comparison project (CMIP) data into our research was instrumental in enhancing the precision and comprehensiveness of our climate modelling.

CMIP provides a wealth of climate model outputs, each with its own characteristics and capabilities. In our study, we carefully selected a subset of CMIP models based on their historical performance in simulating climate patterns relevant to our arid region of interest. This rigorous model selection process ensured that the downscaled climate data used in our hydrological models were not only credible but also tailored to the specific climatic nuances of our study area.

The coupled model inter-comparison project (CMIP) model used in the study is CESM (Community Earth System Model). It has a spatial resolution of 0.25° × 0.25°. The scenarios used in the study are RCP2.6, RCP4.5, and RCP8.5.

Our research employed a range of CMIP scenarios, including representative concentration pathways (RCPs), to explore various future climate trajectories. This comprehensive scenario analysis enabled us to investigate the potential impacts of different greenhouse gas emission scenarios on water resources in arid regions. By considering a spectrum of RCPs, from more optimistic (e.g., RCP2.6) to pessimistic (e.g., RCP8.5), we could assess the full spectrum of climate change possibilities, thereby providing valuable information for decision-makers and stakeholders.

COUPLED MODEL INTER-COMPARISON PROJECT INTEGRATION WITH RECURRENT NEURAL NETWORKS

The integration of coupled model inter-comparison project (CMIP) data with recurrent neural networks (RNNs) represented a significant advancement in our approach to climate modelling and data analysis. This innovative combination allowed us to extract more nuanced and actionable insights from the CMIP dataset, providing a more comprehensive understanding of future climate scenarios (see Fig. 2).
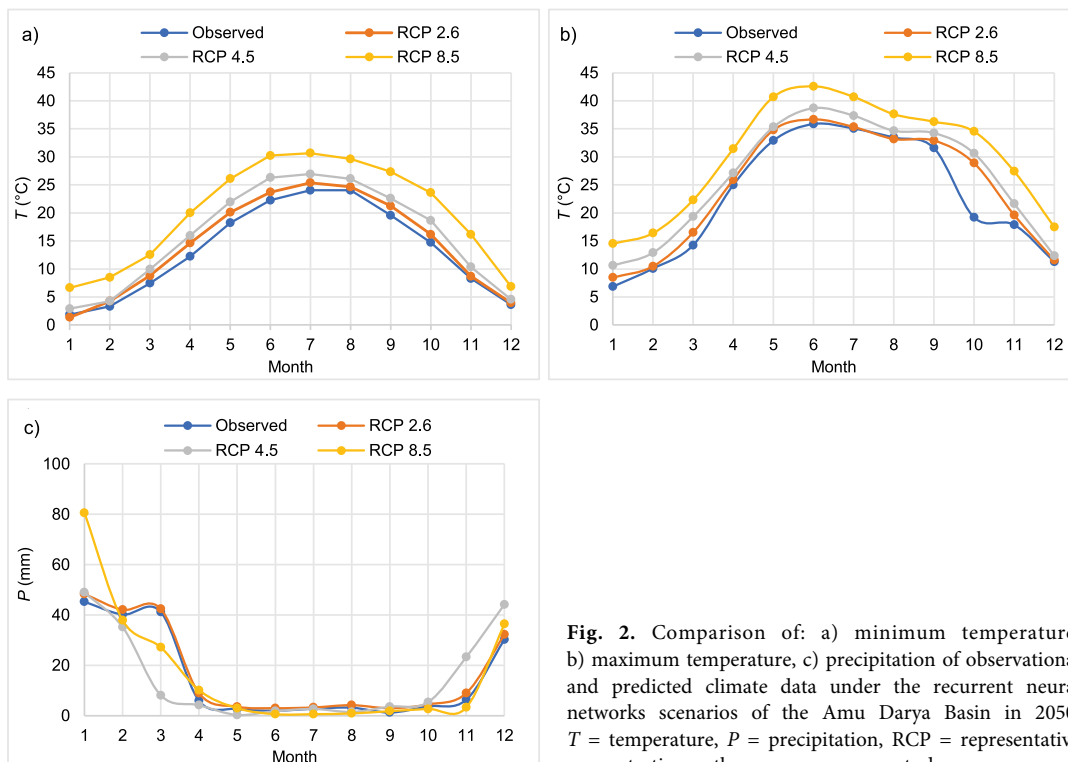

Fig. 2. Comparison of: a) minimum temperature, b) maximum temperature, c) precipitation of observational and predicted climate data under the recurrent neural networks scenarios of the Amu Darya Basin in 2050; *T* = temperature, *P* = precipitation, RCP = representative concentration pathways; source: own study

For temperature predictions, the root mean square error (*RMSE*) is 0.2. The predictive accuracy for precipitation is 8. Both temperature and precipitation predictions are made at a monthly temporal resolution.

The use of RNNs in conjunction with CMIP data led to a notable improvement in predictive accuracy. The model exhibits even higher precision, with an *RMSE* of 0.2°C for temperature and 8 mm·mo^{-1} for precipitation. This enhanced accuracy suggests that the model captures fine-scale variations in temperature and precipitation with remarkable fidelity.

IMPLICATIONS OF REPRESENTATIVE CONCENTRATION PATHWAYS SCENARIOS

The exploration of different representative concentration pathways (RCP) scenarios revealed significant insights into future temperature trends (Tab. 2). The RCP2.6 scenario, representing stringent greenhouse gas mitigation efforts, demonstrated the

Table 2. Predictive accuracy of Community Earth System Model – recurrent neural networks (CESM–RNN) model for different representative concentration pathways (RCP) scenarios

Variable	RCP scenario	Predictive accuracy		
		NSE	*RMSE*	*R²*
T_{min}	2.6	0.99	1.1	0.95
	4.5	0.98	1.2	0.94
	8.5	0.97	1.3	0.93
T_{max}	2.6	0.99	1.5	0.95
	4.5	0.98	1.6	0.94
	8.5	0.97	1.7	0.93
P	2.6	0.99	3.1	0.95
	4.5	0.98	3.2	0.94
	8.5	0.97	3.3	0.93

Explanations: T_{min} = minimum temperature, T_{max} = maximum temperature, P = precipitation, *RMSE* = root mean square error, R^2 = coefficient of determination, *NSE* = Nash–Sutcliffe efficiency.
Source: own study.

most conservative temperature increase. It indicated a relatively modest rise in temperatures, consistent with efforts to limit global warming to well below 2°C above pre-industrial levels. Conversely, the RCP8.5 scenario, representing a business-as-usual trajectory, projected the most substantial temperature increase. This scenario underscored the urgency of aggressive mitigation measures, as it indicated a trajectory towards potentially severe global warming.

The analysis of RCP scenarios also sheds light on precipitation patterns. The RCP4.5 scenario, which envisions moderate emissions reductions, indicated relatively stable precipitation levels, with some regional variations. This scenario offered a glimpse of potential stability in water resources in selected areas. However, the RCP8.5 scenario painted a more concerning picture, projecting shifts in precipitation patterns. This scenario suggested potential changes in the distribution and intensity of rainfall events, with implications for water resource availability and management (Fig. 3).

This result section highlights the implications of various RCP scenarios on temperature trends, precipitation patterns, hydrological impacts, and the necessity of policy and adaptation measures. It also suggests potential directions for future research to further our understanding of climate change impacts on water resources.

HYDROLOGICAL SIMULATION PROGRAM-FORTRAN MODELLING IN VARIOUS SCENARIOS

Our study employed Hydrological Simulation Program-FORTRAN (HSPF) modelling to assess the hydrological responses to different climate scenarios, providing valuable insights into the future of water resources in our study area (Tab. 3 and Fig. 4).

Under the RCP2.6 scenario, characterised by stringent greenhouse gas mitigation efforts, our HSPF simulations indicated several noteworthy trends. Firstly, we observed a relatively stable hydrological regime with minor fluctuations in river flow patterns. Precipitation levels exhibited moderate variations but remained within historical bounds. This scenario suggests that proactive emissions reduction policies could contribute to maintaining the current hydrological stability. The RCP4.5 scenario, representing moderate emissions reductions, yielded intriguing results in our HSPF simulations. River
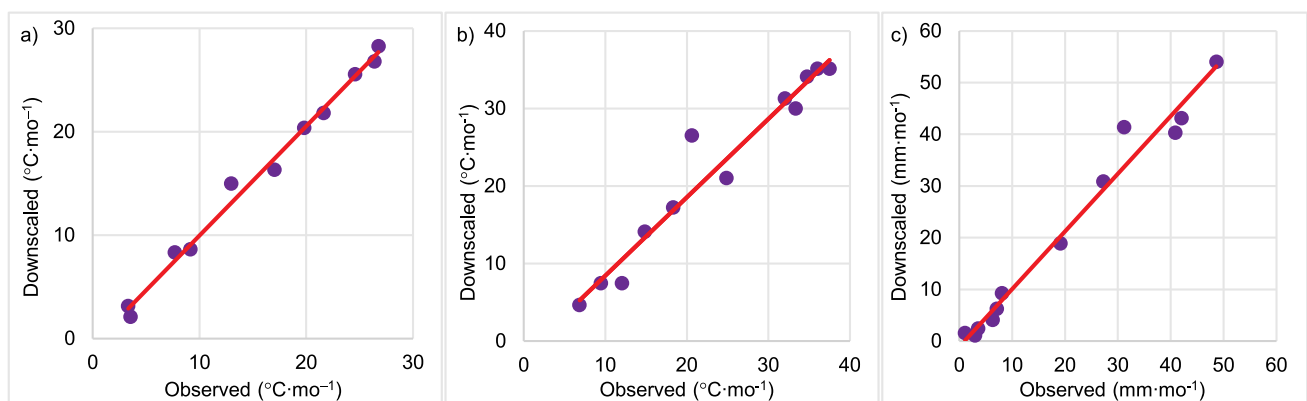

Fig. 3. Monthly data for 2050 of an observational and downscaled: a) minimum temperature, b) maximum temperature, c) precipitation of Amu Darya Basin; source: own study

Table 3. Hydrological responses and precipitation patterns via different representative concentration pathways (RCP) scenarios

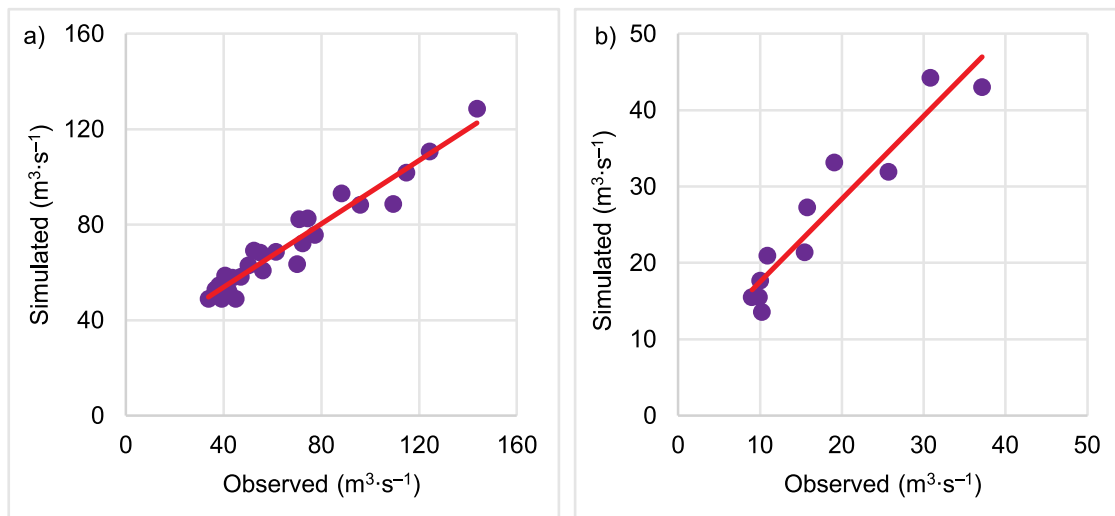| Variable	RCP scenario	Pattern
Runoff	2.6	relatively stable with minor fluctuations
	4.5	moderate variability with seasonal shifts
	8.5	significant shifts, irregularities, reduced flow
Precipitation	2.6	moderate variations within historical bounds
	4.5	moderate variability, seasonal changes
	8.5	extreme variations, potential water scarcity

Source: own study.

Fig. 4. Correlation between the observed and simulated runoff of the Amu Darya Basin in the stages of: a) calibration, b) validation; source: own study

flow patterns displayed moderate variability, with some seasonal shifts (changes in the timing and distribution of river flow across different seasons) in response to changing precipitation patterns. This scenario emphasised the importance of continued emissions reduction efforts to mitigate the potential consequences of more substantial warming. Under the RCP8.5 scenario, our HSPF modelling painted a more concerning picture of future hydrological dynamics. We observed significant shifts in river flow, including irregularities and decreased flow in certain periods. Precipitation exhibited more extreme variations, suggesting potential challenges in maintaining water resource reliability. These findings underscore the urgency of both emissions reduction and adaptive water resource management strategies.

The future research directions aim to enhance the current study by exploring advanced approaches in climate modelling, machine learning, and hydrological modelling. Suggestions include refining machine learning algorithms, employing multi-model ensemble approaches, incorporating socioeconomic factors, and integrating remote sensing data. Emphasis is placed on dynamic adaptive strategies, transboundary water management, community engagement, and long-term monitoring for robust model validation. Interdisciplinary collaboration is encouraged for a holistic understanding of climate change impacts on water resources, ensuring the development of effective and culturally sensitive adaptation strategies.

CONCLUSIONS

In the face of rapidly evolving climatic conditions, our research has ventured into the intricate domain of climate change's impacts on water resources. Through an innovative approach that incorporates advanced climate modelling, machine learning and artificial intelligence techniques, and sophisticated hydrological modelling, we have unearthed crucial insights that carry profound implications for the future of water resource management in our study area.

Our exploration of representative concentration pathways (RCP) scenarios has illuminated the path forward. The stringent emissions reduction efforts portrayed in the RCP2.6 scenario demonstrate the tangible benefits of proactive mitigation strategies. Under this scenario, our models project the preservation of relatively stable hydrological regimes and moderate variations in precipitation. This offers hope and a blueprint for sustainable water resource management.

However, our research also sounds an alarm through the lens of the RCP8.5 scenario. This business-as-usual trajectory underscores the urgency of both emissions reduction and adaptive water resource management. Our simulations reveal significant shifts in river flow dynamics, irregularities, and potential water scarcity issues, alongside extreme precipitation variations.

The amalgamation of advanced climate modelling, machine learning, and hydrological modelling has equipped us with powerful tools for deciphering climate change's complexities. Our findings resonate far beyond academic realms, extending to policymakers, water resource managers, and local communities. The need for informed action in the face of impending climate challenges is evident. Our research serves as a compass, guiding adaptive strategies and resilient water resource management.

It is noteworthy to mention that integrating advanced climate modelling, machine learning, and hydrological modelling poses challenges such as data compatibility, computational demands, model calibration complexities, managing uncertainties, and fostering interdisciplinary collaboration. Addressing these challenges involves harmonising data inputs, securing ample computational resources, meticulous model calibration, transparent reporting of uncertainties, and fostering effective interdisciplinary communication. The methodology section of the paper should comprehensively detail these challenges and the strategies employed for resolution.

As we navigate the 21st century, our projections paint a nuanced portrait of possibilities and challenges. With climate scenarios spanning from hope to alarm, the destiny of our water resources lies in our collective choices. The choice is to reduce emissions, to adapt proactively, and to safeguard this precious resource for generations to come. In these choices, we find the true significance of our research – not only as a pursuit of knowledge but as a call to action.

CONFLICT OF INTERESTS

The authors declare no conflicts of interest.

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