1. Introduction

Sustaining an optimal reservoir operation under various uncertainties is challenging in changing climate scenarios for hydropower production. The increasing population, urbanization, and industrialization raise the demand for the energy consumption of fossil fuels, water, material, and available natural resources, which further poses the issue of energy security and a clean environment (Madsener and Sunik 2011; Saraswat and Digalwar 2021). The large energy requirement in India is fulfilled by nonrenewable sources, which are fast depleting (Sharma et al. 2021). Hydropower is a vital source of renewable energy, which provides over 72% of all renewable energy globally (Gernaat et al. 2020). However, only about 17% of the hydropower potential of 150,000 MW has been tapped in India (Kumar et al. 2010). For India, hydropower and small hydropower are the second-highest contributors toward renewable energy consumption, which is close to 12% of the total capacity (Sharma et al. 2013). The impacts of climate change on hydropower production affect energy generation in the near term and by the end of the twenty-first century (Lehner et al. 2005; Liu et al. 2016; Turner et al. 2017; Ali et al. 2018). Thus, tremendous opportunities in hydropower generation and its future expansion exist, which help us meet the soaring energy demands. However, hydropower production is directly related to the water availability in reservoirs that depends on streamflow, characterized by the processes’ uncertainties resulting in streamflow (Lehner et al. 2005). The uncertainty associated with precipitation, temperature, and wind pattern of a region affects the streamflow uncertainty (Redmond and Koch 1991; Shook et al. 2015). Biemans et al. (2009) have analyzed the effects of precipitation uncertainty on discharge calculations for 294 river basins worldwide and shown that average precipitation uncertainty (approximately 30%) can lead to higher uncertainty in discharge (approximately 90%). Quantification of uncertainties associated with future streamflow projection is a critical challenge for climate change impact studies (Xu and Singh 2004) as it necessitates obtaining the range of possible future variations in streamflow projections (Hingray 2019).

Characterizing and quantifying uncertainty projection of streamflow and hydropower potential considering the climate change projections is important to plan for adaptation and mitigation (Deser et al. 2012b). It is essential to quantify and discuss the role of different uncertainties and their propagation to future hydrological projections as it is a fundamental characteristic of prediction (Finger et al. 2012). The estimated variables’ uncertainty sources are forcing uncertainty, model uncertainty, and internal climate variability (Hawkins and Sutton 2011; Deser et al. 2012b; Topál et al. 2020). The relative importance of different uncertainty sources varies depending on the type of variable, temporal, and spatial scales, and specifically its nature (Hawkins and Sutton 2011; Deser et al. 2012b; Gao et al. 2020). For example, model uncertainty reflects our lack of knowledge or inability to encapsulate the
existing knowledge within the climate models, and it is considered as potentially reducible as models improve (Deser et al. 2012b). The multimodel ensemble members (MMEs) are generally used to estimate the model uncertainty (Singh and AchutaRao 2020), whereas internal climate variability (ICV), refers to natural variability that arises from processes in the coupled land, biosphere, ocean, atmosphere, and cryosphere system in the absence of external forcing (Deser et al. 2020; Hyun et al. 2020), considered as irreducible (Madden 1976; Hawkins and Sutton 2009; Deser et al. 2012a; Fischer et al. 2014; Bhatia and Ganguly 2019; Lehner et al. 2020). ICV dominates climate uncertainty over decadal prediction horizons at regional to local scales, where stakeholders are more interested (Kumar and Ganguly 2018). It is typically handled by considering multiple initial condition ensemble members (MICE), assuming that it satisfactorily captures the internal variability (Deser et al. 2020; Upadhyay et al. 2021). The MICE are generated by applying minor perturbations to the initial state of the model such that the different climate projections behave as surrogates of climate variability (Deser et al. 2012a; IPCC 2013; Asch et al. 2016; Kumar and Ganguly 2018; Innocenti et al. 2019).

The importance of ICV has received considerable attention recently from the scientific community (Deser et al. 2012b, 2014, 2020; Lehner et al. 2020; Bhatia and Ganguly 2019; Upadhyay et al. 2021). Several studies have explored the role of internal variability to assess future climate outcomes such as surface air temperature, a vertical profile of recent tropical temperature trends and precipitation (Deser et al. 2012a,b, 2014, 2020; Lehner et al. 2020; Mitchell et al. 2020). A few studies have quantified the role of ICV in estimating streamflow (Fatichi et al. 2014; Champagne et al. 2020), extreme precipitation (Bhatia and Ganguly 2019; Upadhyay et al. 2021), sea level rise (Tsai et al. 2020), air quality, and associated health risks in a warming world (Saari et al. 2019). Mankin et al. (2020) have criticized the initial condition large ensemble members as they are resource intensive, redundant, and biased. Despite this criticism, they have shown that large ensemble members provide unique information consistent with the insights and support robust adaptation decision-making regarding freshwater resources. Climate variability may cause large uncertainties in climate at a regional scale (Hawkins and Sutton 2011; Deser et al. 2012b, 2014). Recently, Upadhyay et al. (2021) have quantified the relative contribution of uncertainty due to ICV and model uncertainty in the depth and volatility of Indian summer monsoon rainfall extremes. They have shown that ICV is comparable and even higher than model uncertainty in estimating extreme precipitation indices in central India. However, the understanding role of ICV in various meteorological variables and its translation to streamflow and hydropower estimation has received relatively less attention globally. A few researchers have considered the translation of different uncertainties of climate variables to hydropower and analyzed it using hydrological models (Poulin et al. 2011; Finger et al. 2012; Oyerinde et al. 2016). Here, we consider the uncertainties associated with precipitation, maximum temperature ($T_{\text{max}}$), minimum temperature ($T_{\text{min}}$), wind, and its impact on streamflow estimation and subsequently on hydropower production, as the range of uncertainty in input data, has a significant influence on the output, which may not be neglected in the communication of results (Biemans et al. 2009).

Several studies have analyzed the impact of climate change on hydropower production and shown that it affects energy generation in the near term and by the end of the twenty-first century (Lehner et al. 2005; Liu et al. 2016; Turner et al. 2017; Van Vliet et al. 2016; Ali et al. 2018). Carvajal et al. (2017) have assessed the sensitivity of hydropower production using 40 multimodel ensemble members and shown that annual hydroelectric power production ranges between −55% and +39% of the mean historical outputs for the period 2071–2100. For seven large hydropower projects of India, Ali et al. (2018) have assessed climate change impacts on hydropower production, analyzed model uncertainties and projected an increase in mean hydropower production and annual streamflow in non-snow-dominated areas. Similarly, Caceres et al. (2021) have evaluated the impact of climate on hydropower using 21 GCMs and quantified the role of model uncertainty of 134 hydropower plants of South America. However, studies on the role of ICV in estimating hydropower have rarely been studied using large ensemble members. For example, Finger et al. (2012) have examined uncertainties due to internal variability, which is intrinsically sampled by assessing the interannual variability within the projected 28-yr duration. The role of the ICV using large ensemble members in estimating hydropower production in India is still unexplored, despite exploring the impact of climate change on hydropower production.

The variability in water and energy demand is a crucial driver for multiple management and planning interventions, such as the construction of new storage and modifications of the operating rules (Dang et al. 2020a). Despite receiving significant attention regarding ICV, limited attention is given to the planning and management aspect (Siderius et al. 2021). Understanding variability in hydropower projections also helps maintain electric grid stability as hydropower operations are mainly affected by ICV and model uncertainties of climate variables such as changes in the timing and magnitude of precipitation patterns (Bradley et al. 2006). Various variabilities can affect the usable capacity of hydropower plants and their operations, which can also inform the scheduling of system reserves within a transmission zone to meet reliability standards (Caceres et al. 2021). Schaeffl (2015) have discussed the importance of local factors, modeling uncertainties for future hydropower production in different parts of the world. This study attempts to translate the meteorological variables’ uncertainties due to ICV and model uncertainty to hydropower production at a basin scale. We analyze the role of model uncertainty and ICV in estimating streamflow and hydropower generation. We analyze the effect of bias correction of meteorological variables such as precipitation, $T_{\text{max}}$ and $T_{\text{min}}$, and wind data on streamflow estimation and its translation to hydropower production estimation. Our study may help scientists and policymakers to understand and communicate the role of internal variability at a basin scale and provide a way
to assimilate multiple sources of information to justify actions in climate change adaptation.

The following section of the paper shows the study area and dataset used for the analysis, followed by the methodology section. In the methodology section, we first discuss a flowchart for uncertainty analysis. Then, the subsection provides details of streamflow and potential hydropower estimation. We discuss the uncertainty analysis in this paper’s results and the discussion and conclusions section.

### 2. Study area and data

India has experienced significant changes in temperature and precipitation over the past few decades, which is likely to change by the end of the twenty-first century (Mishra and Lilhare 2016; Mohammad and Goswami 2019; Almazroui et al. 2020). India is the fifth-largest producer of hydroelectric power globally, with a 50.07-GW capacity (International Hydropower Association 2021). India’s power grid is divided into northern, western, eastern, southern, and northeastern regions (Halder 2013). The western region covers the Maharashtra, Gujarat, Madhya Pradesh, and Goa states of India, with the highest capacity for hydroelectric potential (Jain et al. 2007; Halder 2013; Sharma and Batta 2020). This study considers the three major hydropower plants, Sardar Sarovar, Ukai, and Kadana, located in Gujarat, India. The details of these hydropower plants are given in Table S1 in the online supplemental material, and more details can be obtained from India Water Resources Information System (India-WRIS; https://indiawris.gov.in/wris/). Gujarat is the fifth largest Indian state in the western region of India and the ninth largest state by population, with approximately 60.4 million (Ministry of Home Affairs India 2011). The study area and location of the three basins are shown in Fig. 1. We consider the hydropower plants with greater than 100-MW capacity for our analysis. The Sardar Sarovar Project has six riverbed power houses (RBPHs) with 200-MW capacity and five canal head power houses (CHPHs) with 50-MW capacity (Sahoo et al. 2014). The Ukai and

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**Fig. 1.** (left) Study area: the location of the three basins of India is shown with the basin watershed. The red triangle shows the dam’s location, and the circle shows the location of gauges considered for calibration and validation of the VIC hydrological model. (right) The Mahi, Narmada, and Tapi basins are given from top to bottom, respectively. The shaded part represents the catchment area contributing to the dam location.
Kadana Dams have hydropower with an installed capacity of 305 and 240 MW, respectively (Ghose et al. 2019; Sharma and Kumar 2018).

We use 50 multiple initial condition ensemble members of phase 6 of the Climate Model Intercomparison Project (CMIP6) EC-Earth3 to analyze the role of internal variability, which are available from the Earth System Grid Federation (https://esgf-data.dkrz.de/projects/esgf-dkrz/) (Hazeleger et al. 2012; Bilbao et al. 2021). We use eight multimodel ensemble members from CMIP6 to analyze model uncertainty. The models considered for the model uncertainty analysis are ACCESS-CM2, CanESM5, EC-EARTH3, GFDL-ESM4, INM-CM4-8, INM-CM5-0, MRI-ESM2-0, and NorESM2-LM, which are available from World Climate Research Program Coupled Model Intercomparison Project (https://esgf-node.llnl.gov/projects/cmip6/). The resolution of each model is given in Table S2. We consider low-to-moderate emission scenarios shared socioeconomic pathway (SSP) 2–4.5 (approximately corresponding to the RCP4.5 scenario) for the analysis (Meinshausen et al. 2020; Eyring et al. 2016). We selected models from CMIP6 based on data availability of precipitation, maximum temperature ($T_{\text{max}}$), minimum temperature ($T_{\text{min}}$), and wind for the historical period (1985–2014) and the future period (2015–2100) under SSP2-4.5 (SSP245). We use one initial condition realization (r1i1p1) to analyze model uncertainty.

For hydrological modeling, we use the observed daily gridded precipitation ($0.25^\circ \times 0.25^\circ$) and minimum and maximum temperature ($1^\circ \times 1^\circ$) from the India Meteorological Department (IMD) (Pai et al. 2015), regridded at $0.25^\circ \times 0.25^\circ$ resolution. Observed daily wind speed data were obtained from (Sheffield et al. 2006; Ali et al. 2018) at $0.25^\circ \times 0.25^\circ$ resolution. All model (MICE/MME) data are interpolated at $0.25^\circ \times 0.25^\circ$ gridded daily precipitation, $T_{\text{max}}$, $T_{\text{min}}$, and wind datasets over Narmada, Tapi, and Mahi basins using linear interpolation. We use observed monthly streamflow data from India-WRIS to calibrate and validate the Variable Infiltration Capacity (VIC) macroscale hydrologic model (Liang et al. 1994). We used vegetation parameters from advanced very-high-resolution radiometer global land cover information at a 1-km spatial resolution (Hansen et al. 2000; Tiwari and Mishra 2019; Sheffield and Wood 2007), and soil data from the Harmonized World Soil Database, version 1.2 (http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/). The storage and height of the reservoir are obtained from Sardar Sarovar Narmada Nigam Ltd. (https://sardarsarovardam.org/hydrology.aspx) for Sardar Sarovar reservoir. For the Ukai and Kadana reservoirs, we obtained data of storage and height relationship from India-WRIS to compute hydropower potential.

3. Methodology

We have analyzed the role of ICV and model uncertainty in estimating streamflow and hydropower production for three hydropower plants. The methodology considered for the proposed work is divided into three sections, as shown in Fig. 2.

First, the data collection and preprocessing section show the different data used for the analysis. We use observed precipitation ($P$), $T_{\text{max}}$, $T_{\text{min}}$, wind ($W$), and streamflow of different gauges, as shown in Fig. 1 for calibration and validation of the VIC hydrological model. We use Earth system model (ESM) outputs ($P$, $T_{\text{max}}$, $T_{\text{min}}$, and $W$) to estimate streamflow and potential hydropower. ESM outputs have large systematic biases relative to observational datasets owing to the imperfect representation of the model’s physical processes (Grillakis et al. 2017; Upadhyay et al. 2021). Thus, it should not be directly used to develop climate change adaptation policies without some form of prior bias correction (Sharma et al. 2007; Piani et al. 2010; Grillakis et al. 2017). The objective of bias correction is to adjust the statistical properties of climate simulations with observations. Several studies have used quantile mapping (QM) bias correction and shown that it substantially reduces the biases (Maraun 2013; Cannon et al. 2015; Ngai et al. 2017; Harilal et al. 2021; Tiwari et al. 2021). Recently, Chen et al. (2021) have compared bias-corrected climate model outputs and postprocess model output for streamflow estimation and recommended the use of bias correction. Haddeland et al. (2012) have analyzed the effects of bias correction of radiation, humidity, and wind estimates on evapotranspiration and runoff estimates and shown that estimates are relatively similar. Differences between simulated and observed radiation, humidity, and wind values are smaller than for temperature and precipitation for the bias- and non-bias-corrected hydrological projections. Bias correction may affect the consistency between the ESM output variables such as $P$, $T_{\text{max}}$, $T_{\text{min}}$, and $W$ (Wang et al. 2009; Haddeland et al. 2012; Ehret et al. 2012; Muerth et al. 2013). The use of bias-corrected data is an open question and unresolved issue among scientists, especially for climate change impact studies such as hydropower production and agricultural production (Ehret et al. 2012; Hempel et al. 2013; Laux et al. 2021). Thus, the effect of bias correction on estimated streamflow and potential hydropower is explored in this study.

We use observed and climate data for each variable, such as daily $P$, $T_{\text{max}}$, $T_{\text{min}}$, and $W$ of each ensemble member (MICE/MME), to analyze the effect of bias correction. We perform quantile–quantile mapping (Maraun 2013) for bias correction for each variable separately. We use the “qmap” library of Rpy2 in Python for data from 1985 to 2014 and try to match quantiles at intervals of 0.01. We estimate parameters for bias correction using observed and historical ensemble member data (1985–2014). These parameters are then applied to historical and SSP245 data to obtain bias-corrected historical and SSP245 data. We perform analyses for bias- and non-bias-corrected data separately.

The modeling and calculation section shows the flowchart to estimate streamflow and potential hydropower production. First, we calibrate and validate the VIC hydrological model using different gauge streamflow data to obtain calibrated hydrological parameters. Streamflow is estimated using calibrated parameters and climate data (bias- and non-bias-corrected data). These streamflow estimates and storage–height relationships are used to calculate potential hydropower. The last
section of the flowchart shows the data and duration used for uncertainty analysis. The details about streamflow estimation and potential hydropower estimation are given below.

### a. Streamflow estimation

We estimate streamflow using the VIC hydrological model (Liang et al. 1994) at the reservoir for three hydropower plants. The VIC is a semidistributed model developed based on energy and water balance equations solved for individual grid cells. The VIC generate baseflow and streamflow using the Arno model conceptualization (Todini 1996) and the infiltration mechanism utilized in the Zhao (1992). We use observed daily precipitation, $T_{\text{max}}$, $T_{\text{min}}$, wind, vegetation parameters, soil parameter files, and observed streamflow data to calibrate and validate the model. In the VIC model, the assumption is that water can only enter through the atmosphere, and water entering the channel cannot flow back to the soil (Dang et al. 2020b). The observed meteorological forcing data such as $P$, $T_{\text{max}}$, $T_{\text{min}}$, and $W$ are fed as input data. We first simulate baseflow and surface runoff from each grid cell. Then, runoff from individual cells is routed to gauge location using the routing model developed by Lohmann et al. (1996). Channel routing based on the linearized Saint-Venant equation is used to simulate the discharge at the gauge location by assuming that all runoff exits a cell flows in a single flow direction (Gao et al. 2010; Zhang et al. 2017).

We have calibrated and validated the model using the Handia, Mandleshwar, and Sandia gauge stations for the Narmada basin.
Similarly, we consider Sarangkheda and Burhanpur for the Tapi basin and Mataji and Khanpur for the Mahi basin. The calibration and validation results for the three basins are shown in Table 1. The calibrated parameters for all three basins are given in Table S5. The time series of observed streamflow and VIC simulated monthly streamflow are given in Fig. S1.

We use Nash–Sutcliffe model efficiency coefficient (NSE) (Nash and Sutcliffe 1970) and coefficient of determination ($R^2$) (Nagelkerke 1991) performance criteria, which are commonly used metrics in hydrological and climate impact studies. We use simulated monthly data and observed data to calculate NSE and $R^2$ to analyze the performance of the VIC. We estimate streamflow using the bias- and non-bias-corrected data of each MICE and MME ensemble member separately using parameters obtained after calibration and validation. We also performed separate analyses for historical, near-term, midterm, and far-term data. We route the streamflow to the dam location to calculate potential hydropower.

### b. Potential hydropower estimation

We calculate hydropower production for all the ensemble members using the estimated streamflow. We calculate developed hydropower potential (DHP), the maximum possible hydropower generated using the available water and existing hydroelectric facilities (Liu et al. 2016). First, we calculate the monthly releases using estimated streamflow and generic regulation rules described by Hanasaki et al. (2006), which contain the effect of yearly and monthly variability. We calculate monthly release $R_m$ (m$^3$ s$^{-1}$) using Eq. (1), given by Hanasaki et al. (2006), which can be used where irrigation is not considered. Hanasaki et al. (2006) have developed a reservoir operation scheme for global river routing models, which uses reservoir specifications, global runoff datasets, and water demand downstream. Here, we note that DHP does not represent the actual hydropower production as it does not consider socioeconomic factors such as water use variability, power consumption variation, and consumer behavior. We assume that the reservoir is primarily used for hydropower production. The monthly release from the reservoir is generally not influenced by monthly inflow when storage capacity is large compared to the mean annual inflow. However, monthly release fluctuates if storage capacity and mean annual inflow are of the same order (Ali et al. 2018):

$$R_m = \left( \frac{c}{0.5} \right)^2 \frac{k}{k_i} + \left[ 1 - \left( \frac{c}{0.5} \right)^2 \right] n_0, \quad 0 < c < 0.5$$

$$R_m = \left( \frac{c}{0.5} \right)^2 \frac{k}{k_i} + \left[ 1 - \left( \frac{c}{0.5} \right)^2 \right] n_0, \quad c > 0.5$$

where $c$ is the ratio of maximum storage capacity to mean total annual inflow, $c = C/I_a$; $C$ is the maximum storage capacity of the reservoir (m$^3$); $I_a$ is the average total annual inflow (m$^3$ yr$^{-1}$); and $k_i$ is the release coefficient that considers water stored in the reservoir at the beginning of the operational year (Hanasaki et al. 2007; Ali et al. 2018). It is calculated as $k_i = S_{beg} \alpha \times C$, where $S_{beg}$ is the storage available at the beginning of the operational year, and $\alpha$ is an empirical coefficient suggested based on sensitivity analysis. In this study, the $\alpha$ value considered is 0.85, as suggested by Hanasaki et al. (2007). $I_m$ is monthly inflow (m$^3$ s$^{-1}$), and $I_a$ is mean annual inflow (m$^3$ s$^{-1}$). India’s environmental flows are usually considered the minimum flow to be released downstream from a dam. There are several methods for estimating environmental flow in the literature (Jain and Kumar 2014; He et al. 2018; Amrit et al. 2019). Jain and Kumar (2014) have provided the assessment of environmental flow requirements of Indian rivers and suggested that river ecosystems may be reasonably maintained at 10%–20% of mean annual runoff or some percentage of 75% dependable annual flow, depending on hydrological variability. However, this study assumes 10% of monthly inflow as environmental flow. Further, the Bureau of Indian Standards provisions (IS 7323:1994) specifies the following zones for the operation of multipurpose reservoir systems: 1) spill zone, 2) flood control zone, 3) conservation zone, 4) buffer zone, and 5) dead storage zone. The code specifies that the flood control zone is the storage space for absorbing high flow flows to prevent and reduce downstream flood damages. In the absence of quantitative recommendations, we use 10% of storage as flood control as a specific use case. Thus, to incorporate the components of environmental flow and flood protection, we considered the following two constraints for the analysis. First, the monthly release should not be less than 10% of the monthly inflow to the reservoir. Second, at any point, the storage in the reservoir should not be greater than storage capacity, and a minimum of 10% of storage capacity is maintained for flood control and maintaining minimum water levels. We calculated the storage using the continuity equation and compared calculated storage with observed storage [billion cubic meters (BCM)], which was obtained.
from India-WRIS to ensure the method’s accuracy. We observe that the calculated storage values are slightly higher than those observed, as we have not considered irrigation demands and other demands for the analysis. Then we calculate the height using the storage height relationship. DHP can be calculated based on monthly release, storage capacity, and installed hydraulic capacity (IHC) (Liu et al. 2016). The equation to calculate DHP is given by Eq. (2), which ensures that DHP will not exceed IHC.

\[
DHP = \min(R_m \times h \times g, \text{IHC}),
\]

where \(R_m\) is monthly release, \(h\) is a hydraulic head (m), and \(g\) is an acceleration due to gravity (m s\(^{-2}\)). We analyze the uncertainty resulting from internal variability and model uncertainty in estimating hydropower generated for four periods: historical, near term, midterm, and end term. The monthly power production and uncertainties resulting from internal variability and model uncertainties are analyzed for each period. We also analyze percentage change with respect to the historical period of streamflow and hydropower production to analyze uncertainties and their translation from streamflow to hydropower production.

4. Results

The calibration and validation results for Narmada, Tapi, and Mahi basins are shown in Table 1. We simulated streamflow using the observed precipitation, \(T_{\text{max}}, T_{\text{min}}\), and wind data in the VIC model and compared it with observed data. We consider 0.8 as a threshold for performance criteria (NSE and \(R^2\)) as suggested by previous studies (Huang et al. 2017). Table 1 shows the values of NSE and \(R^2\), which are higher than the threshold for all gauge stations except the Khanpur gauge. We analyzed the time series of simulated streamflow and compared it with observed data, which show better agreement with each other (Fig. S1). However, simulated streamflow overestimates observed streamflow for the Mahi basin’s Khanpur gauge. It shows NSE values as 0.77 and 0.62 for the calibration and validation period, respectively (Table 1), which may be due to its location (downstream of the dam Fig. 1). We have not incorporated the reservoir module into the VIC model to simulate the streamflow (Yun et al. 2020).

a. Effect of bias correction

We analyze the effect of bias correction of meteorological variables such as \(P, T_{\text{max}}, T_{\text{min}},\) and \(W\) and its impact on streamflow estimation for each ensemble member from MICE and MME. We compare monthly mean meteorological variables and estimated streamflow of each ensemble member with the observed data. Figure 3 shows variations of meteorological variables of the Narmada basin and estimated streamflow at Sardar Sarovar Dam for the historical data. Non-bias-corrected monthly precipitation from MICE shows lower precipitation than observed for monsoon (June–September). We observe that bias-corrected precipitation tries to match for July and increase precipitation values for August and September with respect to observed data. For \(T_{\text{max}}\) and \(T_{\text{min}}\), bias correction does not significantly improve the performance. Mean monthly non-bias-corrected wind from each ensemble member of MICE shows higher values than observed wind data for all months. The difference between bias-corrected mean wind data and observed data reduces after bias correction. Still, the difference between ensemble member data and observed data shows that quantile–quantile mapping does not remove bias effectively for wind data. The streamflow estimated using meteorological non-bias-corrected data underestimates compared to observed data, while bias-corrected data show better agreement with the observed data (the last column of Fig. 3). However, we observe that streamflow estimated using bias-corrected data slightly overestimates compared to observed data for August and September. Overall, mean monthly data from each ensemble member of MICE show better agreement with each other, indicating lower ICV, as shown in the first and second rows of Fig. 3. We also observe that bias correction further reduces ICV, indicating that it cannot preserve the ICV, which is considered irreducible.

b. Uncertainty analysis for meteorological variables and streamflow

The mean monthly variations of \(P, T_{\text{max}}, T_{\text{min}},\) wind, and estimated streamflow of ensemble members from MME and its comparison with observed data shows that model uncertainty is higher than ICV. Mean monthly precipitation exhibit higher model uncertainty for monsoon than \(T_{\text{max}}, T_{\text{min}},\) and wind. This model uncertainty also translates to streamflow and shows the higher model uncertainty in estimating the streamflow. For example, two ensemble members (INM-CM4-8 and INM-CM5-0) overestimate streamflow observed, while another two ensemble members (ACCESS-CM2, CanESM5) underestimate streamflow for non-bias-corrected data, especially for monsoon (Table S4). Bias-corrected data of MME shows an improvement for all the variables and tries to match with observed data. However, we observe high model uncertainties even after bias correction as quantile–quantile mapping bias correction does not seem able to handle high variability and seasonality. We performed a similar analysis for Kadana and Ukai (Fig. S2). Meteorological variables show similar behavior for Tapi and Mahi basins as the Narmada basin. There is a significant difference between streamflow estimated using bias- and non-bias-corrected data for Kadana Dam, which is not observed for Ukai Dam. This difference between streamflow estimated using the bias- and non-bias-corrected data is observed for other periods, such as near term, midterm, and far term, especially for monsoon months (Fig. S3).

To analyze the role of ICV and model uncertainty in estimating the streamflow, we consider different periods such as historical (1985–2014), near term (2015–44), midterm (2045–74), and far term (2075–2100) (Fig. 4). We consider the interquartile range (IQR—the difference between the 75th and 25th percentile) as the measure for uncertainty in estimating the streamflow within ensemble members (MICE/MME) (Upadhyay et al. 2021). Figure 4 shows IQR in estimating streamflow at Sardar Sarovar Dam for all four periods. We observe lower internal variability and model uncertainty for the streamflow estimated...
using the bias-corrected data than non-bias-corrected data for historical periods, indicating the effect of bias correction. We also note a significant difference between the mean monthly streamflow estimated using bias- and non-bias-corrected data. For example, mean monthly streamflows are approximately 2000 and 5000 m$^3$ s$^{-1}$ when estimated using August’s historical non-bias- and bias-corrected data, respectively. This difference further increases from near-term to far-term, as shown in Fig. S3. However, streamflow and uncertainty due to ICV increase from near-term to far-term for MICE. The third and fourth row of Fig. 4 shows that model uncertainty is higher than ICV and increases in mean streamflow from near-term to far-term for MME. Higher model uncertainty in estimating streamflow is observed for monsoon months (Fig. 4). Model uncertainty reduces using bias-corrected data, especially for a historical period. We observe higher mean streamflow, ICV and model uncertainty only for monsoon and postmonsoon (October–December), which agrees with other studies (Shah and Mishra 2018; Nilawar and Waikar 2019). Similarly, we analyze the results for the Kadana and Ukai Dams as given in Fig. S4, which also show similar patterns of streamflow uncertainties. Here, we highlight the uncertainty induced due to ICV increases toward the far-term irrespective of bias correction. Thus, it is important to internalize the effect of internal variability for planning and to manage water resources systems.

c. Uncertainty analysis for potential hydropower

Uncertainty analysis for potential hydropower shows that ICV and model uncertainty in estimating the mean monthly hydropower production plays a significant role for all months. Figure 5 shows IQR for mean monthly potential hydropower estimated using the Sardar Sarovar Dam’s historical, near-term, midterm, and far-term streamflow data. Uncertainties in estimating the hydropower are also lower for bias-corrected data as we observe for streamflow. The reduction in ICV shows that bias correction does not preserve the internal variability. A significant increase in mean hydropower production is observed between June and July for midterm and end term for non-bias-corrected data of MICE, while historical data show a smooth transition. However, we observe a similar increase for all periods using bias-corrected data as it represents the start of the monsoon. MICE data capture the phenomenon due to starting of the monsoon. We observe uniform and lower internal variability throughout all months than model
uncertainty. There is no significant increase in uncertainty toward the end of the twenty-first century (end term) as the calculation depends on the hydropower plant’s installed capacity and storage capacity. However, we observe that the lower bound of IQR increases toward the end term, while the upper bound remains almost constant for monsoon and postmonsoon. The third and fourth rows of Fig. 5 show the model uncertainty in estimating hydropower production. We observe higher model uncertainty in estimating hydropower production, especially for monsoon for non-bias-corrected data, while bias-corrected data show higher model uncertainty for nonmonsoon. Similarly, model uncertainty increases toward the end term for nonmonsoon months, which we do not observe for estimated streamflow. We also performed a similar analysis for the Kadana and Ukai Dams as given in Fig. S5, which also shows a similar pattern as the Sardar Sarovar Dam. However, uniform hydropower production, model uncertainty and ICV in estimating hydropower are almost constant throughout the year for the Ukai. Overall, we can say that the uncertainty bounds for hydropower production are not similar to the streamflow uncertainty.

d. Percentage change analysis

For further analysis, we performed the percentage change analysis to compare the role of ICV and model uncertainty in estimating streamflow and hydropower. Figure 6 shows the...
percentage change of mean monthly streamflow and hydropower of near term, midterm, and end term with respect to historical bias-corrected data for Sardar Sarovar. Mean percentage change shows the increase of streamflow for all months. However, this increase in streamflow is not reflected in hydropower production. For example, mean hydropower production decreases toward the far term for February–May. This decrease is more prominent for MICE than MME. On the contrary, potential hydropower production for monsoon and postmonsoon shows an increase in hydropower production. We observe significant variability in percentage change obtained using MICE for June, which indicates the starting of the monsoon, such as percentage change in ICV ranges between −40% and 150% for streamflow and between −20% and 40% for hydropower (first row of Fig. 6). In comparison, model uncertainty does not show this significant change.

Mean percentage change in model uncertainty in streamflow estimation and variability increase from near term to end term. Similarly, percentage changes analysis of streamflow and hydropower is also performed for Kadana and Ukai as given in Fig. S6. For Kadana, percentage change clearly shows an increase in mean and uncertainty in estimating streamflow...
and hydropower production toward the end of the century (far term) (Fig. S6a). The percentage change variability in estimated streamflow and hydropower due to ICV is even higher for June, as observed for Sardar Sarovar. However, a similar trend is not observed for the Ukai Dam. Figure S6b shows a higher percentage change and variability in estimating the Ukai Dam’s streamflow, especially for ICV. However, similar variability and increase in mean percentage change are not observed for potential hydropower. Despite an increase in streamflow, a decrease in hydropower production is observed for February–April. Overall, the percentage change for streamflow is from approximately −48% to 240%, while for hydropower is from approximately −20% to 70% change for all cases, which indicates that increasing streamflow does not increase hydropower production significantly.

5. Discussion and conclusions

Hydropower production can help meet the increasing energy demands due to urbanization and the increasing population in India. Hydropower, the extensively used renewable energy sensitive to streamflow change, is characterized by various uncertainties. An improved understanding and better prediction of hydropower empower the stakeholders for planning and decision-making, such as estimating the potential energy production and determining design parameters such as water level, minimum operation level and installation capacity of hydropower based on future projections. However, the crucial role of internal climate variability on hydropower production in India is still unexplored. The high variability in precipitation, $T_{\text{max}}$, $T_{\text{min}}$, and wind, which directly or indirectly affects the streamflow and hydropower production, along with acknowledging the importance of internal variability, motivated us to explore further the role of internal climate variability in projections of future hydropower production.

Model uncertainty is considered as potentially reducible as models improve. In contrast, internal variability is considered as irreducible (Deser et al. 2012a,b; Eyring et al. 2019). This distinction and relative contribution are not often appreciated and communicated to stakeholders (Eyring et al. 2019). ICV poses inherent limits to climate predictability, which may affect the goal of adaptation guidelines (Deser et al. 2012a). Hydropower fuels social and economic development, ensure electricity security and acts as a renewable electricity production pillar (Schaeflri 2015). We demonstrate the role of ICV in the three basins of India. It is also essential to compare it with the model uncertainty as it is considered a prominent source of uncertainties. Thus, this study analyzes the role of internal variability and model uncertainty in estimating the streamflow and its translation for hydropower estimation. We estimate streamflow using the VIC hydrological model.

Previous studies have noted that the uncertainty introduced by the VIC model is significantly less than that presented by input meteorological forcing from climate models (Raje and Krishnan 2012; Priya et al. 2020; Priya 2017). Thus, we have considered uncertainty associated with the meteorological forcing input from climate models in this study. Several studies have analyzed the effect of reservoirs on the calibration of a hydrological model and found that the model without reservoirs attains a reasonable modeling accuracy (de Paiva et al. 2012).
2013; Abbaspour et al. 2015; Dang et al. 2020a). Recently, Dang et al. (2020a) have found that the calibration process of a model with and without reservoir implementations yields de facto the same values of the goodness-of-fit statistics, which suggests that the model parameterization helps compensate for a structural error such as the absence of the water reservoirs. However, they show that the model with reservoirs presents higher discharges at the peak of the monsoon season than the model without reservoirs. The increase in discharge during the monsoon season because of the reservoir may be neglected for our study as we consider 10% storage as flood storage as one of the constraints, and hydropower generation also depends on the installed hydraulic capacity. Various authors have analyzed the performance of CMIP6 models for modeling the Indian summer monsoon (ISM) (Choudhury et al. 2022; Rajendran et al. 2022). Recently, Choudhury et al. (2022) have analyzed the evolution of the ISM rainfall (ISM) simulations from CMIP3 to CMIP6 models, shown that CMIP6 models have demonstrated notable progress in simulating the interannual, multidecadal variability, but marginal improvement in simulating the ENSO–ISM correlation. They have also indicated that phases of the annual cycle are generally well simulated by almost all CMIP6 models with correlations greater than 0.9. Thus, this study considers the eight CMIP6 models based on the data availability. However, several other studies have found that some CMIP6 models failed to capture some monsoon phenomena, such as spatial statistics, the number of extreme events, and the monsoon’s onset phase (Mitra 2021; Singh 2023). Here, we show that ACCESS-CM2 and CanESM5 underestimate streamflow (Fig. 4), which is not suitable for streamflow estimation, especially for monsoon, which is consistent with Mitra (2021).

Three steps are taken to translate the impact of climate change on streamflow and hydropower generation. First, we analyze the uncertainties of each climate variable, such as precipitation, \(T_{\text{max}}, T_{\text{min}}\), and wind, which are inputs to the hydrological model. Second, the uncertainties of climate variables are propagated to streamflow by using the ensemble members of each variable as input to the VIC model using the same calibrated parameters. Third, streamflow uncertainty is propagated to hydropower production by considering ensemble members. There are many controversies in using the bias-corrected climate model outputs for climate change impact studies in the scientific community (Ehret et al. 2012; Chen et al. 2013; Maraun 2016; Maraun et al. 2017). This study also analyses the effect of bias correction by comparing the results of bias- and non-bias-corrected data. Our results show that bias correction does not preserve the internal variability in streamflow estimating, which further impacts the potential hydropower estimation. Other findings from this study are that model uncertainty contributes more to total uncertainty than ICV in estimating monsoon’s streamflow and potential hydropower. However, we observe that role of ICV is increasing toward the far term. The estimated mean streamflow increases during monsoon and postponsoon seasons only. For nonmonsoon, both uncertainties play a significant role in hydropower estimation, while it is not evident from estimated streamflow. The uncertainty resulting from ICV and model uncertainty increases from near term to far term for estimated streamflow, while we have not observed a similar increase for hydropower production. However, the lower bound of IQR increases toward the far term (2075–2100) compared to the historical data for hydropower production. Mean potential hydropower decreases toward the far term, especially for February–May, despite increasing uncertainty for estimated streamflow. This decrease in hydropower is more prominent for MICE than MME. A higher percentage change in ICV is observed for streamflow (from −40% to 150%) than hydropower (from −20% to 40%) for June. In comparison, model uncertainty does not show this significant change. The range of percentage change for streamflow is much higher (from −48% to 240%) as compared to the hydropower (from −20% to 70%), which is consistent with Qin et al. (2020).

This study uses quantile mapping for bias correction for individual ensemble members of MICE and MME. Recently, Ayrar et al. (2021) have developed an ensemble bias correction method to preserve internal variability. Further study may consider using the ensemble bias correction approach to understand the role of ICV better. The present study considers fixed duration data for investigation using a historical period (1985–2014) and future periods such as 2015–44 (near term), 2045–74 (midterm), and 2075–2100 (far term). The future scope includes the trend analysis for hydropower production. We use VIC hydrological model for the estimation of streamflow. We have not considered hydrological model uncertainty for the analysis, which may play a significant role in estimating the streamflow. In this study, we have only used SSP245, which is not sufficient to represent the full spectrum of scenario uncertainty. However, we have performed a separate analysis for SSP858 for non-bias-corrected data for the Narmada basin (shown in Figs. S7–S9). Our results show no significant change in patterns of uncertainty from the SSP245 to SSP858 for near, mid-, and far term, despite changes in the magnitude. While we have considered two emission scenarios from MICE output from one model and one initial condition from MMEs, future studies need to include multiple initial condition ensembles, multiple model ensembles, and hydrological model uncertainty for all available SSPs to understand the full spectrum of uncertainties. We have calculated the monthly releases using generic regulation rules described by Hanasaki et al. (2006). Further study may consider applying different reservoir operating policies for calculating the monthly release by considering the irrigation and municipal water demand under different demand scenarios. We use 50 multiple initial condition ensemble members from only one model (EC-Earth3) to quantify the internal variability by assuming that it captures all the variability and represents the internal climate variability. Multiple single-model initial condition large ensemble members (SMILEs) are now available, which may provide new insights for analyzing the role of internal climate variability (Lehner et al. 2020; Wood and Ludwig 2020; Deser et al. 2020).

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Data availability statement. The multiple initial condition ensemble members of the CMIP6-EC-Earth data are downloaded from Earth System Grid Federation (https://esgf-data.dkrz.de/projects/esgf-dkrz/). The multiple models of CMIP6 are downloaded from World Climate Research Program Coupled Model Intercomparison Project (https://esgf-node.llnl.gov/projects/cmip6/). The precipitation and temperature data-sets are obtained from the India Meteorological Department (IMD). The observed streamflow data of the hydrological observation stations are obtained from the India Water Resources Information System Portal (India-WRIS; https://indiawris.gov.in/).

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