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Questioning the use of ensembles versus individual climate model generated flows in future peak flood predictions: Plausibility and implications

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Abstract

Accurate estimation of design floods is necessary for developing effective flood-management strategies. Climate change (CC) studies on floods generally consider alterations in mean runoff using ensembles compared to a base period. In this study, we examined the plausibility and implications of applying individual climate model-generated flows versus their ensembles to estimate peak floods (magnitude and timing of occurrence), using Budhigandaki River Basin of Nepal as a case study. Annual maximum one-day floods were derived for four future climate scenario projections (*cold-dry*, *cold-wet*, *warm-wet*, and *warm-dry*) from simulated daily flow series. Future floods of six return periods estimated for the individual climate scenarios were compared with their "Ensemble" (combiner for the ensemble series is the arithmetic mean of daily floods), "Average," and 'Baseline." Results showed that magnitudes of the flood peaks are such that those estimated using "Ensemble" < "Average" < individual series. We conclude that ensemble series should not be used for flood estimation because of the averaging effect. Designers should consider at the least the "Average" instead of the "Ensemble" series while designing climate-resilient flood structures. Furthermore, the occurrences of flood peaks are likely to be confined within the monsoon season for the "Ensemble" but spread out in the other months for the individual climate scenarios. This could have direct implications on the availability and mobilization of resources as well as the need for a year-round operational early warning system for flood risk management.

KEYWORDS

average, climate change, ensemble, flood, frequency, timing of occurrence

1 | INTRODUCTION

The Intergovernmental Panel on Climate Change (IPCC) has projected heavy precipitation leading to flooding in most regions of Africa and Asia (with high confidence), North America (medium to high confidence), and Europe (medium confidence) with an increase in global temperature by 1.5–2°C (IPCC, 2021). A considerable number of studies on the impact of climate change (CC) on river hydrology predict that the flood peaks and frequency are likely to increase in the future with varying magnitudes in different parts of the globe (Devkota & Gyawali, 2015; Gosling et al., 2017; Hettiarachchi et al., 2018; Hirabayashi et al., 2013; Huang et al., 2020; Lane & Kay, 2021; Lutz, ter Maat, et al., 2016; Marahatta, Aryal, et al., 2021; Pandey et al., 2020; Tabari, 2020).

Furthermore, reasonably accurate predictions of future climate extremes are necessary to estimate the design floods, plan and develop strategies of flood management, and mitigate their adverse impacts (Bhattarai, Bhattarai, et al., 2022; Devkota et al., 2020; Qi et al., 2022; Zhang et al., 2021). Existing policies, planning strategies, and implementation mechanisms of flood management need to be continuously tested and updated for their climate resiliency as new data becomes available (Dosio et al., 2022; Kundzewicz et al., 2014). This is in the spirit of the Paris Agreement of the United Nations Framework Convention on Climate Change (UNFCCC) which calls for "recommendations for integrated approaches to avert, minimize and address displacement related to the adverse impacts of climate change" (UNFCCC, 2016). It is also aligned with the UN Sustainable Development Goal (SDG) 13: "Take urgent action to combat climate change and its impacts" (Sanchez Rodriguez et al., 2018; UN-DESA, 2021).

It is noted here that there could be an infinite number of future climate scenarios, among which some particular cases are represented by general circulation models (GCMs) or regional climate models (RCMs). Climate change-related uncertainty is omnipresent in hydrological studies. The choice of GCMs or RCMs, adopted downscaling procedure, and selected hydrological model used for flow simulation along with the quality of observed data contribute substantially to the total uncertainty (Saha et al., 2021; Sassi et al., 2019; Tabari et al., 2021; Try et al., 2022; Wobus et al., 2021). In order to moderate GCM/RCM-related uncertainties and cancel out underlying data-related errors, CC studies are generally carried out using multi-model ensembles (Alodah & Seidou, 2019; Bai et al., 2020; Lane & Kay, 2021; Thober et al., 2018). Ensembles can be applied in hydrological studies using the following two approaches:

i. *Ensembling climate data*: In this approach, an ensembled climate dataset (for example, precipitation and temperature) is generated considering multiple CC models (GCM/RCMs). This single climate dataset is used as input to a hydrological model for generating a single time series flow data which is then used to carry out flood analysis.
ii. *Ensembling climate-induced flow data*: In this method, different CC models (GCM/RCMs) are entered individually into a hydrological model which is run separately for each such scenario. Individual flows generated in this way corresponding to each climate model are then ensembled into a single flow series, for example by Najafi and Moradkhani (2015).

We understand that there are numerous ways to derive an "Ensemble" series of climate or flows (for instance, independence weighted mean method (Bishop & Abramowitz, 2013), Bayesian model averaging (Yang et al., 2012), Reliability ensembling average (Tegegne et al., 2020) and Weighted Ensemble Averaging based on Taylor's skill score (Suh et al., 2016), among others). We have adopted the most common arithmetic averaging method (Bai et al.,2020; Su et al., 2016; Reboita et al., 2021; Romshoo et al.,2020) in our analysis. Therefore, in this paper, "ensemble" series explicitly refers to the flows obtained by calculating the arithmetic average of the flows corresponding to the individual CC models.

Ensembles, calculated using either the climate data or climate-induced flow data, as discussed above, could be deemed sufficient for monthly or seasonal planning and water allocation purposes because these studies generally rely on the flows averaged over a certain duration. However, floods are instantaneous extreme events. Therefore, flood studies are based on instantaneous flood peaks that can be generated by any of the extreme climate events. Generally, there are discrepancies on the magnitude and/or distribution of precipitation predicted by different climate models (Suh et al., 2016; Tegegne et al., 2020; Thober et al., 2018). In other words, the annual maximum precipitation predicted by each model differs in volume and occurs on different days of the year. The ensemble of two or more such series, thus, lowers the value of annual maximum flow. Moreover, studies have shown that the use of ensembles to evaluate possible changes in future extreme flows could be inapt. For instance, Kay et al. (2021) report less than ±9% changes, relative to the baseline, in future 20-year return period floods in the Great Britain using ensemble data while 25%–40% change using individual climate projections. Similarly, Bai et al. (2020) demonstrated variations as high as 50% in future extreme climate indices using individual climate models in the North China Plains while less than 10% from the multi-model ensembles compared to the baseline. Likewise, Marahatta, Aryal, et al. (2021)

and Marahatta, Devkota, and Aryal (2021) projected up to 23% change in the annual precipitation in the far future using different climate models in a Nepalese basin whereas the projected change using their multi-model ensemble was less than 15%. Hence, use of ensembled climate (primarily precipitation) or flows largely impedes the analysis of hydrological extremes such as floods.

Despite a number of studies considering future climate scenarios and their ensembles, comparison of the outputs of individual climate models and ensembles in the way we have carried out to answer an important question on the implications of using CC ensembles of future flood scenarios has been seen as a research gap in contemporary literature. We aim to contribute to this gap through our study. Moreover, this sort of comparative analysis focusing on the peak floods (monsoon season) has not been carried out in Nepal which possesses very typical hydrological conditions in which 80% of the annual precipitation and runoff occurs during the monsoon months (DHM/GoN, 2008, 2018).

Against this backdrop, this study aims to examine the plausibility and implications of using individual climate model-generated flows versus ensembled flows to estimate future peak floods. We use the simulated flows from Marahatta, Devkota, & Aryal, (2021) and Marahatta, Aryal, et al., (2021) corresponding to four IPCC CMIP5 GCMs representing possible extreme climatic conditions (*cold-dry*, *cold-wet*, *warm-dry*, and *warm-wet* as explained in Lutz, Immerzeel, et al. (2016) and Lutz, ter Maat, et al. (2016)), separately to assess the floods of different return periods. Moreover, we use the second ensemble approach (flow ensemble as explained above) to comparatively assess floods at the damsite of the proposed Budhigandaki Hydropower Project (BGHP) in the Budhigandaki River Basin of Nepal (Figure 1).

The following specific objectives have been set to achieve the overarching aim of this study:

i. To assess the likely change in magnitude of future floods due to CC.
ii. To answer the question raised on the implications of using CC ensembles of future flood scenarios.
iii. To analyze the impacts of CC on the timing of occurrence of projected flood peaks annually.

2 | MATERIALS AND METHODS

2.1 | Study area

Budhigandaki River Basin, lying in central Nepal (Figure 1), has been taken as a case in this study. Its catchment area is approximately 5000 km^2 at the BGHP damsite; about one-fourth (1300 km^2) lies in the Tibetan part of China while the remaining is in Nepal. The elevation of the basin ranges from 322 to 8055 meters above sea level (masl). The average annual basin rainfall is 1495 mm while its mean annual discharge at the confluence of Trishuli River is 240 m^3/s (Marahatta, Devkota, & Aryal, 2021). Additional features of the basin can be found in (Marahatta, Aryal, et al., 2021) and (Devkota et al., 2017).

2.2 | Data used and definition of important terms

i. Four daily flow series at the BGHP dam site simulated by Marahatta, Devkota, and Aryal (2021) and Marahatta, Aryal, et al. (2021) corresponding to the four IPCC CMIP5 GCMs representing four climatic conditions (C-D: *cold-dry*, C-W: *cold-wet*, W-D: *warm-dry*, and W-W: *warm-wet*) were used for the analysis.
ii. Two climate projections, namely, RCP 4.5 (stabilization scenario) and RCP 8.5 (high emission scenario) have been selected.

For the sake of clarity, different terms pertaining to flows encountered in this paper are defined below.

Time window: A 30-years period.

Baseline (BL): 1983–2012; Near Future (NF): 2021–2050, Mid Future (MF): 2046–2075, and Far Future (MF): 2070–2099.

Individual series: This is the simulated daily flow series from a hydrological model using bias-corrected climate data (precipitation and temperature) downscaled from a GCM representing one of the considered extreme climatic conditions (C-D, C-W, W-W, and W-D).

Maximum flow series: This refers to the annual flow series obtained by extracting the maximum daily flow value of each year for the considered time window. Maximum flow series has been calculated for each climatic condition from the individual series.

Ensemble series (EN): This is the daily flow series calculated by taking the arithmetic average of the flow data of the four individual series (C-D, C-W, W-W, and W-D) for each day. Maximum flow series of the ensemble is obtained by extracting the maximum daily flow value of each year.

Average flow series (Avg): This refers to the flow series obtained by averaging the annual maximum daily flow values of each year of the four individual series.

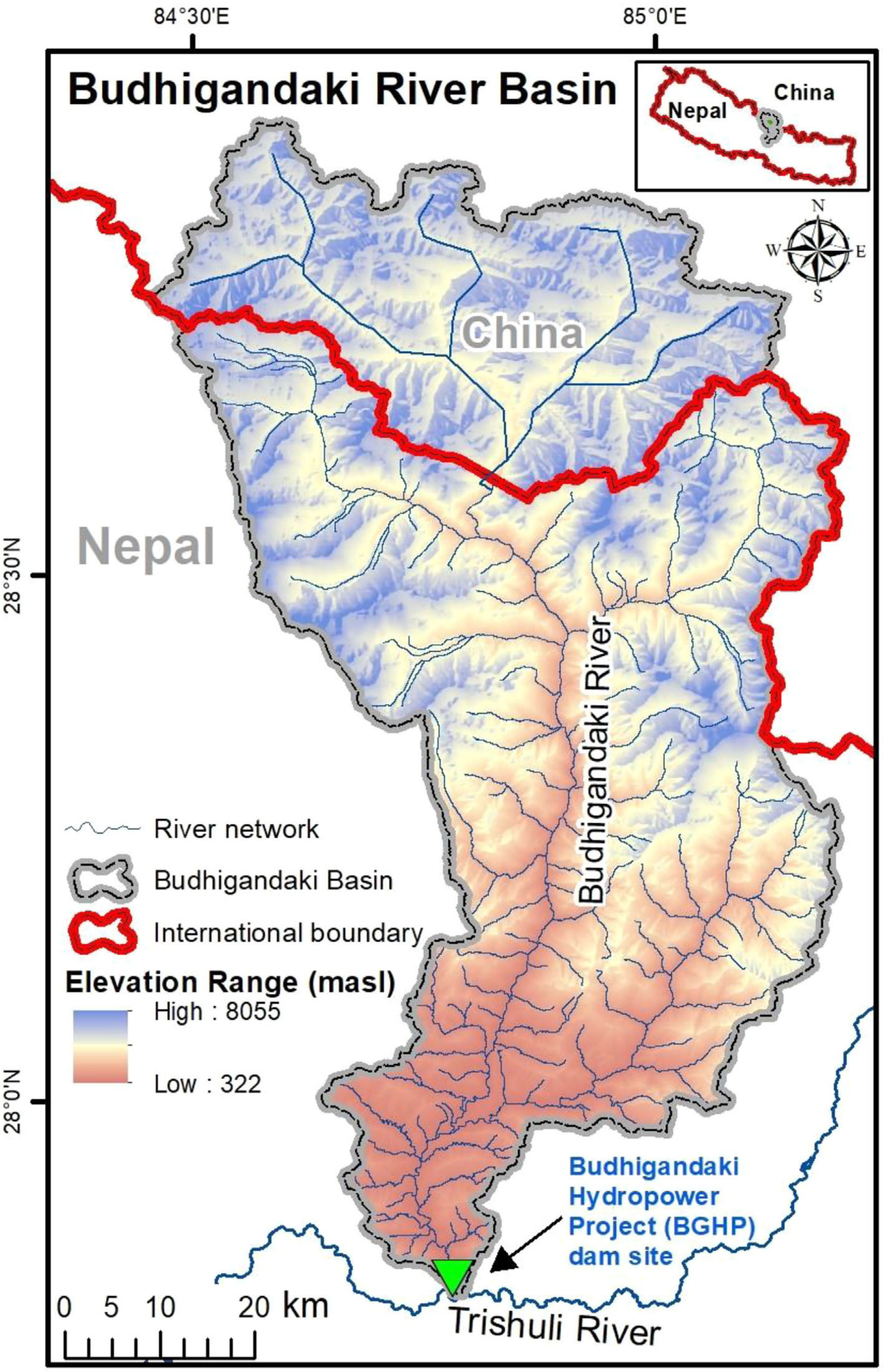


FIGURE 1 Location map of Budhigandaki River Basin.

2.3 | Assumptions

This study has been carried out assuming the following:

i. The current and future data series are divided into four time windows, namely, BL, NF, MF, and FF. We consider "quasi-non-stationarity" of climate which we define as a stepped varying condition in which the climate is assumed to remain constant during a particular time window (e.g., the baseline or near-future) but varies across the different time windows.
ii. Because instantaneous flood data is not available at the study site, we use the one-day maximum data instead of flood peaks as its proxy. However, the same methodology can be applied where instantaneous flood peaks are available.
iii. Gumbel, Log Pearson III, or Log Normal distribution are generally used in flood frequency analysis. Gumbel distribution has been found better than the other

two in many case studies in Nepal, including Budhigandaki Basin. Therefore, Gumbel distribution is used for flood frequency analysis in the study.

iv. Future climate is expected to be represented by either one of the four extreme climatic conditions, that is, *cold-dry*, *cold-wet*, *warm-wet*, and *warm-dry* as defined by Lutz, Immerzeel, et al. (2016) and Lutz, ter Maat, et al. (2016).

v. Simulated historical and future flows from Marahatta, Aryal, et al. (2021) and Marahatta, Devkota, and Aryal (2021) are representative of the flows of the respective periods.

2.4 | Methods

i. The selected four climatic scenarios of each RCP (Table 1) are fixed such that their hindcasted data very closely matches the observed historical data of the study as prescribed by Lutz, Immerzeel, et al. (2016) and Lutz, ter Maat, et al. (2016). The same approach has been applied in different studies across diverse geographical settings (Bhattarai, Devkota, et al., 2022; Dahri et al., 2021; Dhakal et al., 2022; Shrestha & Pradhanang, 2022; Sreedevi & Eldho, 2022; Tenfie et al., 2022).

ii. Mean daily flows for the baseline and future using respective climate data were generated by a well-calibrated and validated hydrological model—SWAT. Details of the input climate and basin physical data, SWAT model setup, and its calibration and validation can be found in (Marahatta, Aryal, et al., 2021). The methodological framework of our study is presented in Figure 2.

iii. Using the simulated data, one-day annual maximum flows (floods) were extracted for each year for the considered time horizon. A total of 37 flood series (baseline, four climatic conditions, their ensemble, and their average, each for two RCPs and three time windows) were analyzed (Figure 2). Gumbel distribution was fitted to all these datasets in order to estimate the flood magnitudes of different return periods. Flood magnitudes of all the aforementioned scenarios were compared with the baseline.

iv. The timing of occurrence of the annual one-day maximum floods for each year in all the scenarios was extracted. Additionally, the impact of using individual climate scenarios versus their ensembles on the timing of occurrence of the one-day annual maximum floods were also assessed and compared with the base case.

3 | RESULTS AND DISCUSSION

3.1 | Flood statistics

The mean and standard deviation of the flood peaks for the baseline and considered scenarios are listed in Table 2. The mean and standard deviation of all the four future series, their ensemble, and average are greater than the baseline. Moreover, the mean and standard deviation of both RCPs of all three time windows and four individual climatic series are greater than that of their respective "Ensemble" series. In addition, the ensembled values for all the years (2021–2099) and for both RCPs are less than the average values. It is interesting to note that out of the considered 80 future years, the ensemble values are higher than the minimum flood peaks among the four individual climatic series in only 23 and 27 years for RCP 4.5 and 8.5, respectively.

3.2 | Predicted flood magnitude

Floods of different return periods for all the climate scenarios estimated by fitting Gumbel distribution are presented in Figure 3. The simulated baseline flood values are 856, 1154, 1268, 1304, 1415, and 1526 m^3/s for 2-, 10-, 20-, 25-, 50-, and 100-years return periods, respectively. Future floods can be expected to be greater than baseline for all return periods. Such future floods of four individual series are projected to increase to 1327 m^3/s (by 55%)

TABLE 1 General circulation models (GCMs) adopted in this study for simulation of daily flows.

Climate scenario[a]	RCP 4.5	RCP 8.5
Cold-dry (C-D)	HadGEM2_CC_rcp45_r1ilp1	HadGEM2_CC_rcp85_r1ilp1
Cold-wet (C-W)	GFDL-EXM2G_rcp45_r1i1p1	GFDL-EXM2G_rcp85_r1i1p1
Warm-wet (W-W)	CanESM2_rcp45_r3i1p1	CanESM2_rcp85_r3i1p1
Warm-dry (W-D)	MPI-ESM-LR_rcp45_r3i1p1	MIROC-ESM-CHEM_rcp85_r1i1p1

[a]Nomenclature of the climate scenarios as given by Lutz, Immerzeel, et al. (2016) and Lutz, ter Maat, et al. (2016).

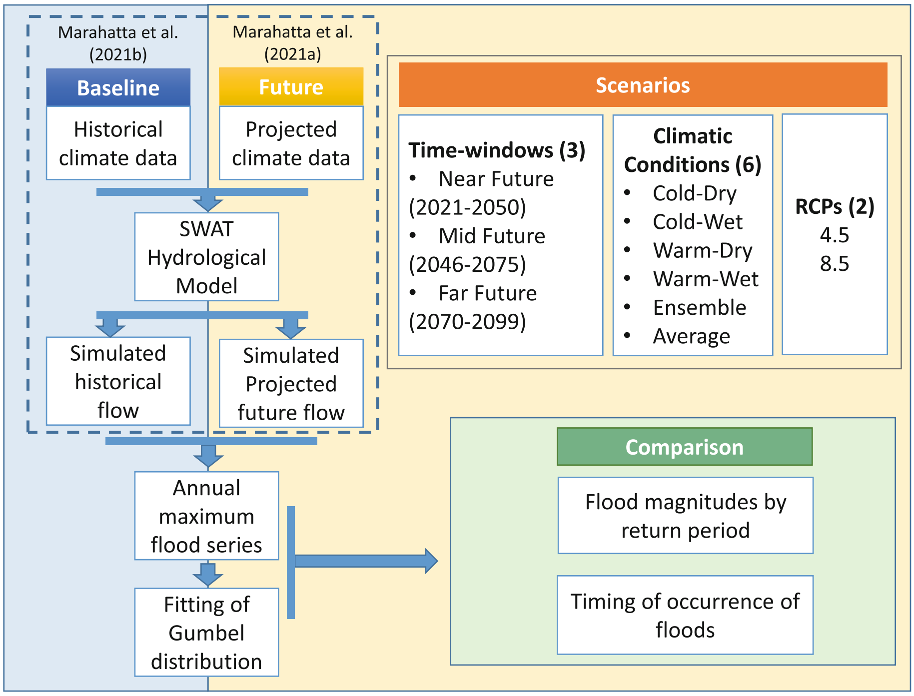


FIGURE 2 Overall methodology applied in this study. Simulated data (inside the dashed block) is adapted from Marahatta, Aryal, et al. (2021) and Marahatta, Devkota, & Aryal, (2021).

TABLE 2 General characteristics of floods.

Scenarios	Statistics	Baseline	Cold dry	Cold wet	Warm wet	Warm dry	Ensemble	Average
RCP4.5 /NF	Mean (m^3/s)	882	1475	1609	1824	1453	1087	1590
	Stdev (m^3/s)	176	447	412	569	306	155	195
RCP4.5 /MF	Mean (m^3/s)	882	1784	1620	2016	1514	1134	1733
	Stdev (m^3/s)	176	467	313	736	309	187	217
RCP4.5 /FF	Mean (m^3/s)	882	1829	1741	1896	1546	1179	1753
	Stdev (m^3/s)	176	519	357	677	483	201	233
RCP8.5 /NF	Mean (m^3/s)	882	1378	1739	1789	1720	1071	1657
	Stdev (m^3/s)	176	337	524	605	814	184	276
RCP8.5 /MF	Mean (m^3/s)	882	1663	1915	2125	2202	1222	1976
	Stdev (m^3/s)	176	672	743	603	727	232	390
RCP8.5 /FF	Mean (m^3/s)	882	2119	2379	2822	2287	1522	2402
	Stdev (m^3/s)	176	583	978	787	801	261	444

Abbreviations: FF, far future; NF, near future; MF, mid future; Stdev: standard deviation.

in RCP 8.5 C-D 2-years flood to 5951 m^3/s (by 290%) in RCP 8.5 C-W 100-years flood compared to the baseline; the changes being lesser for the near future and lower return periods. The change in predicted floods with respect to the baseline is the highest for W-W in all time windows in RCP 4.5: 1738 m^3/s (103%) to 3904 m^3/s (156%) in NF; 1904 m^3/s (122%) to 4703 m^3/s (208%) in MF; and 1793 (110%) to 4370 m^3/s (186%) in FF. In the case of RCP 8.5, the highest change is projected to be in W-D for NF 1596 m^3/s (87%) to 4695 m^3/s (208%) and MF 2092 m^3/s (144%) to 4859 m^3/s (218%) while C-W for FF 2230 m^3/s (161%) to 5951 m^3/s (290%). The projected floods estimated from the "Ensemble" series are, thus, only slightly higher than baseline. They are in the range of 8 and 73%. In the case of RCP 4.5, the variation ranges between 1063 m^3/s (24%) and 1652 m^3/s (8%) for NF; 1106 m^3/s (29%) and 1818 m^3/s (19%) for MF; and 1148 m^3/s (34%) and 1915 m^3/s (25%) for FF. Similarly, the variations with baseline were between 1043 m^3/s (22%) and 1745 m^3/s (14%) for NF; 1187 m^3/s (39%) and 2070 (37%) for MF; and 1483 m^3/s (73%) and 2477 m^3/s (62%) for FF in the case of RCP 8.5. Contrary to the individual series, change percentages of ensemble series are found to be lower in higher return periods to baseline values.

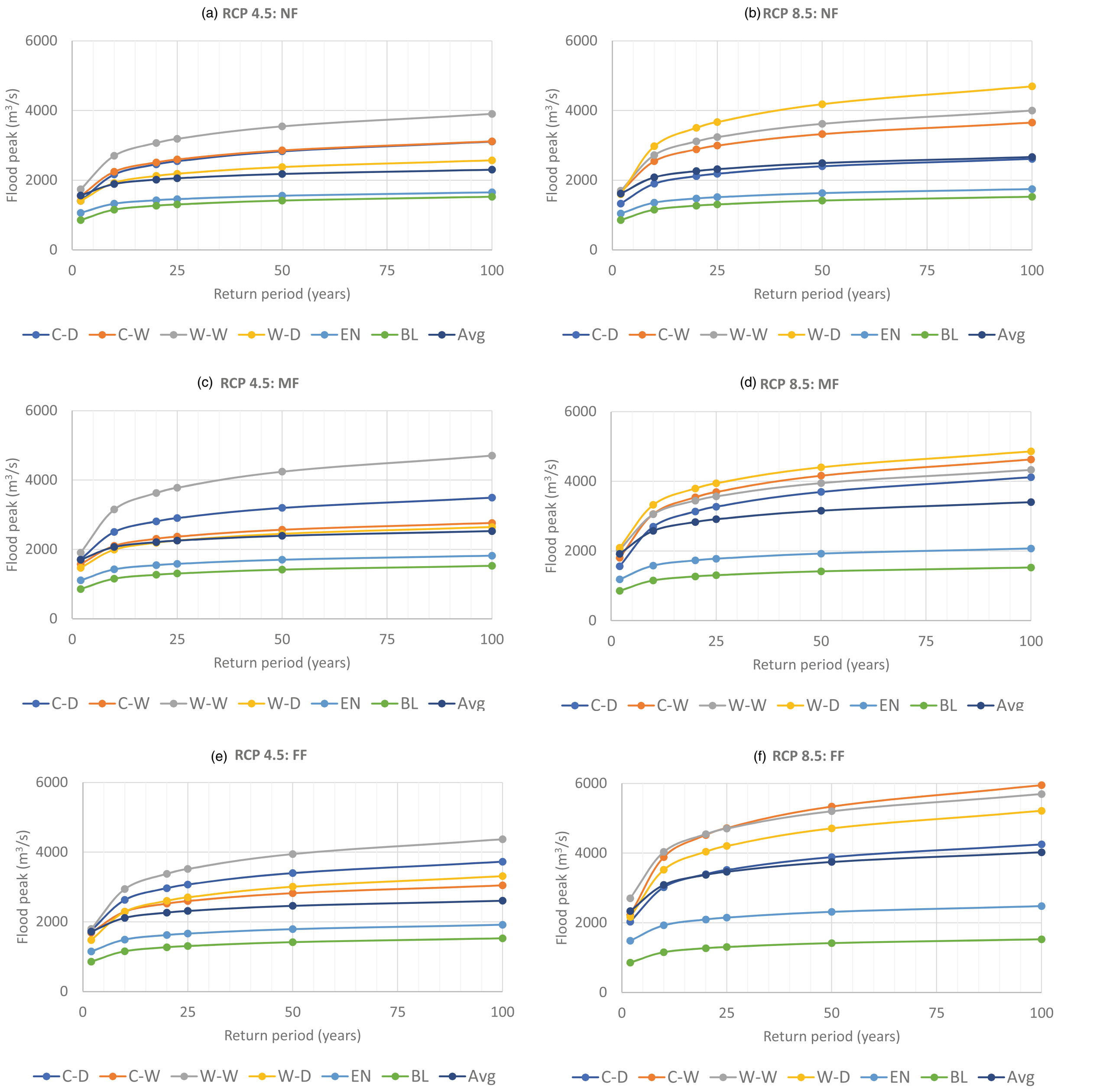


FIGURE 3 Floods of various return periods for the baseline and future climatic conditions. (Avg, average; BL, Baseline; C-D, cold-dry; C-W, cold-wet; EN, Ensemble; FF, Far Future; MF, Mid Future; NF, Near Future; W-W, warm-wet and W-D, warm-dry.)

Similar patterns of increasing future floods were reported by recent studies. For example, two studies in China quantified changes in future flood magnitude varying from −3% to 42% (Yin et al., 2018) and in the range of 22%–117% by 2099 compared to the baseline due to CC (Zhang et al., 2021). Try et al. (2022) projected the future flood peaks to increase by 10%–54% in the Mekong Region with larger variations in the far future and higher emission climate scenarios. Another study considering an ensemble of 30 RCMs mentioned that there is not much variation in the predicted flood peaks of West African rivers in the mid-century period as a result of CC (Stanzel et al., 2018). Hosseinzadehtalaei et al. (2021) estimated an increase of 16%–84% in the flood volumes in a Belgian city in the future due to CC. Hence, we infer from these studies that a qualitative increase can be predicted in the flood magnitudes with time, but the quantitative measures across the study areas are different which are attributed to their respective geographical locations and basin characteristics.

Flood magnitudes of RCP 8.5 are higher than RCP 4.5 in most cases (Figure 3). The difference in the predicted floods with respect to the baseline is more for RCP 8.5 than for RCP 4.5. This difference is found to increase with increasing return period. For example, for the RCP 4.5/NF/W-W case, the difference is 134% for a 10-years flood and 156% for a 100-years flood. Additionally, the floods of RCP 8.5 are higher than RCP 4.5 in all the cases (four climatic conditions, their ensemble, and three time windows) except for C-D of NF and W-W of MF. The difference in the flood magnitudes between RCP 4.5 and 8.5 varies from as low as −46% (C-D; 100 years) to as high as +67% (W-D; 100 years). These values are in good agreement with a past study on the Budhigandaki Basin in which flood frequency analysis was carried out for extreme floods due to CC (Marahatta, Devkota, & Aryal, 2021). Although the flood magnitudes can be expected to increase in the future relative to the baseline conditions, no distinct trend or pattern over time can be generalized. These predictions are quite similar to those made in other previous global (Hosseinzadehtalaei et al., 2021; Mori et al., 2021), regional (Kay et al., 2021; Mohanty and Simonovic, 2021; Wobus et al., 2021) and local studies (Devkota & Maraseni, 2018; Kumar et al., 2022; Mahato et al., 2021; Meema et al., 2021; Tabari et al., 2021).

Flood magnitude of a given return period (estimated using Gumbel distribution) is a function of average and standard deviation of the considered flood series and the reduced variate, which in turn is a function of the return period (Appendix A). Furthermore, the numerical value of the reduced variate increases with the return period. The higher (lower) the mean value of the series, the more (less) is the starting flood value, in our case 2-year return period flood (Q_2) for that series. The standard deviation of the data series impacts the rate of increase, that is, the higher (lower) the standard deviation, the steeper (gentler) is the rate of increase in flood values with subsequent return periods. Therefore, the future floods are larger than baseline for all return periods because the mean and standard deviation of all the future flows are greater than those of the baseline series (Table 2).

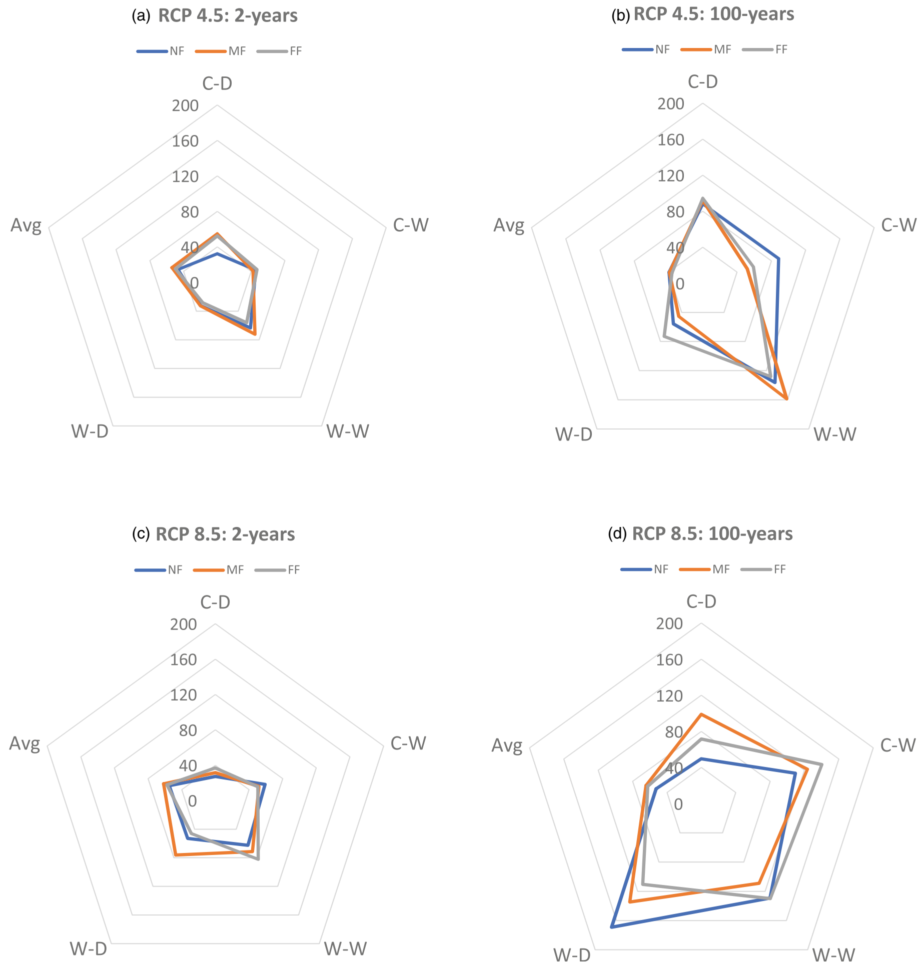
3.3 | Implications of using ensemble series on future flood estimation

The percentage change (degree of impact) in flood magnitudes corresponding to the different climatic conditions with respect to those estimated from the "Ensemble" series for two return periods (2-years and 100-years as samples) are presented in Figure 4. It can be seen that predicted floods under all the individual climatic conditions are larger than those of the "Ensemble" for all the considered (two RCPs, six return periods, three time windows, and five climatic conditions) cases. Twenty cases have been shown in Figure 4 as samples for the purpose of illustration and discussion. The differences are generally the highest for W-W for all future periods and in both RCPs. They are in the range of 63%–136% for NF, 72%–159% for MF, and 56%–128% for FF in the case of RCP 4.5. These values range from 63%–130% for NF, 71%–109% for MF, and 82%–130% for FF in the case of RCP 8.5. In RCP 4.5, the minimum difference with respect to the "Ensemble" is seen in the W-D scenario for 2-years and NF and MF of 100-years case and in the C-W scenario of FF. However, the minimum difference in the flood magnitudes with respect to the "Ensemble" is in C-D for almost all the scenarios of RCP 8.5. The difference of the predicted floods of each climate scenario and the "Ensemble" is found increasing with the return period. For example, in the case of RCP 4.5/W-W/NF, the difference is 63% for a 2-years return period flood while it is 136% for a 100-years flood. Furthermore, the floods of RCP 8.5 are higher than corresponding floods of RCP 4.5 in 20 out of the 30 cases (mostly in C-W, W-D, and Avg for all time windows). The remaining 10 cases were contrary to general expectation.

We would like to note here that our study makes use of the flow data (individual climate model and ensemble) that was generated by a previous study (Marahatta, Aryal, et al., 2021; Marahatta, Devkota, & Aryal, 2021). Marahatta, Aryal, et al. (2021) and Marahatta, Devkota, & Aryal, (2021) carried out a rigorous selection procedure to select four extreme GCMs each for RCP 4.5 and RCP 8.5. It can be seen from their results that the precipitation as well as corresponding 1-day maximum flows are higher in RCP 8.5 than RCP 4.5 in most scenarios with some exceptions. Interestingly, other studies such as Jose et al. (2016) mentioned that RCP 4.5 future climate projections increase the precipitation while RCP 8.5 tends to reduce the precipitation in some European cities. Similarly, taking the case of a Spanish basin, Pellicer-Martinez and Martinez-Paz (2018) mention a 70% and 79% reduction in flows (compared to the baseline) for RCP 4.5 and 8.5 scenarios, respectively. These exceptions could most probably be due to the inherent assumptions of the GCMs, their boundary conditions as well as the choice of bias correction parameters. These could be areas of further research.

"Ensemble" daily flows are calculated by taking the arithmetic mean of the flows of a particular day of the considered (four) GCMs for each RCP. These values turn out to be smaller than those of the individual climatic series. This is because the annual maximum peak daily flow occurring on a particular day of one (climatic condition which is denoted by a GCM) series gets lowered by the non-maximum annual values of the other scenarios of the same day while calculating the ensemble series. Let us take two examples:

FIGURE 4 Degree of impact on flood magnitudes (percentage change) of the individual climate scenarios with respect to ensemble values (Avg, average; C-D, *cold-dry*; C-W, *cold-wet*; EN, Ensemble; FF, Far Future; MF, Mid Future; NF, Near Future; W-W, *warm-wet*; W-D, *warm-dry*).



i. The maximum of the "Ensemble" of RCP 4.5 in 2021 (806 m^3/s) occurred on 30th August. The flows of the same day for *cold-dry*, *cold-wet*, *warm-wet*, and *warm-dry* scenarios are respectively 403, 606, 1227, and 989 m^3/s. The maximum flows of these scenarios respectively occurred on 2 August (953 m^3/s), 17 August (1022 m^3/s), 18 August (1339 m^3/s), and 6 September (1310 m^3/s).
ii. Another example is of 6 September in which the maximum flow (1310 m^3/s) was for the *warm-dry* scenario. However, on the same day, flows of the other three scenarios were 394 (*cold-dry*), 708 (*cold-wet*), and 666 m^3/s (*warm-dry*) resulting in to an ensembled value of 770 m^3/s.

Such occurrences of maximum floods in different days for the climate scenarios led to the maximum of the "Ensemble" data being lower than the minimum of the individual scenarios. If the maximum flood peaks of all the climate scenarios would occur on the same day, the average would be somewhere in between those estimated by the individual scenarios. In this sense, our results are comparable to some previous studies which pointed out the implication of such averaging as substantial smoothening of the flood wave with the severe underestimation of the computed design floods (Bhagat, 2017; Ding et al., 2015; Ding et al., 2016; Fangmann & Haberlandt, 2021; Samantaray & Sahoo, 2020).

Furthermore, such smoothening results into less scattering of the data about the mean in the "Ensemble" series which lowers the standard deviation (see Appendix A). This is the reason why the "Ensemble" mean and standard deviation throughout the future are lower than those of the maximum floods of the four individual climatic series. As a result, floods of any given return period estimated using ensembled series are highly underestimated compared to those for the individual climatic conditions. Therefore, the results and explanation given above clearly indicate that ensemble series should not be used for flood estimation.

3.4 | Plausibility of using average series on future flood estimation

Percentage change in the magnitude of mean and standard deviation values of the "Average" scenario with respect to the "Ensemble" scenario for the different scenarios are given in Appendix A (Figure A1). The mean and the standard deviation are expected to increase within 46%–53% and 16%–26%, respectively, for RCP4.5, and 55%–62% and 50%–70%, respectively, for RCP8.5. These statistics clearly show that considering the "Average" instead of the "Ensemble" leads to a significant increase in the estimated future flood peaks (Figures 3 and 4). Hence, designers should consider at the least the "Average" series instead of the "Ensemble" series while designing climate-resilient flood structures. However, the level of uncertainty associated with the adopted flood values should be reported to the decision makers as floods estimated using the "Average" series are still lesser in magnitude than the individual series.

3.5 | Impacts on the timing of occurrence of peak floods

The timing of occurrence of the maximum annual peak flows derived from daily data for the baseline and future climatic conditions over the years until the end of this century is plotted in Figure 5. In the baseline, the annual maximum flows generally (> 80% of the time) occur in the monsoon season (mostly in July and August). In the case of "Ensemble" series too, 68 out of 90 occurrences in RCP 4.5 and 72 out of 90 occurrences in RCP 8.5 were found to be in July and August. However, in the other projected CC cases, flood peaks are expected to occur in other months of the year except in December, January, and February. Nevertheless, most of the flood peaks are concentrated in the monsoon season. In two climatic scenarios (*cold-dry* and *warm-wet*), there is a possibility of such flows occurring in September for both RCPs. Magnitudes of the annual peaks and their number of occurrences under RCP 4.5 and RCP 8.5 were surprisingly similar (Figure 5).

Thus, it can be inferred that the occurrence of high floods in the future is likely to be spread out over the year. Furthermore, density of occurrence of such annual floods is most likely to shift forwards even within the monsoon season (July–August in the baseline to August–September in the future). Lutz, ter Maat, et al. (2016) also project a seasonal shift in the river hydrology due to CC in the future in the Hindu Kush Himalayan region. Therefore, flood management based on future ensemble data is likely to face temporal risks, especially in developing countries where early warning systems, disaster preparedness, and response are not as effective as in the developed countries. This has direct implications on the availability and needful mobilization of financial resources, expertise, technology, and tools for effective flood management. Year-round operational flood early warning systems instead of monsoon-based ones (e.g., operated by DHM in Nepal) could play essential roles in flood risks management in the future.

With many proposed hydropower projects, Nepal could benefit through construction of multi-purpose storage-type projects that could act as flood cushions (Baniya et al., 2023; Bhattarai et al., 2023). More importantly, long-term projections are very important to inform multi-million dollar investments in large water resource development projects which take decades to construct and are expected to last for at least a century. These project developers and decision-makers should be made aware of the level of stress associated with the climate (and flood) extremes during the study phases of the projects. This enables them to take effective decisions on the degree of risk that the project is ready to adapt to during its functional lifetime.

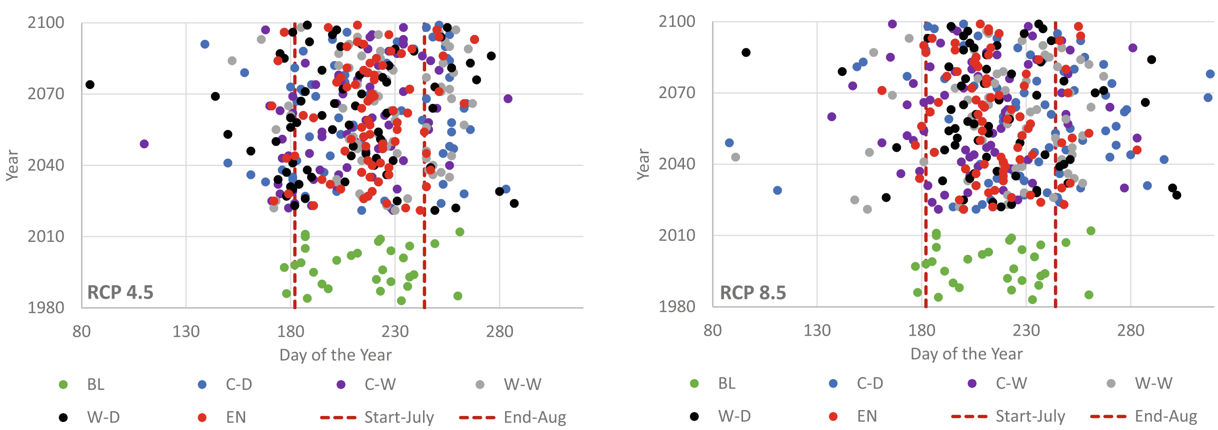


FIGURE 5 The occurrence of maximum annual peak flow in the baseline and different climate change conditions (Avg, average; BL, baseline; C-D, *cold-dry*; C-W, *cold-wet*; EN, ensemble; FF, far future; MF, mid future; NF, near future; W-W, *warm-wet*; W-D, *warm-dry*).

4 | CONCLUSION

This study aims to examine the plausibility and implications of using flows generated from individual climate scenarios versus their ensembles to estimate peak floods in the face of CC. Baseline period was fixed from 1983 to 2012 while the future was divided into three time windows (Near Future, Mid Future, and Far Future) each spanning 30 years, until the end of this century (2021–2099). Four climatic conditions (C-D: *cold-dry*, C-W: *cold-wet*, W-D: *warm-dry*, and W-W: *warm-wet*) for the Budhigandaki River Basin of Nepal and their corresponding simulated flows at the BGHP dam site were considered. The analysis was carried out for two RCPs, 4.5: stabilization scenario and 8.5: high emission scenario for each future time window.

Our findings suggest that flood magnitudes of all the considered scenarios are projected to be larger than the baseline for all return periods. However, floods predicted using ensembled data are closer to the baseline values. Additionally, the "Ensemble" values for both RCPs are lower than the respective "Average" of the maximum floods of the four climatic conditions. Future floods under all climatic extremes are expected to be larger than those obtained using the respective ensembles. Because of averaging of the mean and standard deviation, the floods of different return periods estimated using ensemble series are likely to be highly underestimated. The magnitudes of the floods are such that those estimated using "Ensemble" < "Average" < individual series. Furthermore, it was seen that the occurrences of flood peaks are likely to be confined within the monsoon season considering the "Ensemble" series while they can be expected to be spread out also in the other months for the individual climate scenarios. Even within the monsoon, the timing of occurrence of annual floods is most likely to shift forwards from July–August to August–September in the future. This could have direct implications on the availability and mobilization of resources as well as the need for a year-round operational early warning system for flood risk management.

It can be concluded that floods of any given return period estimated using ensembled series are highly underestimated compared to those for the individual climatic conditions. Thus, our results clearly indicate that ensemble series should not be used for flood estimation. Additionally, "Average" series are still lesser in magnitude than the individual series. Moreover, the approach of using ensembled or average values for assessing future CC-induced floods is misleading. Rather, flows (and floods) generated using individual climate models are more representative of plausible future flood scenarios. Therefore, designers should consider at the least the "Average" series instead of the "Ensemble" series while designing climate-resilient flood structures. However, the level of uncertainty associated with the adopted flood values should be reported to the decision-makers. Flood management based on ensemble data is risky in terms of its occurrence, especially in underdeveloped countries that require robust and year-round flood early warning systems in place.

Assessing the practicalities and economic implications of the adopted design flood values under changing climate considering a large number of plausible climate scenarios could be a continuation of this research. Analogous to this study, the impact of ensembled data on low-flows could be areas for further exploration to have a broader understanding of the impacts of CC on the overall hydrology. Additionally, carrying out a similar assessment with the recently available CMIP6 climate datasets for the study basin using appropriate GCMs and shared socioeconomic pathways (SSPs) could be other avenues of future research.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

As per the requirement and on request we have to issue to send data.

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APPENDIX A

Flood of T year return (Q_T) can be expressed as

$$Q_T = \overline{Q} + K_T.S,$$

where $\overline{Q}$ = Average of the instantaneous flood data. S = Standard deviation of the flood data. K_T = Frequency factor.

For Gumbel distribution, K_T is defined as

$$K_T = \frac{y_T - y_n}{s_n}$$

y_n and s_n are correction factors which depends on the sample size (Subramanyam, ...).

Here, y_T is a reduced variates corresponding as a return period, T, as:

$$y_T = -\ln\left[\ln\left(\frac{T}{T-1}\right)\right].$$

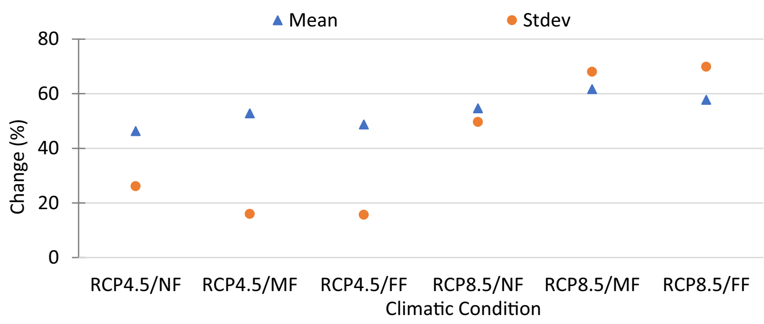

FIGURE A1 Percentage change in the magnitude of mean and standard deviation of the "Average" scenario with respective to the "Ensemble" scenario for the different climatic conditions.