Future Changes in Precipitation Over Northern Europe Based on a Multi-model Ensemble From CMIP6: Focus on Tana River Basin

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2 **ensemble from CMIP6: Focus on Tana River Basin**

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Abstract

Accurate climate predictions help policymakers mitigate the negative effects of climate change and prioritize environmental issues based on scientific evidence. These predictions rely heavily on the outputs of GCMs (General Circulation Models), but the large number of GCMs and their different outputs in each region confuses researchers in their selection. In this paper, we analyzed the performance of a CMIP6 (Climate Model Intercomparison Project Phase 6) multi-model ensemble for precipitation data over Northern Europe. We first evaluated the overall performance of 12 CMIP6 models from GCMs in thirty years of 1985-2014. In addition, future projections were analyzed between 2071 and 2100 using SSP1-2.6 and SSP5-8.5 (Shared Socioeconomic Pathways). Then, simulations were statistically improved using an ensemble method to correct the systematic error of the CMIP6 models and then the capacity of postprocessed data to reproduce historical trends of climate events was investigated. Finally, the possible spatio-temporal changes of future precipitation data were explored in Tana River Basin. The results of this study show that different CMIP6 models do not have the same accuracy in estimating precipitation in the study area. However, the ensemble method can be effective in increasing the accuracy of the predictions. In addition, this study projected a change in the monthly precipitation data over Tana River Basin by 2.46% and 2.06% from 2071 to 2100 compared to the historical period, based on SSP1-2.6 and SSP5-8.5, respectively.

Keywords: climate change; CMIP6; multi-model ensemble; Northern Europe; precipitation; Tana basin.

1 Introduction

Climate is changing in the Arctic and northern lands twice as fast as in other areas on the Earth (Anisimov et al., 2007; Cohen et al., 2014). Although the effects of climate change have been investigated previously in different Arctic areas (e.g., Jylhä et al., 2009; Callaghan et al., 2010; Olsson et al., 2015; Ashraf et al., 2016; Pascual et al., 2021), recently, research has shown that ecosystem responses to climate change vary among these regions (Danby and Hik, 2007; Callaghan et al., 2011; Van Bogaert et al., 2011; Elmendorf et al., 2012; Callaghan et al., 2013; Kivinen et al., 2017). However, less emphasis has been given to the possible changes in local Sub-Arctic areas than the broader pan-Arctic scale.

GCMs (General Circulation Models, also called Global Climate Models) are commonly employed to simulate climate behavior (Hwang and Graham, 2013; Rupp et al., 2013). These models simulate and predict the climatic data across the entire planet (Su et al., 2013). Due to differences in various GCMs structure, assumptions, parametrization, the applied procedures for the calibration processes, etc., their predictions differ from place to place and time to time (Kay et al., 2009; Kumar et al., 2013; Khan et al., 2018). As a result, performance evaluation of different GCMs has been emphasized as a precondition for any climatic research (e.g., Purich et al., 2013; Miao et al., 2014; Ahmadalipour et al., 2015; Gulizia and Camilloni, 2015; Moise et al., 2015; Lovino et al., 2018; Raghavan et al., 2018; Zazulie et al., 2018; Rivera and Arnould, 2019). To evaluate GCMs, the IPCC (Intergovernmental Panel on Climate Change) has published six ARs (Assessment Reports). These include six models named FAR (First AR), SAR (Second AR), TAR (Third AR), CMIP3 (Climate Model Intercomparison Project Phase 3, AR4) (Das et al., 2012; Zhou et al., 2014), CMP5 (AR5), and CMIP6 (AR6) (Stouffer et al., 2017). However, recent studies have shown that the CMIP6 models can better predict climatic parameters than others (e.g., Gusain et al., 2020). In addition, projections of all of the mentioned models can be post-processed, representing the local scales better. Furthermore, Ensemble methods (improving techniques) combine multiple models to produce improved results. Finally, the multi-source methods take advantage of different models by reducing the impacts of systematic biases, errors, and the sensitivity to the factors which decrease the accuracy of estimations (Todini, 2001; Tebaldi and Knutti, 2007; Heidinger et al., 2012; Bishop and Abramowitz, 2013; Kim et al., 2020; Zhai et al., 2020).

In this paper, we analyzed the performance of a CMIP6 multi-model ensemble for precipitation data over Northern Europe. We evaluated the overall performance of different CMIP6 models; future projections (up to 2100) were analyzed using SSP1-2.6 and SSP5-8.5 (Shared Socioeconomic Pathways), simulations were statistically improved and the capacity of postprocessed data to reproduce historical trends of climate events was investigated, and finally, the possible spatiotemporal changes of future precipitation were explored in Tana River Basin.

2 Materials and methods

2.1. Study Area

Based on the classification devised by the United Nations geoscheme, Northern Europe covers the area between the latitudes 50° and 75° and the longitudes -25° and 35° including Denmark, Estonia, Finland, Iceland, Ireland, Latvia, Lithuania, Norway, Sweden and United Kingdom (UNSD, 2019) with various climates consisting from Subarctic to Humid continental. The present study was performed in Northern Europe, focusing on the Tana River Basin (Figure 1). The basin (16,389 km²) is situated in the middle parts of Finnmark in Norway (69%) and the northern parts of Lapland (31%) in Finland). Previous studies have

indicated that the Sub-Arctic and Arctic regions, such as the Tana basin, are expected to be more influenced by climate change (e.g., IPCC 2007; Lotsari et al., 2010).

Figure 1. Study area: (A) Northern Europe (B) Tana River Basin

2.2. Data and Methodology

Precipitation simulations were gathered from the runs of 12 GCMs from CMIP6 ensemble (Table 1). The CMIP6 simulated data were evaluated against the GPCC (Global Precipitation Climatology Centre; Schneider et al., 2018) data on a 1° resolution. The assessment and projection presented in this study are based on historical monthly precipitation data from 1985 to 2014 and future outputs data from 2071 to 2100 under the SSP1-2.6 and SSP5-8.5 scenarios. For this purpose, based on the performance of the models in the baseline period, an ensemble method was employed and then the main focus of the paper is on the effects of climate change across Tana River Basin. In the following, an overview of the proposed method is elaborated.

Table 1. List of the analyzed CMIP6 models in this paper

Model	Institute	Horizontal resolution	Ensemble members
BCC-CSM2-MR	Beijing Climate Center, China Meteorological Administration, China	$1.125^\circ \times 1.125^\circ$	3
CanESM5	Canadian Centre for Climate Modelling and Analysis, Canada	$2.81^\circ \times 2.81^\circ$	50
CESM2	National Center for Atmospheric Research, USA	$1.25^\circ \times 0.94^\circ$	3
CNRM-CM6-1	National Center of Meteorological Research, France	$1.4^\circ \times 1.4^\circ$	10
FGOALS-g3	Institute of Atmospheric Physics, China	$2^\circ \times 2^\circ$	3
GFDL-ESM4	Geophysical Fluid Dynamics Laboratory, USA	$1.25^\circ \times 1^\circ$	1
GISS-E2-1	Goddard Institute for Space Studies, USA	$2.5^\circ \times 2^\circ$	5
HadGEM3-GC31-LL	Met Office Hadley Centre, UK	$1.88^\circ \times 1.25^\circ$	4
IPSL-CM6A-LR	Institute Pierre Simon Laplace, France	$2.5^\circ \times 1.25^\circ$	10

MIROC6	Japan Agency for Marine-Earth Science and Technology, Japan	1.4°×1.4°	3
MRI-ESM2-0	Meteorological Research Institute, Japan	1.125°×1.125°	2
NorESM2-LM	Norwegian Climate Service Centre, Norway	2.5°×1.9°	3

First, to evaluate and predict the effects of climate change on precipitation in Northern Europe, different metrics were used in this study including: (1) bias which describes the error, (2) correlation coefficient (CC) which describes the collinearity between observational data and the estimations, (3) mean, (4) mean absolute error (MAE) describing the average magnitude of the estimation errors, (5) mean error (ME), (6) median, (7) centered root mean square difference (RMSD) and (8) root mean squared error (RMSE) which present the errors and (9) standard deviation (StD) which is proportional to the radial distance from the origin (e.g., Duan et al., 2016; Moradian and Yazdandoost, 2021).

Then, to improve the climate predictions, an ensemble method was employed. Recent studies have shown that ensemble averaged data generally offer better predictions than individual models do (Becker et al., 2014; Ma et al., 2015; Madadgar et al., 2016; Rahmani-Rezaeieh et al., 2020; Sajedi Hosseini et al., 2020; Sheikh Khozani et al., 2020; Danandeh Mehr, 2021). The employed technique combines multiple models to produce improved results, originating from the idea that when the dispersion of a model simulations increases, that model becomes more important (Shannon and Weaver, 1947; Hwang and Yoon, 1981). Let the matrix contains m alternatives of CMIP6 models and n objectives of precipitation events in each 1° cell (m×n elements):

$$\text{Matrix} = \begin{bmatrix} \text{Pr}_{11} & \text{Pr}_{12} & \dots & \text{Pr}_{1n} \\ \text{Pr}_{21} & \text{Pr}_{22} & \dots & \text{Pr}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \text{Pr}_{m1} & \text{Pr}_{m2} & \dots & \text{Pr}_{mn} \end{bmatrix} \quad (1)$$

In this matrix, Pr_{ij} represents the performance of alternative i (the CMIP6 model) for objective j (monthly precipitation data from 1985 to 2014). The degree of diversification d_j of the information provided by the outcomes of objectives j can be defined as:

$$d_j = 1 + \frac{1}{\ln(m)} \times \sum_{i=1}^m P_{ij} \cdot \ln(P_{ij}) \quad (2)$$

Where P_{ij} is the normalized Pr_{ij} :

$$P_{ij} = \frac{\text{Pr}_{ij}}{\sum_{i=1}^m \text{Pr}_{ij}} \therefore \sum_{i=1}^m P_{ij} = 1 \quad (3)$$

And the final weights are obtained as follows:

$$\text{Weight}_j = \frac{d_j}{\sum_{j=1}^n d_j} \therefore \sum_{j=1}^n \text{Weight}_j = 1 \quad (4)$$

In the final step, the performance of the proposed method was analyzed and a detailed assessment of the effects of climate change on precipitation was done over Tana River Basin based on the proposed technique.

3 Results and discussion

In the first step, monthly area-averaged precipitation data of the analyzed CMIP6 models were plotted verses observational data in different Violin plots (Figure 2). The plots depict the groups of simulated precipitation data through their quartiles and the spacings between different parts of the plots indicate the degree of dispersion in the data (Thrun et al., 2020). The plots also show the probability density of the data at different values, smoothed by a Kernel density function (Rosenblatt, 1956; Parzen, 1962; Hintze and Nelson, 1998). As the figure indicates, all CMIP6 models show some level of underestimation; however, the findings illustrate substantial inter-model variability over the studied area. These results are consistent with what the research of Yazdandoost et al. (2021) has shown. In evaluating the CMIP6 models, they also found that these models have the highest evaluation error in areas with heavy rainfall.

Figure 2. Violin plots of monthly area-averaged precipitation (mm) of the analyzed CMIP6 models verses observational data (1985-2014)

Figure 3 offers a more quantitative way of the climate model errors by showing the Taylor diagram of CMIP6 precipitation estimations against in situ observational data, using the CC along with the RMSD and StD (Taylor, 2001). This figure clearly shows that none of the CMIP6 models can reproduce the precipitation pattern apparent in the observed data. Results from this figure, along with previous studies (e.g., Rivera and Arnould, 2019; Gusain et al., 2020), emphasize the need for post-processing the CMIP6 outputs before any further analysis.

Figure 3. Taylor diagram of CMIP6 precipitation simulations against observations (1985-2014)

Since the study area has a diverse climate with a wide range of precipitation values, obtaining information on the estimated precipitation and observational values throughout it is a step of the evaluation process. In order to capture the spatial precipitation patterns, Figure 4 shows the distribution maps of monthly ME over the study area during the historical period. This figure indicates that all the CMIP6 models capture a similar spatial precipitation pattern and none of them have been able to estimate the patterns. Most of the models have underestimated the amount of coastal rainfall in Norway. In addition, they have overestimated the data in the United Kingdom. In general, HadGEM3-GC31-LL and MRI-ESM2-0 have been more successful in estimating the rainfalls. The findings illustrated that the outputs of the 12 CMIP6 models exhibited less systematic error in Finland, Sweden, and the eastern parts.

Figure 4. Spatial distribution maps of monthly ME and the area-averaged data (mm) over Northern Europe (1985-2014)

Figure 5 further shows the future precipitation change to the observed ratio (P/P_{obs}) versus the future change to the historical ratio (P/P_{his}) for the historical period of 1985-2014 and future period of 2071-2100. According to this figure, the blue dots representing the historical data should be on the bisector axis, which indicates that the mean of the observed observational data is close to the modeling. Among the models, the GFDL-ESM4 model and later the HadGEM3-GC31-LL and GISS-E2-1-G have this characteristic. In addition, among these models, BCC-CSM2-MR and later CanESM5, CNRM-CM6-1, and FGOALS-g3 show the most changes in future precipitation based on SSP1-2.6 and SSP5-8.5. Furthermore, this figure shows that the FGOALS-g3 model has the worst performance according to these criteria.

Figure 5. Future precipitation changes to the observed ratio (P/P_{Obs}) plotted against the future change to the historical ratio (P/P_{His}). This figure is inspired by Moshir Panahi et al. (2020)

As CMIP6 simulations are not forced with all of the historical climatic and oceanic boundary conditions and are not expected to simulate observational data at high spatio-temporal scales, assessments are usually performed over a large spatial domain averaged over a long-term period. Figure 6 shows time series of spatially averaged monthly precipitation data over the whole study area. The figure indicates that some models do capture the general climatology and some exhibit substantial differences in the future relative to the historical data (i.e., BCC-CSM2-MR, CanESM5, GISS-E2-1-G, HadGEM3-GC31-LL, and IPSL-CM6A-LR).

Figure 6. Time series of spatially averaged monthly precipitation data in the historical and prediction periods

Figure 7 shows the difference between the modeled precipitation values for the SSP1-2.6 and SSP5-8.5 relative to the historical periods of the models. This figure and recall from Figure 5, CESM2, GFDL-ESM4, MIROC6, MRI-ESM2-0, and NorESM2-LM have predicted a decrease in precipitation between 2071 and 2100 for the SSP1-2.6 scenario.

Figure 7. Stem plot of the modeled precipitation values for SSP1-2.6 and SSP5-8.5 relative to the historical periods of the models

While bias is a major issue, Figure 8 depicts groups of bias data through their quartiles in Box plots. The plots also have outliers as individual points, indicating variability outside the upper and lower quartiles. The figure indicates that in term of Bias, CESM2, FGOALS-g3, MIROC6 and NorESM2-LM seem best to capture the variability of precipitation during the study period. However, it is necessary to perform the bias correction methods to reduce the uncertainties. Also, Figure 9 illustrates the monthly Bar chart of MAE for the historical and prediction periods. The figure reveals that based on MAE, compared to the other CMIP6 models, MIROC6 and CNRM-CM6-1 performed better during the study period.

Figure 8. Monthly Box plots of Bias for the historical (1985-2014) and prediction (2071-2100) periods

Figure 9. Monthly Bar chart of MAE (mm) for the historical (1985-2014) and prediction (2071-2100) periods

Concerning Figure 2-9, results showed that none of the employed raw CMIP6 models had provided accurate magnitudes of precipitation compared to the observations. Results from these figures, along with previous studies (e.g., Purich et al., 2013; Gulizia and Camilloni, 2015; Lovino et al., 2018; Rivera and Arnould, 2019; Gusain et al., 2020; Yazdandoost et al., 2021), highlight the need for post-processing the CMIP6 outputs. So, in this study, an ensemble method was employed to improve the climate predictions.

Table 2 summarizes the results for forecast verification of the CMIP6 models against the data derived from the proposed ensemble method. It evaluates the models based on the Bias, CC, MAE, ME, RMSE and StD. In this table, the top three models according to the evaluation criteria were shown in bold. As expected, the merged model never performed the worst in the study area and has been among the best models in Bias, CC, MAE, RMSE, and StD. Results are consistent with previous studies, using different ensemble techniques (e.g., Hargreaves et al., 2007; Donat et al., 2010; Sanderson et al., 2015; Kumar et al., 2021); but employing the utilized method is simple, rational, comprehensible and efficient. Therefore, it can be claimed that the proposed method can provide high accuracy in precipitation forecasts as it corrects the drawbacks and enhances the advantages of individual sources for each 1° cell.

Table 2. Results of the evaluation of the employed ensemble method during the historical period (1985-2014)

Model	Bias	CC	MAE	ME	RMSE	StD
BCC-CSM2-MR	-0.31	0.06	39.76	-28.43	51.52	15.62
CanESM5	0.05	0.25	35.87	-5.46	45.68	18.96

CESM2	0.02	0.15	38.28	-4.39	48.89	23.27
CNRM-CM6-1	-0.10	0.12	36.64	-14.46	47.03	15.55
FGOALS-g3	-0.20	0.02	38.90	-20.96	50.10	17.38
GFDL-ESM4	0.15	0.16	42.49	-0.01	54.71	33.37
GISS-E2-1	0.12	0.20	37.91	-1.37	47.69	19.87
HadGEM3-GC31-LL	0.13	0.14	40.09	1.25	50.63	24.11
IPSL-CM6A-LR	-0.01	0.12	38.50	-8.32	48.91	17.11
MIROC6	0.03	0.14	37.60	-5.64	48.06	23.62
MRI-ESM2-0	0.20	0.17	41.70	3.61	52.96	28.83
NorESM2-LM	0.05	0.10	37.48	-3.73	47.74	21.22
The proposed model	0.02	0.22	35.15	-6.76	44.76	15.12

199

200 In the final step, a detailed assessment of the effects of climate change on precipitation was done over
201 Northern Europe and the Tana River Basin based on the proposed technique. Since the study area has a
202 wide range of precipitation variability, we first focused on capturing the spatial variability of precipitation.
203 Figure 10 shows the distribution maps of monthly precipitation derived from the proposed ensemble method
204 during the historical and prediction periods over Northern Europe and the Tana River Basin. The model
205 can simulate precipitation in regions receiving substantial precipitation (e.g., Ireland and the United
206 Kingdom). We note that the model captures relatively high rainfall changes over the study area between
207 2071 and 2100 compared to the baseline period. This figure indicates that the Tana River Basin is also
208 sensitive to climate change. Overall, this study projected a change of the monthly precipitation in the Tana
209 River Basin by 2.46% and 2.06% from 2071 to 2100 compared to the historical period of 1985-2014 based
210 on SSP1-2.6 and SSP5-8.5, respectively.

Figure 10. Distribution maps of monthly precipitation, derived from the employed ensemble method during the historical (1985-2014) and prediction (2071-2100) periods over Northern Europe and the Tana River Basin

Figure 11 depicts the Scatter plots of monthly precipitation data, derived from the employed ensemble method during the historical and prediction periods over the Tana River Basin. This figure clearly shows that the presented model is suitable for precipitation simulation with values close to the mean values (40~60 mm). However, it cannot estimate the amounts of extreme precipitation events during the historical period. This indicates that although the proposed method has improved the accuracy of the predictions, using the raw CMIP6 data for any applications without bias correction may lead to unreasonable results. Furthermore, from 2071 to 2100, more extreme precipitation events will occur over the basin based on SSP1-2.6 and SSP5-8.5.

Figure 11. Scatter plot of monthly precipitation (mm), derived from the employed ensemble method during the historical (1985-2014) and prediction (2071-2100) periods over Tana River Basin

Figure 12 evaluates the changes in an extreme climate, the situation that the average condition of the weather event is severe (IPCC, 2007; Planton et al., 2008). According to the figure, extreme precipitation events will frequently occur from 2071 to 2100 over the Tana River Basin, based on SSP1-2.6 and SSP5-8.5 (see the tails of the distributions). Projected precipitation data of the hybrid method reveals that the monthly mean precipitation is expected to increase from 54.94 mm during 1985-2014 to 56.29 and 56.07 mm in 2071-2100 based on SSP1-2.6 and SSP5-8.5, respectively. Results are consistent with the report of the IPCC (2014). It also showed an impact from recent climate-related extremes, such as cyclones, droughts, floods, heat waves, etc; however, the it suggested that combinations with extreme weather patterns will increase and as a consequence, the combined effects of these extreme events will be more serious than the effects of individual events (Kaewunruen et al., 2018).

Figure 12. Gamma distribution of monthly precipitation, derived from the employed ensemble method during the historical (1985-2014) and prediction (2071-2100) periods over Tana River Basin

4 Conclusion

In this study, the effects of climate change on precipitation in Northern Europe were evaluated by employing 12 CMIP6 models from GCMs from 2071 to 2100 based on the baseline period 1980-2014 using SSP1-2.6 SSP5-8.5. For this purpose, based on the performance of the utilized CMIP6 models in the historical period, an ensemble method was presented to correct the systematic error of the models. Then, the effects of climate change over the Tana Basin were investigated using the obtained data from the proposed method. Results showed that different CMIP6 models do not have the same accuracy in estimating precipitation in the study area. However, the proposed ensemble method can be appropriate in increasing the accuracy of the predictions.

The proposed approach for developing a merged precipitation model can be further strengthened and extended from different aspects. For example, in this study, weighting process was done based on the values of precipitation data but sensitivity analysis can be done to evaluate other possible parameters such statistical and categorical metrics, etc to improve the efficiency of the proposed algorithm.

Declarations

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Conflicts of interest/Competing interests The authors declare that they have no conflict of interest.

Availability of data and material CMIP6 climate model simulations were obtained from: <https://esgf-node.llnl.gov/search/cmip6/>, whereas GPCC data was obtained from: https://opendata.dwd.de/climate_environment/GPCC/html/download_gate.html.

Code availability Not applicable

Authors' contributions Conceptualization: [Sogol Moradian, Ali Torabi Haghighi], Methodology: [Sogol Moradian, Ali Torabi Haghighi], Formal analysis and investigation: [Sogol Moradian, Ali Torabi Haghighi], Writing the paper: [Sogol Moradian, Ali Torabi Haghighi, Maryam Asadi]; Writing- review and editing: [Sogol Moradian, Ali Torabi Haghighi, Maryam Asadi, Seyed Ahmad Mirbagheri], Resources: [Sogol Moradian, Ali Torabi Haghighi, Maryam Asadi, Seyed Ahmad Mirbagheri], Supervision: [Sogol Moradian, Ali Torabi Haghighi].

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