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UNCERTAINTY OF CLIMATE PROJECTIONS AND AN APPROACH UTILIZING CLIMATE MODEL OUTPUTS FOR HYDROLOGIC COMPUTATION IN THE BA RIVER BASIN

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ABSTRACT

A top-down approach begins with Global Climate Models (GCMs) is a common method for assessing climate change impacts on water resources in river basins. To overcome the coarse resolution of GCMs, dynamic downscaling by regional climate models (RCMs) with bias-correction procedures is utilized with the aim to reflect the meteorological features at the river basin scale. However, the results still entail large uncertainties. This paper examines the ability to capture the observed baseline temperature and precipitation (1986-2005) in the Ba River Basin from GCM outputs, RCM outputs, bias-corrected GCM outputs and bias-corrected RCM outputs by analyzing statistical indicators between historical simulations and observed data in 4 temperature and 6 rainfall stations. Bias-corrected results of both GCM and RCM have significantly smaller errors compared to the unbias-corrected ones. The uncertainty of future climate projection for the mid and late 21th century of the bias-corrected GCMs and RCMs are evaluated. It is found that there is still uncertainty in projected results. A concept of "Decision-Scaling" which combines top-down and bottom-up approaches is proposed to assess the climate change impacts on hydrological system to take into account uncertainties of climate projections by models.

Keywords: uncertainty, climate model outputs, hydrologic system, Ba River basin, decision scaling.

Classification numbers: 3.4.2, 3.5.1, 3.5.2

1. INTRODUCTION

Anthropogenic climate change with manifestation of increased temperature and changed precipitation is predicted to affect water resources in river basins. The method used in traditional international and Vietnamese researches assessing impacts of climate change on water resources, e.g. [1–4], is top-down approach which uses Global Climate Model (GCM) projections in a very starting point. Because of the coarse resolution of GCMs, downscaled and bias corrected climate variables are then used as input to hydrologic models, the output of which is used to drive water system models, bringing basis to determine adaptation options. It must be admitted that, top-down approach provides effective information on the potential impacts of climate change to river basins using an intended future economic development and emission scenarios. However, it entails problems for decision makers to utilize the results due to a number of uncertainties, which derive from different sources, such as imperfect knowledge of the functioning of climate system, variability of climate factors in the affected systems, or future economic development and emission scenarios [5–7].

Ba River Basin (BRB) is the largest river basin in Central Vietnam with total natural area of 13,417 km^2. Majority of the basin is in Gia Lai, Dak Lak and Phu Yen Provinces. Comparing to other river basins in Vietnam, the BRB has limited amount water resources with about 25.72 l/s.km^2 of average annual flow module. Moreover, the annual flow is unevenly distributed, with 70 -75 % of flow concentrated in 3-4 months during the flood season, creating problems of droughts, floods and salinity intrusion, etc. in many places in the basin [4]. It is projected that under climate change condition, the river flow tends to increase in the flood season and decrease in the dry season [8]. Therefore, the BRB is supposed to face with more serious water related disasters and extreme climatic events in the future. Like other researches on ll the previous researches about the impacts of climate change on the BRB is based on top-down approach [4], [8], [9]. Because of uncertainties of the climate models and scenarios, these researches have limited assistance for identifying adaptation policies at different levels.

In order to find a better approach to tailor climate information into adaptation policy strategies in BRB, this paper evaluates the uncertainties of baseline simulations and future projections of 4 groups of climate models: Global Climate Models (GCMs), Regional Climate Models (RCMs), bias-corrected GCMs, bias-corrected RCMs. To overcome the uncertainties of climate projections, a concept of "Decision-Scaling" is introduced to assess the climate change impacts on hydrological system.

2. METHODOLOGY

2.1. Data

- *Observed data:* Daily temperature and precipitation data from 1986-2005 at 4 temperature stations (An Khe, AyunPa, M Drak and Tuy Hoa station) and 6 precipitation stations (An Khe, PoMeRe, AyunPa, Son Thanh, M Drak and Tuy Hoa station) (collected from *Vietnam National Hydro-meteorological Information Center)* are used as the basis for evaluating uncertainties of the baseline simulations.

- *Climate model data:* totally 50 members from 20 GCMs with different AR5 scenarios (RCP2.6, RCP4.5, RCP6.0, RCP8.5) of Intergovernmental Panel on Climate Change (IPCC) are exploited from website of Program for Climate Model Diagnosis & Intercomparison (http://cmip-pcmdi.llnl.gov/cmip5/) on 15th March 2018. These outputs are interpolated from grid points onto the coordinates of the above 4 temperature and 6 precipitation stations by bilinear interpolation method.

2.2. Methods for evaluating the uncertainty of climate model outputs

In recognition of adverse effects of uncertainties in climate model simulations on utilizing the results of climate change impacts assessment on water resources into reality, a number of researches concentrate on evaluating them. In [10], ANOVA analysis is used to quantify four sources of uncertainty in temperature climate model outputs for North America, including differences in GCMs, internal variability simulated by GCMs, differences in RCMs, and statistical downscaling including internal variability. In [11] and [12], uncertainty in projections from GCMs is estimated by Square root error variance (SREV). In general, uncertainty of climate projections is estimated using different statistical indicators according to two approaches: through comparison of historical simulations with observed data; and through analysis of the consistency between multiple climate model simulations.

In this paper, the former approach is used for estimating uncertainty of baseline simulations by analyzing Mean Error (ME), Mean Absolute Error (MAE) indicators and annual variation. The other approach is used to calculate future projections uncertainty using standard deviation (SD) and variation range for analysis. The periods of time in the research includes: 1986-2005 for the baseline, 2016-2035 for the near future, 2046-2065 for the middle of century and 2080-2099 for the end of century. Four groups of climate models are examined:

(1) GCM outputs: 50 members from 20 GCMs in different AR5 scenarios (RCP2.6: 10 members, RCP4.5: 20 members, RCP6.0: 10 members, RCP8.5: 10 members);

(2) RCM outputs: some of the GCM outputs above are dynamically downscaled by RCMs including CCAM, clWRF and PRECIS in different scenarios. There are totally 20 members of this group (RCP4.5: 10 members, RCP8.5: 10 members);

(3) Bias-corrected GCM outputs (BC-GCMs): the results from (1) are systematic-errors adjusted by quantile mapping procedure [1]; and

(4) Bias-corrected RCM outputs (BC-RCMs): the results from (2) are systematic-errors adjusted by quantile mapping procedure [1].

Table 1 shows the list of GCMs and RCMs used in the research.

Table 1. List of GCMs and RCMs used in the research.

GCMs	**RCMs**	
	Model	**Calculated scheme**
ACCESS1-0; BCC-CSM1-1; CanESM2; CCSM4; CESM1-CAM5; CNRM-CM5; CSIRO-Kk3-6-0; GFDL-CM3; GFDL-ESM2G; GFDL-ESM2M; HadCM3; HadGEM2-AO; HadGEM2-CC; INMCM4; IPSL-CM5A-LR; MIROC5; MPI-ESM-LR; MPI-ESM-MR; MRI-CGCM3; NorESM1-M	CCAM	ACCESS1-0; CCSM4; CNRM-CM5; GFDL-CM3; MPI-ESM-LR; NorESM1-M
	clWRF	NorESM1-M
	PRECIS	CNRM-CM5; GFDL-CM3; HadGEM2-ES

3. RESULTS

3.1. The uncertainty of baseline simulations of Climate Models

To evaluate the uncertainty of baseline simulations, outputs of 4 groups of Climate Models are compared with the historical data by analyzing statistical errors and annual variation.

For temperature variables: Table 2 indicates that ME indicators are mostly negative for GCM and RCM outputs (-0.59 and -1.23 in average, respectively), showing a smaller mean value of simulated results compared to the observed data. Moreover, MAE of GCM outputs is slightly larger than that of RCM outputs, but both of them show a significant magnitude of errors (1.49 and 1.29 in average for GCMs and RCMs, respectively). After bias correction procedure is applied, the outputs of GCM and RCM models have much better ability to capture the reality. Particularly, ME values at all the stations in the basin are equal to 0.2 for BC-GCMs and 0.0 for BC-RCMs. The magnitudes of errors are also much improved, with 0.37 – 0.41 for BC-GCMs and 0.31-0.36 for BC-RCMs. Table 2 illustrates ME and MAE value of baseline simulated temperature compared with observed data in BRB.

Table 2. Mean Error and Mean Absolute Error of baseline simulated temperature by Climate Models compared with observed data.

Station	GCMs	RCMs	BC-GCMs	BC-RCMs
ME	-0.59	-1.23	0.02	0
MAE	1.49	1.29	0.40	0.34

Table 3. Mean Error and Mean Absolute Error of simulated precipitation by Climate Models compared with the baseline observed data.

Station	GCMs			RCMs			BC-GCMs			BC-RCMs		
	Rain	**Dry**	**Ann**	**Rain**	**Dry**	**Ann**	**Rain**	**Dry**	**Ann**	**Rain**	**Dry**	**Ann**
ME	-28.9	47.1	-10.9	3.6	119.0	27.6	2.0	6.4	3.3	1.2	2.7	1.7
MAE	42.6	78.1	34.9	40.6	136.2	49.5	35.6	48.0	30.3	34.3	40.4	27.8

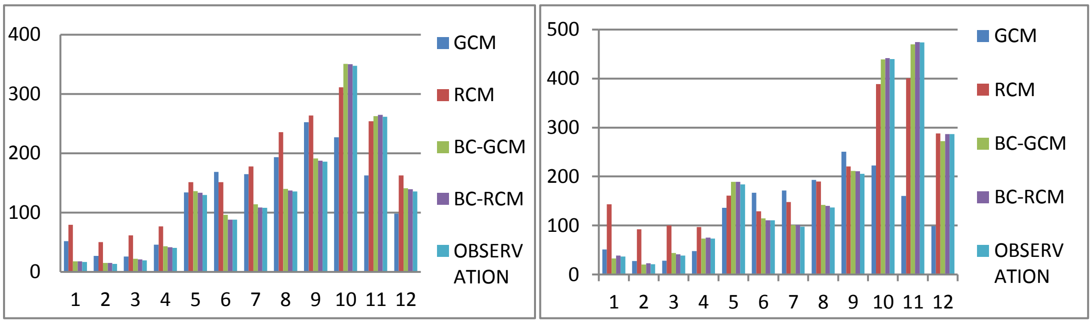

Figure 1. Historical simulated and Observed Annual precipitation variation in An Khe and MDrak station.

For precipitation variables: Table 3 shows that, the mean values of both unbias-corrected GCM and RCM simulations are moderately different from the observed data, with ME(GCMs) = (-10.9) and ME(RCMs) = 27.6, especially in dry season. After correcting systematic biases, the mean errors of both GCMs and RCMs are substantially reduced, better result for BC-RCMs (ME = 1.7) than for BC-GCMs (ME = 3.3). However, the mean absolute errors are unclear improved (MAE of annual values are equal to 30.3 and 27.8 for BC-GCM and BC-RCM outputs, respectively). The improvement of MAE is quite better in the dry season than in rainy season; however, these values are still at high levels. Comparison between simulated and observed annual precipitation variation (Figure 1) in the baseline period shows an apparent better results of the bias corrected climate model simulations, especially in rainy season.

In short, in baseline period, there is not a considerable improvement in climate models results through downscaling process for both temperature and precipitation variables. However, bias correction procedure seems to be more effective to get these simulations closer to the reality. Therefore, the next part only concentrates in evaluating uncertainties of the bias-corrected results of GCM and RCM (BC-GCMs and BC-RCMs) in BRB in the future.

3.2 The uncertainty of future projections of BC-GCMs and BC-RCMs

The consistency between bias-corrected outputs from different member of GCMs and RCMs are analyzed in order to access uncertainties of these 2 groups.

For temperature variables: In general, standard deviation of BC-GCMs is quite larger than that of BC-RCMs with higher magnitude in near future than in distant future (Table 4).

Table 4. Standard deviation of BC-GCMs and BC-RCMs for temperature variables at different percentiles and mean value.

Percentile / Station	BC-GCMs				BC-RCMs			
	10^{th}	**50^{th}**	**90^{th}**	**MEAN**	**10^{th}**	**50^{th}**	**90^{th}**	**MEAN**
2016-2035	0.47	0.50	0.53	0.47	0.23	0.28	0.39	0.28
2046-2065	0.67	0.72	0.75	0.70	0.52	0.63	0.70	0.61
2080-2099	1.07	1.12	1.16	1.12	0.98	1.03	1.08	1.03

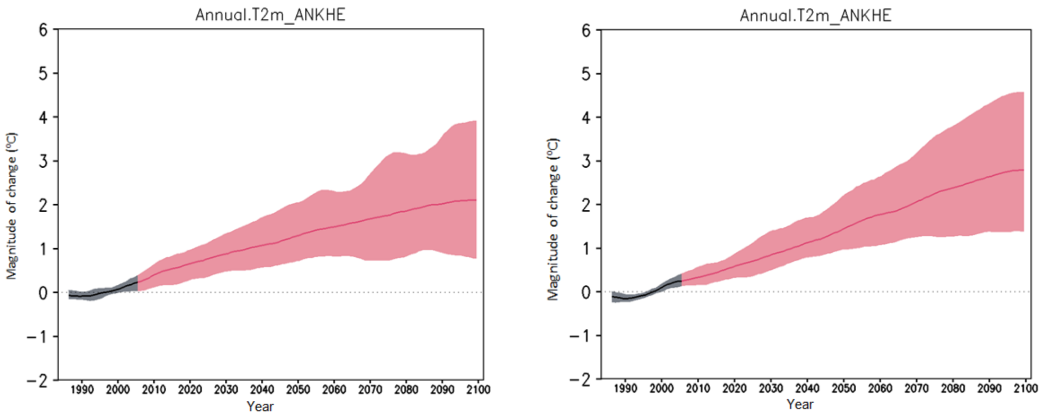

Figure 2. Temperature change during 21^{st} century simulated by BC-GCMs (left) and BC-RCMs (right) at An Khe station.

In 2016-2035, standard deviations values of BC-GCMs at 10^{th} and 90^{th} percentiles are 0.47 and 0.53 respectively, while these indicators of BC-RCMs are 0.23 and 0.28. At the end of the century, the improvement is not considerable. Analyzing variation range of temperature change (Figure 2), it can be seen that, the ranges of both BC-GCMs and BC-RCMs are getting larger during 21^{st} century. In 2100, these range are up to 3-4^{o}C.

For precipitation variables: In overall, the uncertainties of BC-GCMs at all percentiles are at high levels (Table 5). In 2016-2035 period, standard deviation value is 455.33 and 1264.36 at 10th and 90th percentile, respectively. Until the end of the century, these values are 494.83 and 1320.00 respectively, showing a slight increase of inconsistency between different BC-GCM outputs through the century. For the BC-RCMs, the results are improved significantly, but still at high levels. Specifically in near future, standard deviations at 10th and 90th percentiles decrease to 186.82 and 355.66. Until the end of the century, these values are 227.96 and 505.36 respectively. However, variation ranges of precipitation change (Figure 3) show a limited amendment of BC-RCMs compared with BC-GCMs.

In brief, to some extent, it can be said that BC – RCM members have more consistency than BC-GCM members. However, significant uncertainties are still found in the BC-RCM results, especially in distant future.

Table 5. Standard deviation of BC-GCMs and BC-RCMs for precipitation variables at different percentiles and mean value.

Percentile / Station	BC-GCMs				BC-RCMs			
	10th	**50th**	**90th**	**MEAN**	**10th**	**50th**	**90th**	**MEAN**
2016-2035	455.33	636.94	1264.36	761.41	186.82	231.57	355.66	212.83
2046-2065	468.59	677.05	1342.24	747.03	171.43	247.92	401.43	256.57
2080-2099	494.83	713.92	1320.00	768.22	227.96	311.39	505.36	322.84

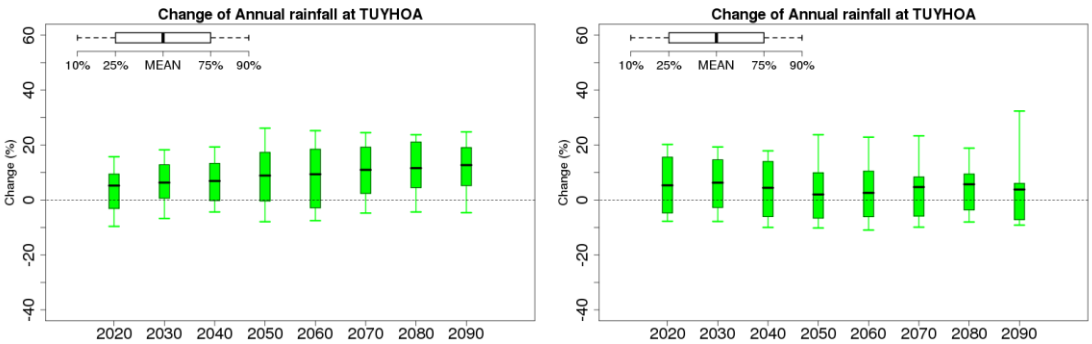

Figure 3. Precipitation change during 21st century simulated by BC-GCMs (left) and BC-RCMs (right) in Tuy Hoa station.

4. INTRODUCTION OF DECISION SCALING METHOD

Top-down approach, which begins with GCM/RCM projections, is commonly used to assess climate change impacts on water resources in the BRB in previous researches. In this approach, climate projections from a single or several GCMs are statistically or dynamically downscaled and systematic bias-corrected with the aim to reflect the meteorological features at the river basin scale. The climate outputs are then used to drive the hydrologic and water resources system models to determine the vulnerabilities of the river basin under a changing climate. Adaptation solutions are finally proposed. It can be seen that this approach produces useful basis for adaptation strategies for an intended future [5]. However, it fails to assist the proposal adaptive measures in the BRB at different levels due to a large range of uncertainties.

The above results for uncertainties evaluation of climate outputs in the BRB in baseline shows that dynamic downscaling with RCMs is not effective in capturing meteorological conditions in the BRB. Once bias correction technique is applied, the results have been improved significantly for temperature values, but the results for precipitation are still limited. For the future, BC-RCM simulations have a higher level of consistency as compared to BC-GCM outputs for both temperature and precipitation values. However, the variation ranges of both BC-GCMs and BC-RCMs are larger during 21st century. In 2100, this range for temperature is (+3) - (+4)^{o}C and for precipitation is ±25% compared with baseline period. Temperature and precipitation are important factors of water balance in river basins. While precipitation relates directly to river flow, temperature affects water balance indirectly through evaporation. Therefore, these magnitudes of uncertainties of temperature and precipitation projections lead to an imprecision in hydrologic and water system models' outputs. As a result, decision makers in BRB would face a grand challenge in proposing adaptation options basing on these results [5], [13].

In the context of uncertainties of future GCM/RCM projections, there is a growing number of alternative climate risk assessment approaches which rely less on the use of climate models. The stochastic method is an alternative which considers a wide range of possible scenarios to assess climate change impacts [6], [13]. Brown et al [6] introduced the "Decision Scaling" framework which follows this approach. The distinguished point of this method among the others is the use of decision analysis as the framework for assessing stochastic bottom-up climate risks of the system with future climate projections from GCM.

Figure 4 is a visual depiction of the Decision Scaling framework. The first stage of the method is identification of historical climate hazards. The decision analysis is given through "Performance threshold" which divided the system performance into 2 domains: taking-action and not-taking-action. This process is conducted through discussion with stakeholders, and local authorities… The next stage is discovery of climate risk of the system. Through stochastic analysis, climate sensitivity of the system is identified. "Climate response function" is developed with the aim to determine the problematic climate conditions. The climate space is then parsed into states that favor 2 alternative decisions of "taking-action" or "not-taking-action" mentioned above. The final stage is to tailor climate information to assist decision making. While the top-down approach uses GCM outputs in the first step as the basis for the assessment process, "Decision Scaling" uses this at the final step to

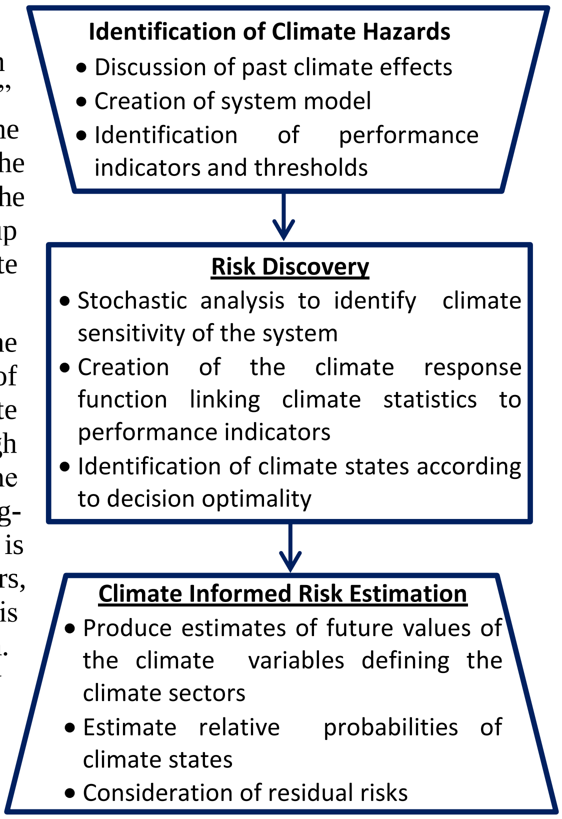

Figure 4. Diagram of Decision Scaling Method [6].

establish the likelihood of occurrence of a particular climate state that favors an alternative decision [6].

The “Decision Scaling” framework has three advantages. Firstly, this method considers a large range of GCMs as a set of plausible of future climate conditions. Therefore it considers a larger range of uncertainties related to future economic development scenarios. Secondly, since the method starts with bottom-up climate risk assessment, it is able to reflect the actual characteristics of the water system and consider water problems directly related to the study area. Thirdly, as the climate space is analyzed based on decision favors, the result of this method have close relevance to different decision options.

The use of Decision Scaling method to assess climate risks of water resources in the BRB will be presented in the next papers.

5. CONCLUSION

This paper quantifies uncertainties of climate model outputs in the BRB in both baseline simulations and future projections. For temperature variables, in baseline, the findings show an apparent improvement of statistical indicators of the bias-corrected GCM and RCM simulations than the original ones. This proves that while the bias correction procedures seem to be effective to get the historical temperature simulations closer to the observations, dynamical downscaling techniques are found limitations in that issue. For projections, BC-RCM outputs have better consistency than BC-GCM outputs in near future, but in distant future, both of them have a wide range of variation. For precipitation variables, it is found that there is still a high level of uncertainties for downscaled and bias corrected outputs of GCMs both in historical simulations and future projections. Although these procedures help the results much better than the original ones, uncertainties still exist and cause difficulties in driving hydrological and water system models to get basis for adaptation proposals.

Decision Scaling method, which combines top-down and bottom-up climate change impacts assessment, is introduced with an expectation of better tailoring climate information into water resources management and giving effective assistance for decision makers in the BRB.

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