

Statistical analysis of river discharge change in the Indochinese Peninsula using large ensemble future climate projections

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2017

**Statistical analysis of river discharge
change in the Indochinese Peninsula
using large ensemble future climate
projections**

by

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A dissertation

submitted in partial fulfillment of the requirement
for the degree of Doctor of Philosophy

Dept. of Civil and Earth Resources Engineering

Kyoto University, Japan

2017

Abstract

According to the 5th Report of the Intergovernmental Panel on Climate Change (IPCC), the average surface temperature could increase by 0.6 to 1.0 degree Celsius at the end of the 21st century. The Indochinese Peninsula, which is mainly consisting of developing countries, are projected to be one of the most vulnerable regions and suffer more from the effect of climate change such as increasing risk of floods and tropical cyclones.

Impacts of climate change on surface water distribution are most clearly represented by river discharge, which integrates all the processes occurring within a watershed (precipitation, infiltration, runoff, evapotranspiration, etc.). Occurrences of floods are almost always followed by a sharp increase in river discharge and associated water level; on the contrary, drought events also frequently happened after prolonged period of exceptionally low flow. Therefore, analyses of its impacts on the changes in statistical properties of river discharge are very importance for water resources assessment, water-related disaster, and developing climate adaptation strategies.

Currently, the studies on analyzing runoff/streamflow projection under climate change can employ the land surface models (LSMs), hydrological models forced by bias-corrected input forcing data or directly use the forcing inputs from Global Circulation Models (GCMs). In general, there have been ongoing improvements in climate model in recent years, which make it be the most promising tools to project future change of associated impacts on the hydrological cycle. Nevertheless, three major uncertainties in GCMs remain to be tackled, e.g., internal variability, future emission scenarios, and model uncertainties. The primary focus of this study is on the first issue, which includes decadal variations in the ocean, inter-annual variability in the extratropical atmosphere, intra-seasonal variation in the tropics, and so on. Fortunately, conducting a large ensemble climate simulation using multi-physics approach could potentially yield the probability density functions of extreme hydrologic variables including annual maximum river discharge without using any parametric models.

These statements would lead to the motivating questions behind this Ph.D. dissertation, which state as follows:

- 1) How can we, at least, increase the trustworthiness of the probabilistic analysis of the future climate by combining results of plausible datasets?
- 2) How do we identify the future hydrological hotspots in the Indochinese Peninsula?

On the first question, relying only on a large number of datasets may prove insufficient for two reasons. Firstly, the data from multi-physics ensemble might not originate from same mother population, thus statistical test to examine whether two independent GCM datasets has the “same” arithmetic mean and come from the same population base. This dissertation utilizes the two-way analysis of variance (ANOVA) *with* and *without replication* to partition the total uncertainty contributed by leading factors: different use of cumulus convection schemes, sea surface temperature (SST) warming patterns. Secondly, the datasets could also have different prior distribution functions. Therefore, the assessment of the difference in the empirical probability of the annual extreme events is essential before merging of the independent climate datasets. This study used the non-parametric, two-sample Kolmogorov-Smirnov test (KS-test) and two-sample Anderson-Darling test (AD-test) to investigate the difference in shape and tail of the empirical distributions.

Hotspot areas in this study are defined as the region where the statistically significant changes in the future annual maximum river discharge properties such as mean, standard deviation, and the extreme flow (95th percentile), are expected. These changes were assessed by conducting several non-parametric analyses, e.g., Mann-Whitney U-test (mean), Levene’s test (standard deviation), and two-sample AD-test (extreme) for the future to the present situation. The primary purpose of these tests is to evaluate whether the changes in river discharge are significant or just occur by chance.

The final products from these two questions allow identification of the hotspot regions at the Indochinese Peninsula and the possible number of combined samples, which will be used to analyze and compare the changes of the empirical probability density between the future and present annual maximum daily discharge.

There is seven chapter in this dissertation. Chapter 1 discusses the sources of hydrologic projection uncertainties, a statistical difference of prior distribution of the annual maximum river discharge from SST warming patterns, prediction of changes ratio of mean, standard deviation, and the 95th percentile. Statistical significance of future changes in annual maximum river discharge and comparison of the empirical probability distribution were discussed.

Chapter 2 describes the Indochinese Peninsula and provide a general overview of general circulation model's configurations that drives the changes of the simulated hydrological cycle. Finally, physically-based, distributed flow routing model (1K-FRM), mathematical construction and its assumption were also discussed.

In Chapter 3, The simulated river discharges were calculated from the distributed flow routing model called 1K-FRM with the total runoff (ROF) as an input forcing from two climate experiments: present climate (1979 – 2010) and future climate (2075 – 2099), which was developed under the SOUSEI project using the MRI-AGCM 3.2H with four kinds of different cloud convection schemes and 3 SST patterns (C1, C2, and C3). The results showed that the primary sources of streamflow projection and its contribution to the total uncertainty were successfully attributed. The results indicated that the use of different convection parameterization schemes to drive the flow routing model is the major cause of the projection uncertainty with the contributing factor of 77 – 99% at the Northern Chao Phraya River Basin, Southern Indochina, and Mekong Delta.

To further expand the scope of the prior chapter, Chapter 4 presented a comprehensive uncertainty quantification method that evaluates the sources of hydrologic (precipitation, ROF) projection that incorporate the effect of interaction into the total uncertainty at the Asia Pacific Region. The results showed that the dominant sources of hydrologic projection uncertainty at the Indochinese Peninsula are mainly derived from the use of different cloud convection schemes. Concerning precipitation, the effect of uncertainty arising from the use of different convection parameterization schemes strongly emerged in both short-term (R3D) and long-term (annual) with contribution ratio between 0.80 – 0.90, and the rest is shared between the SST patterns and the interaction effect. The effect of SST scenarios to the precipitation uncertainty is widely represented through annual timescale at a maritime region along the equator, but mostly negligible at the Indochinese Peninsula. Regarding the runoff generation (ROF), multiple convection schemes constitute the highest share of uncertainty contribution, with the contributing ratio larger than 75 - 90% could be found throughout the Indochinese Peninsula, Indian subcontinent, Southern mainland China, South Korea, and Japan, for both annual and R3D cases. Finally, the statistical significant of these signals were all but affirmed by conducting two-way ANOVA *with replication*.

The second question for the dissertation, which relates to the difference between prior distribution between two independent datasets was addressed by chapter 5. Application of these

tests showed that there is a significant difference between the empirical distribution in most of the SST combination (12 out of 15 cases) at the Ayeyarwaddy, Chao Phraya, the middle part of Mekong, and 8 out of 15 cases in the Salween Basin. The finding also showed that the difference of the probability distribution at Mekong Delta and Southern Indochinese Peninsula are not statistically significant in most of the SST warming patterns combinations. These findings also help to clarify that it is possible to increase a total number of sample in the future annual maximum discharge datasets up to a multi-thousands level, especially at Mekong Delta, Southern Indochina, and Red River, where the sample size of 2,700 are attainable. These findings could provide a stronger foundation for the derivation of empirical probability distributions which should be useful for the hydrological frequency analysis of extreme floods.

The information gathered from chapter 3 to chapter 6 then used to project the future changes of the annual maximum river discharge and its significance, which will be used to locate the hotspot area at the Indochinese Peninsula. Furthermore, this chapter also presents the future projections of the hydrologic variables such as total runoff (ROF), to provide physical reasons to support the finding related to the river discharge. The results showed that the changed in mean, standard deviation, and the 95th percentile of the annual peak discharge (Q_{95}) are expected to increase by most at Mekong Delta, Southern Indochina, and the mouth of the Red River Basin. The changes in the mean of the annual maximum river discharge are projected to be significant at 95% confidence level for all the future SST scenarios at Mekong Delta and the Southern Indochinese Peninsula. Meanwhile, the changes in the future variability and Q_{95} were found to be significant at Mekong Delta, Southern Indochina, Central Chao Phraya Basin, and the middle part of Vietnam for all the SST scenarios. As a result, Mekong Delta and Southern Indochinese Peninsula were chosen as the hotspot areas due to an all-around significant increase of the annual maximum river discharge and large sample sizes to be analyzed. Finally, comparison of the empirical probability density function was made at the two selected river stations from the associated hot spot regions and found a clear pattern of a rightward shift regarding mean and the Q_{95} of these two areas. These changes in the river discharge were traced from the development of the ROF input forcing data; where the changes of streamflow at the large river basin were linked with the changes in the seasonal indices such as JJA and annual ROF rather than short-term extreme ROF indices such as R1D, R3D, R5D, and R7D.

For further research, the statistical analysis on the significant of changes should also expand to

others hydrological variable such as precipitation, total runoff, evapotranspiration, to strongly reaffirms the future trend of river discharge at the Indochinese Peninsula. Moreover, bias correction methods could also be applied with the input forcing and compared with the observation data before any future application.

Keywords: river discharge projection, d4PDF, uncertainty quantification, statistical significance, hotspot areas

Declaration of Authorship

I, Patinya Hanittinan, hereby proclaim that this dissertation and the work presented here are my own and have been generated by me as the result of my own original research with the exception of any work of others which has all been appropriately referenced. It has not been submitted, either in part or whole, for a degree at this or any other university.

Acknowledgement

This dissertation was completed at the hydrology and Water Resources Research Laboratory, Department of Civil and Earth Resources Engineering, Graduate School of Engineering, Kyoto University under the full-time, Ph.D. program called “Human Security Engineering”. It has been more improved thanks to the comments and suggestions from examination committee members, Prof. Yasuto Tachikawa, Prof. Eiichi Nakakita and Prof. Nobuhito Mori.

The author wishes to express his deepest gratitude to his wonderful academic and dissertation supervisor, Prof. Yasuto Tachikawa, whose support, advice, vision, theoretical background, and encouragement greatly helped and allowed him to undertake and complete this research successfully. The author is grateful to him for providing the great opportunity to work under his supervision.

The author would also like to extend his appreciation to other professors and secretary of the laboratory – Prof. Yutaka Ichikawa, Prof. Sunmin Kim, Prof. Kazuaki Yorozu, and Mrs. Mayumi Iwasa – who gave me suggestions, constructive criticisms, and assisted me on a number of things related to researches and administrative procedures.

The author would like to express sincere appreciation to the Program for Risk Information on Climate Change (SOUSEI) and the Data Integration and Analysis System (DIAS), both of which are sponsored by the ministry of Education, Culture, Sports, Science and Technology of Japan, for supporting the runoff generation datasets. The author also commends the Royal Irrigation Department of Thailand, Mekong River Commission, for providing observation river discharge data for this research.

The author also truly appreciates all the friendship that he was able to develop among graduate students, colleagues, friends, and other people, that has made his research and

extracurricular activities even more enjoyable. The author is also grateful to Kyoto university for providing the necessary facilities associated in the Ph.D. study.

The author also expresses his sincere gratitude to the Japanese government (Monbusho: MEXT) scholarship for providing financial support during a stay in Japan, which essentially allows me to keep focusing on research.

Finally, the author would like to thank his parents, grandparents, and his younger sister for their unconditional love, support, sacrifice, and encouragement throughout the period of extended stay abroad. My girlfriend, Sunantha Thongliamnak (MarHnok), deserves recognition for her energetic support, patience, and love that allowed the author to complete his endeavor successfully.

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Chapter 1

Introduction

1.1 Background and study motivation

The rise in greenhouse gases emissions since the beginning of industrial revolution, mainly attributed to human activity driven by economic and population growth (Hegerl et al., 2007), has led to an increase of global average combined land and ocean surface temperature of 0.85°C over the period 1880 to 2012 (IPCC, 2013; Hartman et al., 2013). These recent climate changes have had widespread impacts on socio-economic, human health, and climate systems.

Comparatively, water-related disasters such as flood are among the most destructive natural hazards. The primary effects of flooding include loss of life, damage to buildings and other structures, including highways, bridges, culverts, dams, levees, sewerage systems, water delivery systems, which in turn may result in damage to property and loss of life. Floods are associated with extremes in rainfall (tropical storms, orographic, thunderstorms, extratropical cyclone, etc.). Its occurrence is often local but can develop in a matter of hours to couples of months. Floods are also one of the main components of the hydrological cycle, which has a close relationship with climate. As changes in global climate occur, the hydrological cycle is expected to be intensified and led to the changes in precipitation patterns, and ultimately causes more frequent extreme weather events such as floods and droughts. In addition, climate change will amplify existing risks and create new risks for natural, human systems, and hydrological cycle including the spatiotemporal distribution, variability and trends of precipitation, runoff, and evapotranspiration. These risks are unevenly distributed and generally pose a serious threat to disadvantaged people and communities in countries at all level of development. However, it is developing countries that are most vulnerable to the effects of climate change such as ill-health, exacerbation of poverty, food security, and increasing disaster-related economic losses. Therefore, assessment of potential impact of climate change on water resources is crucial to developing appropriate mitigation and adaptation schemes.

There now many research on climate change and its impact on the environment, economy, society of different regions (Parry et al., 2007), hydrology and extreme events (Trenberth et al., 2007; Hirabayashi et al., 2008; Kundzewicz et al., 2013; Hagemann et al., 2013; Hirabayashi et al., 2013; Thompson et al., 2013; Stahl et al., 2014, Prein et al., 2017), which

are well documented (Solomon et al., 2007). Recent advancement in atmospheric research computational resources have allowed the development of sophisticated mathematical model that describes the general circulation of a planetary atmosphere or ocean called “General Circulation Models (GCMs)”, which attempted to predict the future climate based on the best knowledge of atmospheric greenhouse gases emission scenarios, is proved to be one of the most promising tools to project the future changes and associated impacts in the hydrological cycle. It uses the three-dimensional Navier-Stokes equations on a rotating sphere with chemical, biogeochemical properties of its component, their feedback and interactions (Hartman et al., 2013). It has been used to estimated several hydro-meteorological variables, e.g., temperature, short-wave radiation, wind speed, air pressure at sea level, precipitation, total runoff, for various critical applications in weather forecasting, paleoclimate simulation, and in particular for the evaluation of climate change impacts on hydrology and water resources.

Despite its fundamental roles and years of continuing improvement, it is still difficult to directly utilize the output of GCMs to make a reliable projection of hydrological impacts on a regional scale due to the relatively coarse spatial resolution. They include representation of hydrological phenomena and resolves water balance but do not provide sufficient information to address climate change impacts on water resources (Graham et al., 2007). The standard solution for carrying out the hydrologic simulation on a regional scale is to utilize the output of high-resolution GCMs and combine with a physically-based, hydrological model to simulate the long-term diurnal cycle and long-term average monthly runoff (Wood et al., 1997). There are several advantages of using regional hydrological models for assessing a hydrological impact of climate change rather than using GCMs itself: it has an operational flexibility for model parameters identification and selecting suitable approaches to evaluate an impact at any particular region; can be utilized at several spatial scales and select appropriate dominant process representations in a more computationally efficient way; much easier to handle and faster to operate than GCMs; and can be tailored to the characteristics of available data (Xu et al., 1999; Duong et al., 2014). Naturally, the impact of climate change on surface water distribution cascades from the onset of the relationship between precipitation, infiltration, evapotranspiration, and variability in a total runoff to the endpoint, which is river discharge from the integration of all the processes occurring within a river basin. Therefore, the projection of river discharge is one of the best ways to conduct the impact assessment of hydrology and water-related disaster risk management.

The approach of using GCM outputs as the forcing input data that drives hydrological models has been widely investigated across different spatial scales: global scales (Nohara et

al., 2006; Hirabayashi et al., 2008; Sperna Weiland et al., 2012; Arnell and Gosling, 2013; Hirabayashi et al., 2013; Kundzewicz et al., 2013); regional scales (Sato et al., 2013; Thompson et al., 2013; Duong et al., 2013); and river basin scale (Jiang et al., 2007; Thodsen et al., 2007; Hunukumbura et al., 2012; Champathong et al., 2013; Thompson et al., 2013). However, results from the impact studies are often subjected to significant three sources of uncertainties introduced throughout these climate change hydrological impact assessment (Nawaz and Adeboye, 2006; Knutti et al., 2008; Gosling et al., 2011). Uncertainties are first related to the definition of the greenhouse gases emission scenarios used to force the GCMs and its change over time. Secondly, internal variability which includes inter-annual variability in the extratropical atmosphere, intra-seasonal variation in the tropics, and decadal variations in the ocean is expected to be more relevant for less frequent anomalous climate extremes (Deser et al., 2012; Xie et al., 2015). Model uncertainties, in relation to scale and resolution, cloud microphysics, convection parameterization schemes, and pollution particles (Senior and Mitchell, 1993; Andrae et al., 2004; Jones et al., 2003; Bader et al., 2008; Reichler and Kim, 2008) presents the third source of uncertainty.

Fundamentally, ocean-coupled global circulation models with hyper spatiotemporal resolution are needed to better reproduce meteorological forcing, such as storms associated with tropical cyclones and precipitation systems by explicitly resolves the sub-grid scale processes such as deep convection or the governing mechanism of rain droplets but currently unachievable due to an extraordinary demanding of computing power (Prein et al., 2015).

Fortunately, several developed methods have been applied to evaluate and quantify climate projection uncertainties arising from internal variability, where multi-model ensembles (MMEs) and perturbed physics ensembles (PPEs) are generally the most frequently cited approaches (Hawkins and Sutton et al., 2009; Gualdi et al., 2011). Numerous studies have used the latter method, by exploring simulation sets with a single model but using different perturbed parameters, with the goal of analyzing uncertainties in hydrological projections of surface air temperatures, aerosol forcing, GHG concentrations and precipitation (Murphy et al., 2004; Endo et al., 2012; Mizuta et al., 2014); and recently by using large and diverse sets or realizations to derive probability density function of annual maximum surface temperature and daily precipitation at the regional scales (Kay et al., 2015; Mizuta et al., 2016). There have been several other attempts to quantify climate models probabilistically that have taken similar approach (Andronova and Schlesinger, 2001; Wigley and Raper, 2001; Forest et al., 2002, 2006; Knutti et al., 2002, 2003, 2005, 2006; Murphy et al., 2004; Meinshausen, 2005; Piani et al., 2005; Stainforth et al., 2005). Quantitative evaluation of general structural model

uncertainty requires MME and compliments with the exploration of single-model uncertainties using PPE (Tebaldi and Knutti, 2007). However, for practical purposes, a single forecast of the climate response to increasing greenhouse gasses emissions is far more useful to policymakers when accompanied by some measure of associated uncertainty (Knutti et al., 2008). Therefore, in this research, the projection of future river discharge will be conducted based on the forcing data derived from single 60-km atmospheric general circulation model, MRI – AGCM 3.2H with a large ensemble of realizations simulated by perturbation of initial and lateral boundary conditions. The detailed of the MRI – AGCM 3.2H will be thoroughly described in the next chapter.

1.2 Research objectives

The primary objectives of this study are to analyze the changes of daily river discharge at the Indochinese Peninsula region under changing climate; by using a high-resolution global atmospheric model with a large ensemble. Here are the following detailed objectives:

- To evaluate the source and quantify the hydrologic projection uncertainties from a range of parameters by examining statistical differences of mean in precipitation, total runoff, and daily river discharge projections; provided by GCMs outputs with different cloud convection parameterization schemes and SST warming pattern
- To examine the prior distribution difference of the annual maximum daily discharge in the future climate from various SST warming pattern with large output ensembles.
- To project changes of daily river discharge at the Indochinese Peninsula region using a distributed flow routing model and outputs from general circulation models with large output ensembles.
- To analyze the statistical significance of the detected changes in daily river discharge changes at the Indochinese Peninsula to locate possible hotspot areas where significant changes in related to the peak discharge event could occur.
- To compare the empirical probability distribution function of the annual maximum daily discharge of the present and future climate at the hotspot regions.

1.3 Thesis Outline

This thesis is mainly focused on the analysis of the changes in daily river discharge and quantification of the uncertainty in the future projections. Therefore, the content is consisting of 7 chapters discussing the sources of hydrologic projection uncertainties, statistical difference of prior distribution of the future annual maximum daily discharge from SST patterns, projection of changes ratio of the daily river discharge, statistical significance of future changes in daily river discharge, and comparison of the empirical probability distribution of the daily peak discharge at the hotspot regions.

Chapter 2 illustrated the study area – Indochinese Peninsula. A short introduction on general circulation model's configurations, which drives the changes of a hydrological cycle, will be discussed. Finally, physically-based, distributed flow routing model, mathematical construction and its assumption will be discussed.

Chapter 3 presents a method to evaluate the source of river discharge projection uncertainties from using GCM and attributing the contribution of each component. In this chapter, the simulated daily river discharges were calculated from the distributed flow routing model called 1K-FRM with the total runoff (ROF) as an input forcing from two climate experiments: present climate (1979 – 2010) and future climate (2075 – 2099). The changes of daily river discharge between two periods were computed. Finally, the total projection uncertainty of river will be analyzed by using two-way Analysis of Variance (Hanittinan et al., 2016).

Chapter 4 presents an evaluation of the sources of future precipitation and total runoff projection uncertainties of the Asia Pacific Region. The results will support the findings in chapter 3 and overview of the overall uncertainty for the entire region. The two-way ANOVA was applied to attribute the contribution of total uncertainty arising from the different use of cloud convection parameterization schemes, SST warming patterns, the interaction between these two terms, and the internal variability. Statistical significance of the findings was evaluated by conducting F-test. The null hypothesis H_0 for the statistical significance analysis of river discharge change is defined as follows: there is no significant difference between mean/variance or the annual mean discharge or the future and the present climate (Hanittinan et al., 2017a).

Chapter 5 evaluates the difference in the prior cumulative distribution of the annual maximum daily discharge from the future climate from the large output ensembles called “Database for Policy Decision-Making for Future Climate Change (d4PDF)”, which generated

the climatological forcing outputs from six SST lateral boundary conditions to cover all the uncertainty characteristics (Mizuta et al., 2014). Statistical tests performed in this chapter are two-sample Kolmogorov-Smirnov (K-S test), which is a robust, non-parametric test of the equality of continuous, one-dimensional probability distribution between two independent datasets. The second method is two-sample Anderson-Darling (AD test), which is an alternative to the two-sample KS test but has four advantages over the KS test: more sensibility to shape and scale of a distribution (Anderson and Darling, 1954); more sensitive towards differences at the tails of distributions; applicability to small samples (Petitt, 1976); AD is better capable of detecting minuscule differences, even between large sample sizes (Engmann and Cousineau, 2011).

Chapter 6 presents a projection of daily river discharge at the Indochinese Peninsula represented as the changes ratio between the annual maximum daily discharge of the future climate (2051 – 2110) and the present climate (1951-2010). Statistical significance of changes between two simulated daily river discharge was assessed by comparing mean of the annual maximum daily discharge (Mann-Whitney U test), standard deviations of the annual maximum daily discharge (Levene's test for homogeneity of variance), and cumulative distribution functions (two-sample Anderson-Darling test). The results from this chapter and prior information from chapter 3, 4 and 5 will help locate the hot spot region, where the significant changes of peak discharge could occur and determines the total number of samples used to derive empirical probability density function of the annual maximum daily discharge comparisons between the present and future climate.

The last chapter, chapter 7, summarizes the study with conclusions and remarks.

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Chapter 2

Study area and Modeling approaches

2.1 Study area

The study site is the Indochinese Peninsula, a land-based region in Southeast Asia, which covers from latitude 5°N to 34°N and from longitude 91°E to 109.5°E, as shown in Figure 2.1. It lies roughly southwest of China and east of Indian subcontinent. A total of six countries are neither entirely belonged nor shares some part of the boundary: Thailand, Myanmar, Laos, Cambodia, Vietnam, Malaysia, and China. As one of the dominant circulation systems in the tropical troposphere, the Asian monsoon originated from the establishment of strong convection and the change of direction of the prevailing wind, heavily influences monsoon system of the Indochinese Peninsula (Zhang et al., 2002). It is also affected by the changes from inter-annual climate system over the Pacific and Indian Oceans, which directly causes precipitation and temperature anomalies over this area. There are five major river basins in this area: Mekong River Basin, Ayeyarwaddy River Basin, Chao Phraya River Basin, Salween River Basin, and Red River Basin. More detailed information about these basins will be discussed in the next section.

2.2 River Basins

2.2.1 Mekong River Basin

The Mekong Basin is the tenth-largest river system in the world with a total land area of 795,000 km² from the eastern catchment of the Tibetan Plateau to the Mekong Delta. The Mekong River flows approximately 4,909 km through three provinces of China, continuing into Myanmar, Lao PDR, Thailand,



Figure 2.1 Pictorial map of the Indochinese Peninsula (source: Encyclopedia Britannica)

Cambodia, and Vietnam before emptying into the South China Sea with a few smaller tributaries, forming an area known as the “Nine Dragons”. The Mekong River Basin includes seven broad physiographic regions featuring diverse topography, drainage patterns, and geomorphology. The Tibetan Plateau, Three Rivers Area and Lancang Basin from the Upper Mekong Basin. The Northern Highlands, Khorat Plateau, Tonle Sap Basin and Mekong Delta make up the lower Mekong Basin. The extreme seasonal flow variations and the presence of rapids and waterfalls in the Mekong make navigation difficult. However, the river is the major trade route between Southwestern China and Southeast Asian countries.

2.2.2 Ayeyarwaddy River Basin

The Ayeyarwaddy Basin is the largest river system and most important commercial waterway in Myanmar; and the second largest in the Indochinese Peninsula. It flows relatively straight from north to south before emptying through the Ayeyarwaddy Delta into the Andaman

sea. Its drainage basin of about 255,081 km² cover most of Myanmar arises by the confluence of the Nam Gio and Mali Rivers in Kachin State. Both rivers find their sources in the Himalayan Glacier of Upper Myanmar. In turn, summer monsoon season, which occurs between mid-May and mid-October, the flow volume of the Ayeyarwaddy and its tributaries varies greatly throughout the year. Over a year, the discharge averages 13,000 cubic meters, but up to 32,600 m³/s and a low of 2,300 m³/s near the head of the Ayeyarwaddy Delta.

2.2.3 Chao Phraya River Basin

The Chao Phraya River Basin (hereafter, CPRB) originates in the mountainous in the Northern Thailand and flow relatively north to south. The CPRB is the largest river basin in Thailand, and the fifth largest in the Indochinese Peninsula, with the total drainage area of 157,925 km², which constitutes of two parts: the upper CPRB, consists of four large sub-basins, the Ping, Wang, Yom, and Nan River Basins, together with the catchment area of 33,898 km², 10,791 km², 23,616 km², and 34,440 km², respectively. Confluence of the Ping and Nan River at Paknam Po, Nakhon Sawan Province, where the Chao Phraya River is formed, is the beginning of the lower CPRB, which consists of another four major sub-basins, Pa Sak (catchment area 16,291 km²), Sakae Krang (catchment area 5,191 km²), Tha Chin (catchment area 13,681 km²), and the lower CPRB itself (catchment area 20,126 km²), where the land mainly consists of agricultural and urban areas. The landscape of the river basin is a very wide and gentle slope, especially in the lower part of the basin and the downstream parts of the Yom and Nan Basins, where the gradient is around 1/10,000 at the upstream to 1/50,000 at the Chao Phraya Delta near the Gulf of Thailand (Ogata et al., 2012; Wichakul, 2014).

2.2.4 Salween River Basin

The basin of Salween is a transboundary basin with a total area of 320,000 km² distributed between China (53 percent), Myanmar (42 percent), and Thailand (5 percent). The Salween is about 2,815 km long, which make it the second longest river in Southeast Asia after the Mekong river. The river originates 4,000 m above sea level on the mountain Tangula in the Himalayas on the Tibetan Plateau in China, then flows southward through Yunnan Province, China, down through Shan and Kayah states in the Eastern Myanmar, along the border between Thailand in Myanmar for about 120 km, then again enters Myanmar and passes through Kayan and Mon states before emptying into the Gulf of Mataban in the Andaman Sea. Its extensive

drainage basin supports a biodiversity comparable with the Mekong and is home to about 7 million people.

2.2.5 Red River Basin

The Red River flows from Yunnan Province in Southwestern China through northern Vietnam and emptying into the Gulf of Tonkin. The total catchment area is 169,000 km², of which about half lies in Vietnam. The Red River has four major upstream tributaries, i.e. the Da River on the right side, and the Chay River, the Lo River, and Gam River on the left side. They merge near Viet Tri as a nodal point, which constitutes the border of the upstream and downstream portions of the Red River and the apex of the Red River Delta. The lower Red River Basin is characterized by many branches and their complicated alignment with the silty sand bottom on the flat plain. The climate of the Red River is a mix of tropical and sub-tropical. It is dominated by the monsoon winds of the Southeast Asia. Besides the seasonal variations of the monsoons, which are significant throughout the basin, tropical depressions and typhoons sometimes attack the coastal areas in north Vietnam for May to August, which bring strong wind and heavy rain.

2.3 Forcing Climate Model and Datasets

2.3.1 Short introduction on Global Circulation Models

General Circulation models (GCMs) are the primary tools available for investigating the response of the climate system to various forcings. GCMs have been used for a range of applications, including investigating interactions between processes of the climate system, climate sensitivity, simulating the evolution of the climate system, and providing projections of future climate under greenhouse gasses emission scenarios (IPCC, 2013). GCMs describes key processes of the climate by using highly non-linear mathematical representations. Computation and time are two major constraints in all of this application, and so simplified model with reduced complexity and spatiotemporal resolution can be used with larger ensembles or longer time integration are required. The periodic climate change assessment reports published by International Panel on Climate Change (IPCC) have primarily relied on GCMs projections. In the IPCC fifth assessment, 20 GCMs datasets were utilized to perform the climate experiments under the Fifth Couple Model Intercomparison Project (CMIP5).

CMIP5 is the international project aims to coordinate climate simulations for a common set of experimental designs from several modeling centers worldwide. The results published in the IPCC reports are widely cited as primary sources of the information on climate change and its potential impact at several scales for practitioners and policymakers. Next, a brief overview about the type of GCMs, its characteristics and applicability are provided.

2.3.1.1 Atmospheric General Circulation Models

Atmospheric General Circulation Models (AGCMs) are non-linear partial differential equations in the numerically discretized versions that describe the atmospheric physics and dynamical processes. It mainly utilized to simulate the global atmospheric circulation with several practical applications such as medium-range weather forecasting (3 – 10 days), seasonal forecasting (3 – 12 months). AGCMs consist of a dynamical core which integrates the equation of fluid motion, typically for prognostic variables, e.g. surface pressure, horizontal components of velocity in layers, temperature, and moisture in layers, parameterization of sub-grid scale processes etc.

2.3.1.2 Ocean General Circulation Models (OGCMs)

Ocean General Circulation Models (OGCMs) describe physical and thermodynamical processes in oceans. It generally discretized at the spatial scale larger than 100 km with time integration longer than six months. OGCMs have many important applications, e.g. dynamical coupling with the atmosphere, sea ice, and total runoff; transpire of biogeochemical materials; interpretation of the paleoclimate record. (Barnier, 1998). The ocean model also plays a critical role as they transport energy from tropical to the polar altitudes, which makes OGCMs critical for feedback analysis for any climate change amplification signals on many different time scales.

2.3.1.3 Atmospheric-Ocean General Circulation Models

Atmospheric-Ocean Global Circulation Models (AOGCMs) are the three-dimensional coupling between Atmospheric Global Circulation Models (AGCMs) and Ocean General Circulation Models (OGCMs). Their primary function is to provide a comprehensive understand of the dynamics of the climate systems, one that includes atmosphere, ocean, land, and sea ice. The main drawback of three-dimensional models is that they are highly demanding in terms of computing power, and the vast amount of input data, which some of them may not exist. Therefore, there is a limited number of modeling groups that directly run AOGCMs at regional-scale resolution (Darch, 2010; Flato et al., 2011).

2.3.1.4 Earth System Models

Currently, Earth System Models (ESMs) is the state-of-the-art models that expands the scope of AOGCMs to include representation of biogeochemical processes, i.e. carbon cycle, sulfur cycle, nitrogen cycle, or Ozone and its interaction with the physical climate and so alter its response to forcing such as that associated with anthropogenic greenhouse gases emissions (Flato, 2011). Therefore, the ESM should provide the most comprehensive packages for simulation of future climate response to external forcing.

2.3.2 General Circulation Model data: MRI-AGCM 3.2H

2.3.2.1 MRI-AGCM 3.2H arrangement under SOUSEI program

First, the 60-km-mesh, atmospheric general circulation models produced by Japan Meteorological Research Institute, MRI-AGCM 3.2H (Mizuta et al., 2012), was used. The model has 640×320 grid cells, corresponding to a triangular truncation of 319 with a linear Gaussian grid (TL319) in a horizontal. The number of vertical levels is 64. Three cloud convection parameterization schemes were used for multi-physics ensemble in the model: Arakawa-Schubert (AS) scheme (Arakawa and Schubert 1974), Yoshimura (YS) scheme (Yukimoto et al., 2011; Yoshimura, Mizuta and Murakami, 2015), and Kain-Fritsch (KS) scheme (Kain and Fritsch, 1990, 1993; Kain, 2004). The AGCM climate simulations with the three convection schemes are integrated in two 25-year time period: the present climate (1979 – 2010) and the future climate (2075 – 2100) with the observed sea surface temperature (SST) and three SST changes categories: C1, C2, and C3, which accounted for the uncertainties from geographical distribution, as a lower boundary conditions (Mizuta et al., 2014).

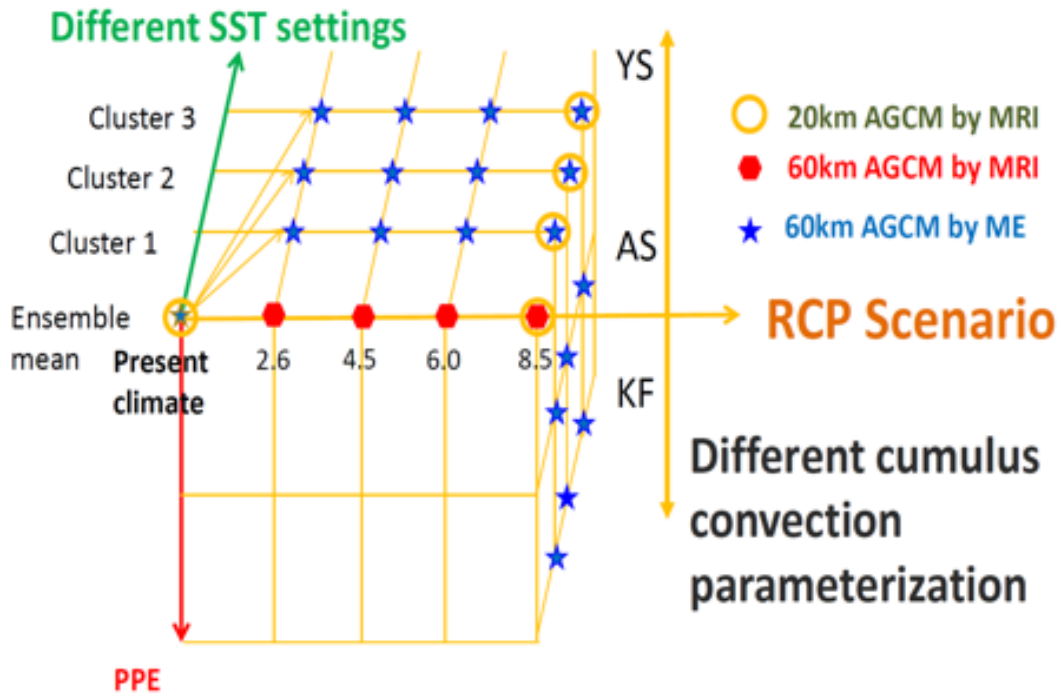


Figure 2.2 MRI-AGCM 3.2H experimental design (Source: Sousei Program)

The SST changes patterns were evaluated by the difference between the 20th-century experiment (20C3M) and the future simulation under the representative concentration pathway (RCP) extreme scenarios called RCP8.5 experiments in the CMIP5 datasets (Vuuren et al., 2011; Talyor et al., 2012). This study used daily precipitation and 3-hourly total runoff (ROF) as the two forcing outputs from the model.

2.3.2.2 MRI-AGCM 3.2H with extremely large output ensembles

The second simulations of MRI-AGCM 3.2H being used in this study is a high-resolution 60-km-mesh AGCM with the same dynamical core as previous arrangement, but with 60-year time-slice experiments for the present climate (1951 – 2010) with 100-member ensembles; and the future climate (2051 – 2110) with 90-member ensemble from six different SST warming patterns, e.g. CCSM4 (CC), GFDL-CM3 (GF), Had-GEM-AO (HA), MIROC5 (MI), MPI-ESM-MR (MP), and MRI-CGCM3 (MR) under the +4K scenario, which the average earth surface air temperature becomes 4 K warmer than the pre-industrial era. For each of the SST, 15-member ensemble experiments were conducted using different initial conditions and small perturbations of SST using Empirical Orthogonal Function (EOF) analysis. The SST, sea ice concentration (SIC), and sea-ice thickness (SIT) are prescribed as the lower boundary conditions; and global-mean concentrations of greenhouse gasses and three-dimensional distributions of ozone and aerosols as the external forcing. The convective parameterization scheme used in the simulation is the Yoshimura scheme, which has been implemented in global

circulation models and gave more realistic simulations of tropical precipitation than the older scheme such as AS or KF schemes (Yukimoto et al., 2011; Mizuta et al., 2012). The land surface scheme in this model is the Simplified Biosphere (SiB) model that computes the total runoff (ROF), which is a summation of the surface and subsurface runoff, into a river channel, and able to predict soil water storage, canopy retention and their temperatures (Sellers et al., 1986, Sato et al., 1989, Hirai et al., 2007). These experiments have been archived at the Data Integration and Analysis System (DIAS) and called “Database for Policy Decision-Making for Future Climate Change (d4PDF)”. Further information about the development can be found at Mizuta et al. (2016) and <http://www.miroc-gcm.jp/~pub/d4PDF/>.

2.3.3 GCMs data handling and processing

The 60-km AGCM datasets provides estimates of several basic climate elements such as total precipitation (PRECIPI), total runoff (ROF), surface runoff (ROFs), surface air temperature at 2 m (TA), surface air relative humidity (RHA), surface air wind speed at 10 m (WIND) etc. Two derived variables, PRECIPI and ROF were used in this study. Description of the climate elements and derived variables are given in Table 2.1. The next subsection will explain briefly about the climate data format stored in the d4PDF database.

2.3.3.1 Raw binary data

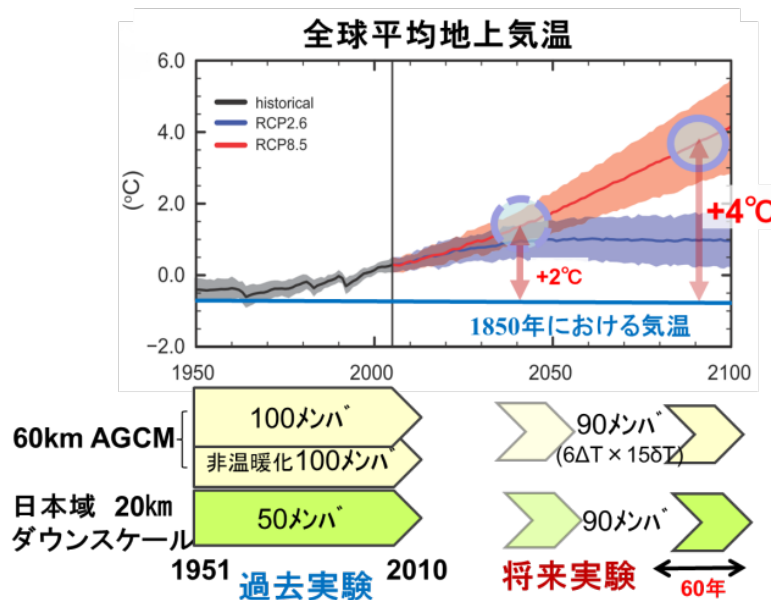


Figure 2.3 d4PDF present and future climate scenarios (source: d4PDF user guide, 2016)

The forcing data contained in the database are encoded in WMO-GRIB and nominal binary (.bin) formats. GRIB (GRIdded Binary) format files is an efficient way for transmitting a large

volume of gridded data to automated centers over high-speed telecommunication lines using modern protocols. By packing information into the GRIB format, records can be made more compact than character oriented bulletins, which allows faster data transmission between computers and can equally well serve as a data storage format.

Each GRIB record intended for either transmission or storage contains a single parameter with values located at an array of grid points, or represented as a set of spectral coefficients, for a single layer, encoded as a continuous bit stream. Logical divisions of the record are designated as “sections”, each of which provides control information and/or data. Language tools like C++, FORTRAN or script languages such as shell and Climate Data Operator (CDO) can be used to convert the binary file into a more “understandable” format. Sample code to convert the raw file into netCDF and ASCII format was conducted using a combination of shell scripts and C++ languages, which will be fully provided in Appendix I of the dissertation.

2.3.3.2 Data Descriptor File

The data descriptor files are stored in GrADS control file in ASCII format, which contains a complete description of the binary data as well as instructions for GrADs on where to find the specific variable and how to read it. This ASCII file has the “.ctl” extension.

2.4 Hydrological Model

Generally, computation of flow routing generated by excess rainfall can easily be done by lumped approaches, e.g, unit hydrograph, linear reservoir modeling, which assumed that flow parameters are transient and treat the complete basin as a homogeneous whole. However, it is difficult to represent spatial heterogeneity from land uses and topography on a basin scale (Liu et al., 2009). Therefore, the 1-km, physically-based, distributed kinematic-wave flow routing model, 1K-FRM, developed by the Hydrology and Water Resource Research Laboratory of Kyoto University, was chosen for this study (Tachikawa et al., 2011; Hunukumbura et al., 2012).

The main components of the model are catchment model, flow model, and topographic model, which will be explained briefly in the next subsection below.

2.4.1 Catchment model

A catchment model was developed using a Digital Elevation Model (DEM). The flow direction is defined using the assigned flow from each grid cell to one of its neighbors, either adjacent or diagonal, in the steepest direction of a downward slope to an immediate

neighboring cell. Each slope element determined by the flow direction is represented by two adjacent grid cells, and final cumulatively formed the catchment topography. Then, the generated total

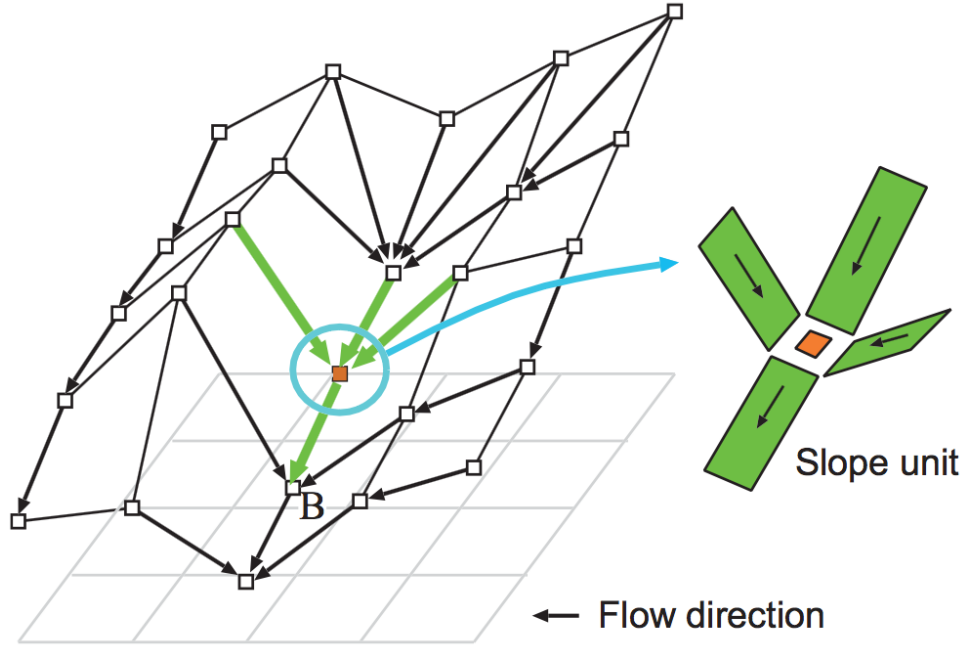


Figure 2.4 Sloped element based on flow direction information

runoff data is routed according to the flow direction information by applying the governing equations to all slope element.

This study utilized catchment topography model generated from the post-processed, scale-free global streamflow network datasets (Masutani et al., 2006) with the spatial resolution of 5 arc minutes.

2.4.2 Flow routing model

The basic form of kinematic wave equations for each rectangular slope element in the 1K – FRM flow routing model is first described as the flow continuity in partial differential form for each cell, which given by:

$$\frac{\partial Q}{\partial t} + \frac{\partial A}{\partial x} = q_L(x, t) \quad (2-1)$$

Where t is time, x is the distance from the top of the rectangular grid, A is cross section area on the regular grid, Q is a discharge, and $q(t)$ is the lateral inflow per unit length of channel unit given as runoff generated by the MRI-AGCM 3.2H. The one-dimensional momentum equation can be written in stylized manning's formula form as follows:

$$Q = \alpha A^m \quad (2-2)$$

$$\alpha = \frac{\sqrt{i_0}}{n} \left(\frac{1}{B}\right)^{m-1}, m = \frac{5}{3} \quad (2-3)$$

Equation (2-2) and (2-3) derives from Manning's equation, which governs the open channel flow characteristics. It also relates discharge and cross-sectional area, which is joined by the continuity equation to route a flow of water in each cell, where i_0 is slope; n is the manning roughness coefficient; B is the width of flow. The flow parameter $m = 1.67$ for the rectangular cross-sectional area. The cross-section with quadratic function shape, $m = 1.44$. The value of B is determined using the regression relationship $B = aS^c$, Where S is the catchment area at the calculated points, and $a = 1.06$ and $c = 0.69$ are constant parameters. The value of n is determined to be $0.03 \text{ m}^{-1/3}\text{s}$ for the channel when catchment area at the calculated point is larger than 500 km^2 and $11.0 \text{ m}^{-1/3}\text{s}$ for slope when catchment area is smaller than 500 km^2 (Tachikawa et al., 2011; Duong et al., 2013).

2.4.3 Topography model

The basic framework of 1K – FRM topological dataset is Hydrological data and maps based on Shuttle Elevation Derivatives at Multiple Scales (HyDroSHEDS; Lehner, 2006) with 1-km spatial resolution. In addition, topographic parameters, e.g. elevation, river number, river length, flow direction, and flow accumulation and simulation processes are determined at every grid cell in the 1K – FRM.

However, for a continental-scale study area like the Indochinese Peninsula, a simple application of 1-km topographic information is not temporally feasible when considering the requirement of large computational resources. To ensure the delicate need to balance spatial resolution, computing time, and application of the flow routing model for the impact assessment due to climate change with a very large domain, the method to efficiently process the flow information across several spatial scales is needed. Thereby, scale-free global streamflow network datasets proposed by Masutani et al. (2006) was chosen to process the topographic information in the 1K-FRM. This method creates an streamflow network for an integrated river basin while conserving fundamental hydraulic information based on the finest-resolution steam flow channel networks with 11 different high spatial resolution: 3 s, 6 s, 9 s, 12 s, and 15 s; medium resolution: 30 s, 1 min, 2 min, and 3 min; low resolution: 5 min, and 10 min. The integrated river basin of the Indochinese Peninsula is illustrated in Figure 2.5.

To successfully perform the hydrologic simulation on the large region with many large river basins, this topographic and physiographic information from individual river basins must be merged together and dealing with the issue of overlapped grid cells at the boundary of those river basins. The proposed method eliminates smaller overlapped grid cells but preserves its information and added to the adjacent following the flow direction information while keeps each basin area unchanged when it joined into the larger topographic map



Figure 2.5 Integrated River Basin of the Indochinese Peninsula from scale-free streamflow network dataset (adopted from Duong, 2014)

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Chapter 3

Evaluation of future river discharge uncertainties in the Indochinese Peninsula simulated by multi-physics ensemble experiments

3.1 Introduction

The Indochinese Peninsula is a widely developing region with a large and growing population. The region has a diverse geographic landscape from mountainous area and plateau to low-lying areas such as swamp and grasslands.

Based on the past observations collected by IPCC, the average surface air temperature in the Indochinese Peninsula has risen about 0.6 – 1.0 °C from the pre-industrial era and projected to continually increase by another 1.25 °C until the end of this century (IPCC, 2013). As a result, this region is likely to experience a greater amount of precipitation and an increase in runoff (Hartman et al., 2013; Hirayabashi et al., 2013), which probably cause widespread impacts on human, climate systems, hydrological cycle, and associated extremes such as floods and droughts. Therefore, the projection of the future daily river discharge is the essential component of effective adaptation strategies.

In general, impacts of climate change on surface water distribution are most clearly represented by the state of river discharge. For instance, the occurrences of floods are almost always followed by a significant increase in the discharge and water level. On the contrary, significant drought event also frequently happened after prolonged period of exceptionally low flow. Therefore, analysis of its impact to river discharge will yield significant values to practical application.

Currently, the studies on analyzing runoff or streamflow projection under changing climate can employ the land surface models, hydrological models forced by bias-corrected input data, or directly use the total runoff outputs from GCMs to simulate river discharge and assess its impact on surface water distribution. However, uncertainties arise from several factors discussed in chapter 1 did become the major obstacles to making the use of hydrological projection in a reliable way.

Generally, the simplest way to produce a more credible assessment of the impact of climate change probabilistically is to possess as many samples as possible. However, relying only on

the sheer number of dataset alone may prove to be insufficient, mainly for two reasons (Hanittinan et al., 2016):

- The climatological mean of forcing datasets from multi-physics such as the different use of cloud convection schemes and multiple sets of lateral boundary conditions such as SST changes patterns in a climate experiment within GCM might not come from the identical source of mother population.
- The prior distribution functions from different multi-physics and lateral boundary conditions may significantly differ with each other for both the shape and tail.

This chapter focuses on the former part; therefore, statistical test to examine whether the mean of two samples from MRI – AGCM 3.2H are originated from the identical or different population, is essential and should serve as a prerequisite to considering pooling hydrologic samples from various physics and boundary conditions.

To examine the uncertainty of river flow projections using GCM outputs with different cloud convection schemes and different sea surface temperatures (SSTs), we conducted the two-way Analysis of Variance (ANOVA) to projected river discharge using the latest 60-km-mesh MRI-AGCM 3.2H with nine ensemble experiments.

3.2 Methodology

3.2.1 Daily river discharge simulation

River discharge simulations were performed using 1K-FRM. The input data for the flow routing model were provided by the 3-hourly total runoff retrieved from the 60-km-mesh atmospheric model MRI – AGCM 3.2H, which releases various hydro-meteorological variables for two climate experimental settings, namely, the present climate (1979 – 2008), and the future climate (2075 – 2099), as shown in Table 3.1. The simulated output is a daily river discharge for each month stored in the free-form, GrADs binary format, for the entire Indochinese Peninsula.

The simulated river discharge was compared using long-term historical daily discharge between 1979-2003 in two gauging stations, Y.14, and C2 in the Chao Phraya River Basin of Thailand. Two statistics, namely the correlation coefficient (R), and the Nash-Sutcliffe model efficiency (NSE) (Nash and Sutcliffe, 1970), were used to evaluate the performance of the flow routing model in the adjusted flow parameters, e.g., Manning's roughness coefficient for slope and Manning's roughness coefficient for river, are given as:

$$R = \frac{\sum_{i=1}^N (Q_{obs}(i) - \bar{Q}_{obs})(Q_{sim}(i) - \bar{Q}_{sim})}{\left[\sqrt{\sum_{j=1}^N (Q_{obs}(j) - \bar{Q}_{obs})^2} \right] \left[\sqrt{\sum_{j=1}^N (Q_{sim}(j) - \bar{Q}_{sim})^2} \right]} \quad (3-1)$$

$$NSE = 1 - \frac{\sum_{i=1}^N (Q_{obs}(i) - Q_{sim}(i))^2}{\sum_{i=1}^N (Q_{obs}(i) - \bar{Q}_{obs})^2} \quad (3-2)$$

Where N is the number of data points, $Q_{obs}(i)$ is the observed daily river discharge in cubic meter per second at time step i , $Q_{sim}(i)$ is the simulated daily river discharge in cubic meter per second at time step i , and $\bar{Q}_{obs}$ is the mean of the observed daily river discharge, also in cubic meter per second. The recommended value of R achieved in the simulation should be at least greater or equal to 0.60 to 1 (Hinkle, Wiersma and Jurs, 2003). Nash's NSE can range from $-\infty$ to 1. An efficiency of 1 ($NSE = 1$) means a perfect match of modeled river discharge to the observed data. An efficiency of $NSE = 0$ indicates the model predictions are as accurate as the simple averaging of the observed data, and $NSE < 0$ happens when the observed mean is better at predicting river discharge than the model itself.

According to Abbaspour (2005) and Madsen (2000), it can assume that the model was able to reproduce the hydrograph for both observed river discharge gauging stations. The calibrated model also performs well for the verification period; even there are some discrepancies for peak discharge and low flow estimation. The flow parameter and performance index are summarized in Table 3.2. During the calibration period, the correlation coefficient (R) ranges from 0.73 to 0.75 at C.2 and Y.14 station. The NSE coefficient ranges from 0.64 to 0.72, which are acceptable for discharge predictions. In the verification period, the model performance was not as good as that in the calibration period, with smaller R and NSE for both stations.

After the flow routing model parameter was verified, the total runoff (ROF) data from MRI-AGCM 3.2H is used as an input to simulate future river discharge in the Indochinese Peninsula. Then, the maximum, minimum and average river discharge from each perturbed ensemble were computed and will be used for further uncertainty analysis using two-way ANOVA with consideration of replication between different Sea surface temperature settings (C1, C2, C3) and multiple cloud convection parameterization schemes (AS, YS, KF).

3.2.2 Analysis of variance

Statistical significance of the difference between two group means, namely, convection parameterization schemes and SST warming patterns, were analyzed and tested using two-way Analysis of Variance (ANOVA) without replication (Storch and Zwiers, 1999).

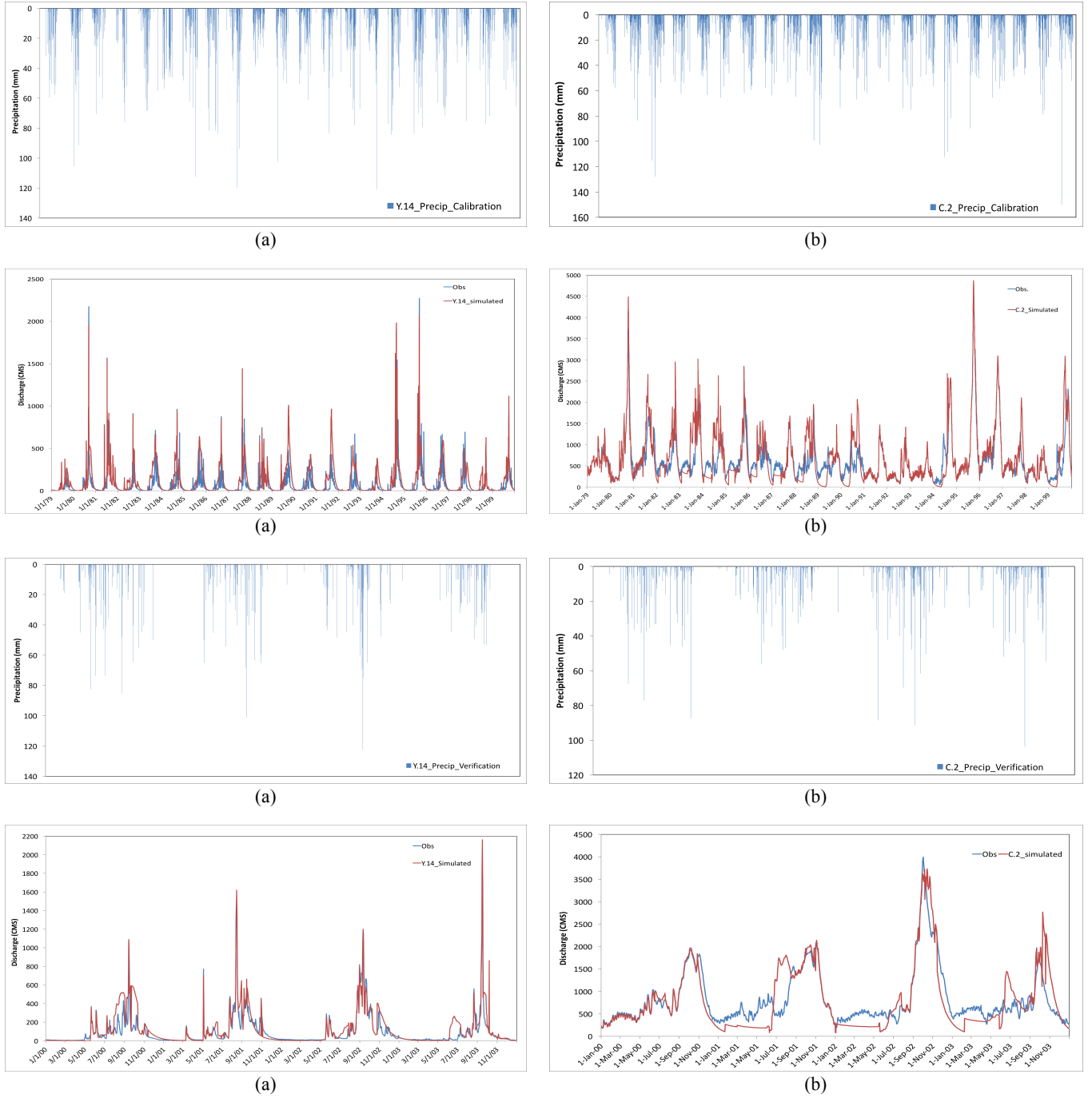


Figure 3.1 Results of 1K-FRM flow routing model calibration and verification at a) Y.14 station and b) C.2 station in Thailand

The statistical analysis decomposes the total variance of the nine ensemble projections into three components: the variation due to the different SST changes; the variation due to the convection schemes, and residual, assumes the effect of the two factors is mutually independent. The data structure of the two-way ANOVA without replication is organized as follows:

$$x_{ij} = \mu + \alpha_i + \beta_j + \varepsilon_{ij} \quad (3-2)$$

Table 3.1 Experimental design

Run Name ¹	Cumulus Convection Scheme	Sea Surface Temperature	Horizontal Resolution (km)
<i>Present-day climate simulations for 1979-2003</i>			
HP_YS	Yoshimura (YS)		60
HP_AS	Arakawa-Schubert (AS)		60
HP_KF	Kain-Fritsch (KF)		60
<i>Future Climate Simulations for 2075-2099</i>			
HF_YS_C1	Yoshimura (YS)	Cluster 1 (C1)	60
HF_YS_C2	Yoshimura (YS)	Cluster 2 (C2)	60
HF_YS_C3	Yoshimura (YS)	Cluster 3 (C3)	60
HF_AS_C1	Arakawa-Schubert (AS)	Cluster 1 (C1)	60
HF_AS_C2	Arakawa-Schubert (AS)	Cluster 2 (C2)	60
HF_AS_C3	Arakawa-Schubert (AS)	Cluster 3 (C3)	60
HF_KF_C1	Kain-Fritsch (KF)	Cluster 1 (C1)	60
HF_KF_C2	Kain-Fritsch (KF)	Cluster 2 (C2)	60
HF_KF_C3	Kain-Fritsch (KF)	Cluster 3 (C3)	60

¹The First character of the run name denotes horizontal grid size: H (High, 60 km). The second character indicates target period: P (Present-day), F (future)

Table 3.2 Model parameters and performance evaluation of the calibrated flow routing model

Gauging stations	Parameter values		Period	R	NSE
	n_slope	n_channel			
Y.14	11.00	0.03	Calibration period (1979-1999)	0.88	0.73
			Verification period (2000-2003)	0.81	0.68
C.2	11.00	0.03	Calibration period (1979-1999)	0.77	0.66
			Verification period (2000-2003)	0.72	0.64

Where x_{ij} is a sample data; μ is the overall mean; α_i and β_j are the 1st and 2nd explanatory variables, which are different cloud convection schemes and SST warming patterns, respectively; and ε_{ij} are the independent and identically distributed (iid) zero-mean standard random errors. To prove whether the different mean values are significant on the total mean, the total amount of variation, denoted as a sum of squares (SS) is calculated by the following equation:

$$S_T = S_A + S_B + S_E \quad (3-3)$$

Where S_T is a total sum of squares, S_A is a sum of squares for the river discharge under different convection schemes, S_B is a sum of squares for the river discharge under SST warming patterns, and S_E is called a residual of the river discharge. In the case of the two independent variables under consideration, we constructed the ANOVA table (see Table 3.3), with a member of the 1st variable and b members of the 2nd variables. The results in total $a \times b$ members, where $a=3$ for three cloud convection schemes AS, YS, and KF; and $b=3$ for three sea surface temperature patterns of Cluster 1, 2 and 3 (Endo et al., 2012; Mizuta et al., 2014). Based on the given assumptions and ANOVA variables (Table 3.3), the sum of square for each independent variable can be computed as follows:

$$S_T = \sum_{i=1}^a \sum_{j=1}^b x_{ij}^2 - \frac{(\sum_{i=1}^a \sum_{j=1}^b x_{ij})^2}{a \times b} \quad (3-4)$$

$$S_A = \frac{(\sum_{j=1}^b x_{1j})^2 + (\sum_{j=1}^b x_{2j})^2 + \dots + (\sum_{j=1}^b x_{aj})^2}{b} - \frac{(\sum_{i=1}^a \sum_{j=1}^b x_{ij})^2}{ab} \quad (3-5)$$

$$S_B = \frac{(\sum_{i=1}^a x_{i1})^2 + (\sum_{i=1}^a x_{i2})^2 + \dots + (\sum_{i=1}^a x_{ib})^2}{a} - \frac{(\sum_{i=1}^a \sum_{j=1}^b x_{ij})^2}{ab} \quad (3-6)$$

By assumes that there is no correlation between the two factors A and B, then:

$$S_E = S_T - S_A - S_B \quad (3-7)$$

From equations (3-4), (3-5), (3-6), and (3-7), the mean square of the first component (MS_A), the mean square of B (MS_B), and mean square of within-group variance (MS_E) can be determined. Subsequently, the statistical significance of the difference of each group mean to the total mean was computed by conducting F-test by calculating ratios of the mean square for each explanatory variable with MS_E as shown in tabulated form (see Table 3.4). There are two separate null hypotheses when conducting a two-way ANOVA. Thus, two F ratios are calculated and tested for statistical significance of each factor. Thus, the criterion for acceptance of null hypothesis rejection is given by:

$$\frac{MS_A}{MS_E} \geq F(a-1, (a-1)(b-1); \alpha) \quad (3-8)$$

Table 3.3 ANOVA tables and its associated variables in each cell

	B ₁	B ₂	B _b	Sum(b)
A ₁	x_{11}	x_{12}	x_{1b}	$\sum_{j=1}^b x_{1j}$
A ₂	x_{21}	x_{22}	x_{2b}	$\sum_{j=1}^b x_{2j}$
A _a	x_{a1}	x_{a2}	x_{ab}	$\sum_{j=1}^b x_{aj}$
Sum(a)	$\sum_{i=1}^a x_{i1}$	$\sum_{i=1}^a x_{i2}$	$\sum_{i=1}^a x_{ib}$	$\sum_{i=1}^a \sum_{j=1}^b x_{ij}$

Table 3.4 ANOVA formulae in a tabulated form

	SS	dF	Mean sum of square	F
A_i	S_A	$a-1$	$MS_A = \frac{S_A}{a-1}$	$F_A = \frac{MS_A}{MS_E}$
B_j	S_B	$b-1$	$MS_B = \frac{S_B}{b-1}$	$F_B = \frac{MS_B}{MS_E}$
	S_E	$(a-1)(b-1)$	$MS_E = \frac{S_E}{(a-1)(b-1)}$	

$$\frac{MS_B}{MS_E} \geq F(b-1, (a-1)(b-1); \alpha) \quad (3-9)$$

Where $(a-1)$ is the degree of freedom (dF) for variance of cloud convection schemes; $(b-1)$ is the degree of freedom for variance of multiple SST patterns; and α is the significant level, which set at 0.01 in this study. Furthermore, the contribution of river discharge of each factor was also computed as a simple ratio of the mean variance of the main effects (cloud convection schemes and SST patterns) given by:

$$R_A = \frac{MS_A}{MS_A + MS_B + MS_W} \quad (3-10)$$

$$R_B = \frac{MS_B}{MS_A + MS_B + MS_W} \quad (3-11)$$

$$R_E = \frac{MS_E}{MS_A + MS_B + MS_W} \quad (3-11)$$

Where R_A , R_B , R_{AB} , and R_W is the contributing ratio of the different SST patterns, different cumulus convection schemes, the interaction between main effects, and the residual errors, respectively.

3.3 Attribution of the uncertainties of the future river discharge projections under changing climate

3.3.1 Contribution of the convection parameterization schemes to the total river discharge projection uncertainty

Spatial distribution mapping of the different cloud convection schemes (YS, AS, KF) contributing ratio to the total uncertainty, represented as a total variance of the daily river discharge in the Indochinese Peninsula, are shown in 4 cases: a) the maximum discharge, b) the average annual 25-year maximum discharge, c) the climatological mean discharge, and d) the minimum discharge, respectively.

In the first two cases, which shown in Figure 3.2, the clearest contributions of the cloud convection schemes ($0.77 \leq R_A \leq 0.99$) is commonly found in the middle to the Northern Chao Phraya River Basin, Southern Indochinese Peninsula, and the Southern part of Mekong River Basin (belongs to the Mekong Delta). On the other hand, the Salween River Basin is much less affected of using different parameterization schemes - with the contributing ratio 0.39 – 21.37% ($0.039 \leq R_A \leq 0.21$). In case c), the cloud convection schemes contributing signals is found to be active on the Chao Phraya River Basin, Southern Indochinese Peninsula, Mekong Delta, and the Red River Basin of Vietnam. Meanwhile, the signal of the convection schemes is projected to be exceptionally weak at the Ayeyarwaddy River Basin of Myanmar, somewhat weak in the Eastern Chao Phraya Basin up to the middle region of Mekong Basin with the contributed ratio between 0.39 – 21.40% ($0.039 \leq R_A \leq 0.21$). For the fourth case, the cloud convection schemes made a sizable contribution of 77 – 99% ($0.77 \leq R_A \leq 0.99$) to the total variance of the minimum daily river discharge at the Red River Basin, and the Mekong Delta. However, the contribution is much less significant in the other basins, e.g. Ayeyarwaddy, Salween, Chao Phraya, and the Northern Mekong Basin

According to the results, it is notable that most of the regions clearly express its consistency of the spatially-distributed signals on the convection schemes to the total river discharge projection uncertainty for the prior three cases (Figure 3.2a, Figure 3.2b, Figure 3.2c), but less so in the fourth case (Figure 3.2d). In the next subsection, the contribution of different SST warming patterns, C1, C2, and C3 will be discussed.

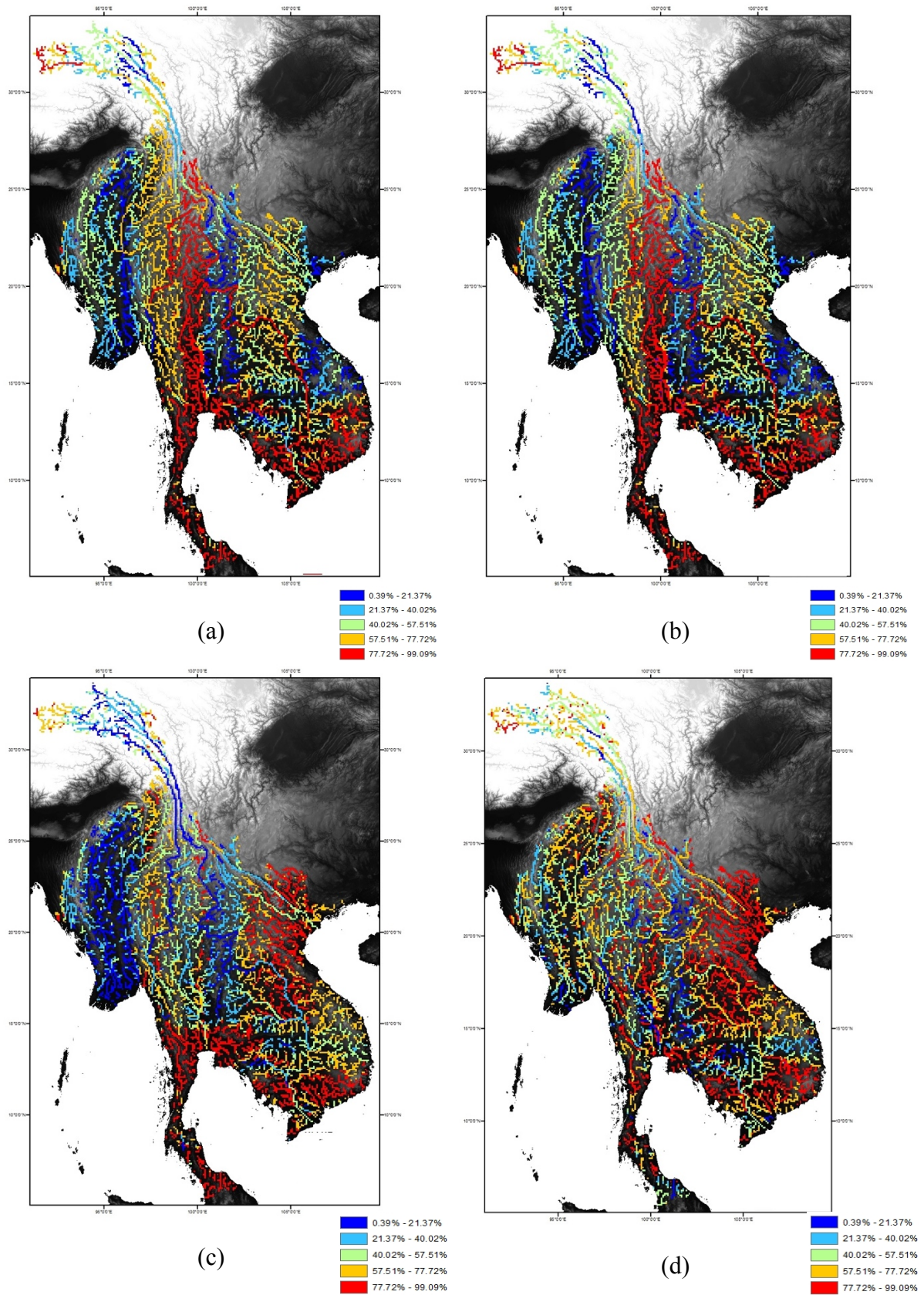


Figure 3.2 Contribution from the different cloud convection schemes to the total variance of a) the maximum discharge, b) the average annual 25-year maximum discharge, c) the climatological mean discharge, and d) the minimum discharge

3.3.2 Contribution of the SST warming patterns to the total river discharge projection uncertainty

For multiple SST warming scenarios (see Figure.3.3), the attribution to the overall prediction uncertainty of the future daily river discharge of the Indochinese Peninsula are presented in the similar four cases. In the first two cases, the SSTs showed little role in contributing to the total variance in river discharge at the Chao Phraya Basin, the Red River Basin, and Mekong Delta. The SSTs also showed similar signals in case b, but some differences occurred in the Salween Basin, in which case b showed the stronger contribution from the SSTs patterns to the total variance of river discharge than a case a. Figs. 3c and 3d show signals from SSTs in case c and d, which can be seen that the effect of weak signals from SSTs in the lower Chao Phraya Basin, the middle part of the Mekong, and much of the Red River Basin are clearly visible.

For the fourth case, overwhelmingly weak signals of SSTs patterns are vividly illustrated for the most region of the Indochinese Peninsula. The results of the different SSTs mostly point to a strong, consistent response across all cases in most of the basin, except for the Ayeyarwaddy and Salween Basin, which showed contradicted SSTs patterns with the other drainage basins; and has 3 out of 4 similar results in all cases.

The results of the two-way ANOVA in all four cases (Figure 3.3a, Figure 3.3b, Figure 3.3c, and Figure 3.3d) indicate that the variance due to different SST patterns plays relatively smaller proportion to the total uncertainty of the daily river discharge in much of the region in the Indochinese Peninsula when compared with the contribution from the variance due to the different cloud convection parameterization schemes.

In the next subsection, the statistical significance of the proportion of the total projection uncertainty of each component will be assessed through the determination of F-statistics, which its outcomes shall numerically account for both primary sources of future river discharge variance of the Indochinese Peninsula.

3.3.3 Testing for statistical significance of the cloud convection schemes and SST warming patterns to the total daily river discharge projection uncertainty

For the first two cases (see Fig.3.4a and Fig. 3.4b), most of the Irrawaddy, Salween, and the Red River Basin, results are clearly indicated that the effect of various convection parameterization schemes to the total projected uncertainty of river discharge is not significant. However, different convection parameterization schemes appeared playing a meaningful role

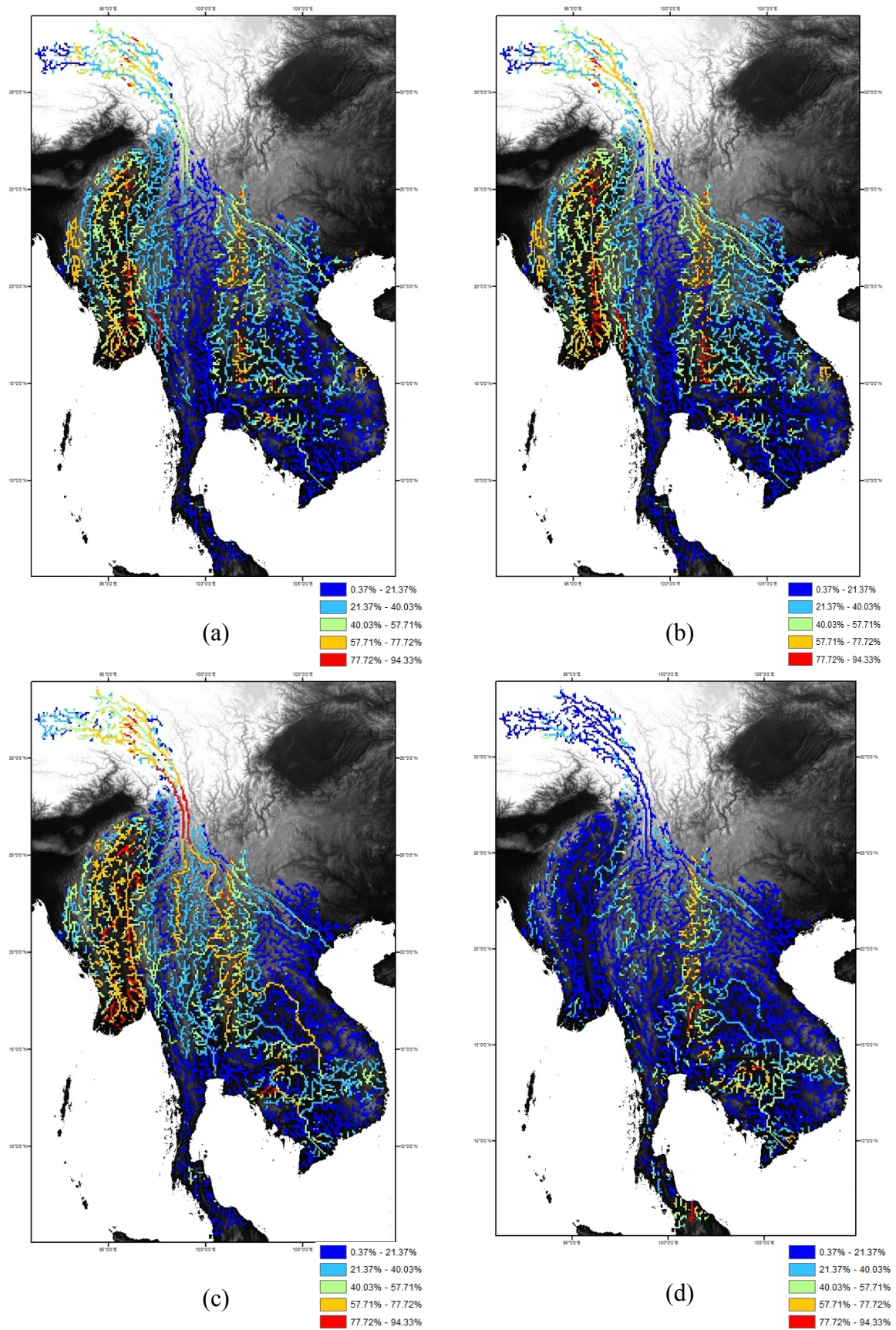


Figure 3.3 Contribution from the various SST patterns to the total variance of (a) the maximum discharge, (b) the average annual 25-year maximum discharge, (c) the climatological annual mean discharge, and (d) the minimum discharges.

at the Chao Phraya Basin, and the main Mekong river channel.

Figure 3.3c indicates that for the lower Chao Phraya Basin and the Mekong Delta, the effect of changing cloud convection scheme has made statistically significant impacts on the total variance of river discharge, based on the rejection of null hypotheses. Meanwhile, the effect of the parameterization schemes is not quite as prominent for the case of the annual minimum flow, which most regions show little statistical significance to its total projection uncertainty. For Figure 3.4a and 3.4b, results demonstrated that changing pattern of SSTs is not going to affect the overall uncertainty of daily river discharge in the statistically meaningful way for the clear majority of the region in Indochinese Peninsula. However, one important exception was found at the main channel of Mekong River. For Figs. 3.4c and 3.4d, results were broadly similar with Figs. 3.4a and 3.4b, where multiple SST warming patterns were projected not to affect an outcome of the river discharge in a significant way.

3.4 Conclusion

As a result, the implication of hydrologic frequency analysis for the results showed in Figure 3.3, and Figure 3.4 are summarized as follow:

1) In the region where null hypotheses of the different convection parameterization schemes and SST warming patterns are *rejected* indicates the significant effects of these factors to the uncertainty in the future daily river discharge projections, and its outcome should be treated as such a different GCMs input. Hence, it may imply that accurate hydrologic frequency analysis using ensemble datasets of extreme discharge in the rejected area might not be the best possible outcome.

2) In the region where null hypotheses of cloud convection schemes and SSTs are *not rejected* indicates the opposite result, which means none of these factors have significant effects to the uncertainty of river discharge projections. Thereby, the ensemble of daily river discharge samples in the non-rejected region can be utilized for the hydrologic extreme frequency analysis and should lead to a more credible water resources impact assessment.

The overall results of F-test demonstrate that the cloud convection schemes dominate the total projected uncertainties of daily river discharge in the Indochina region.

The results in this chapter are consistent with several prior findings (Endo et al., 2012; Murakami et al., 2012). Both conducted the ANOVA based on the 60-km AGCM model

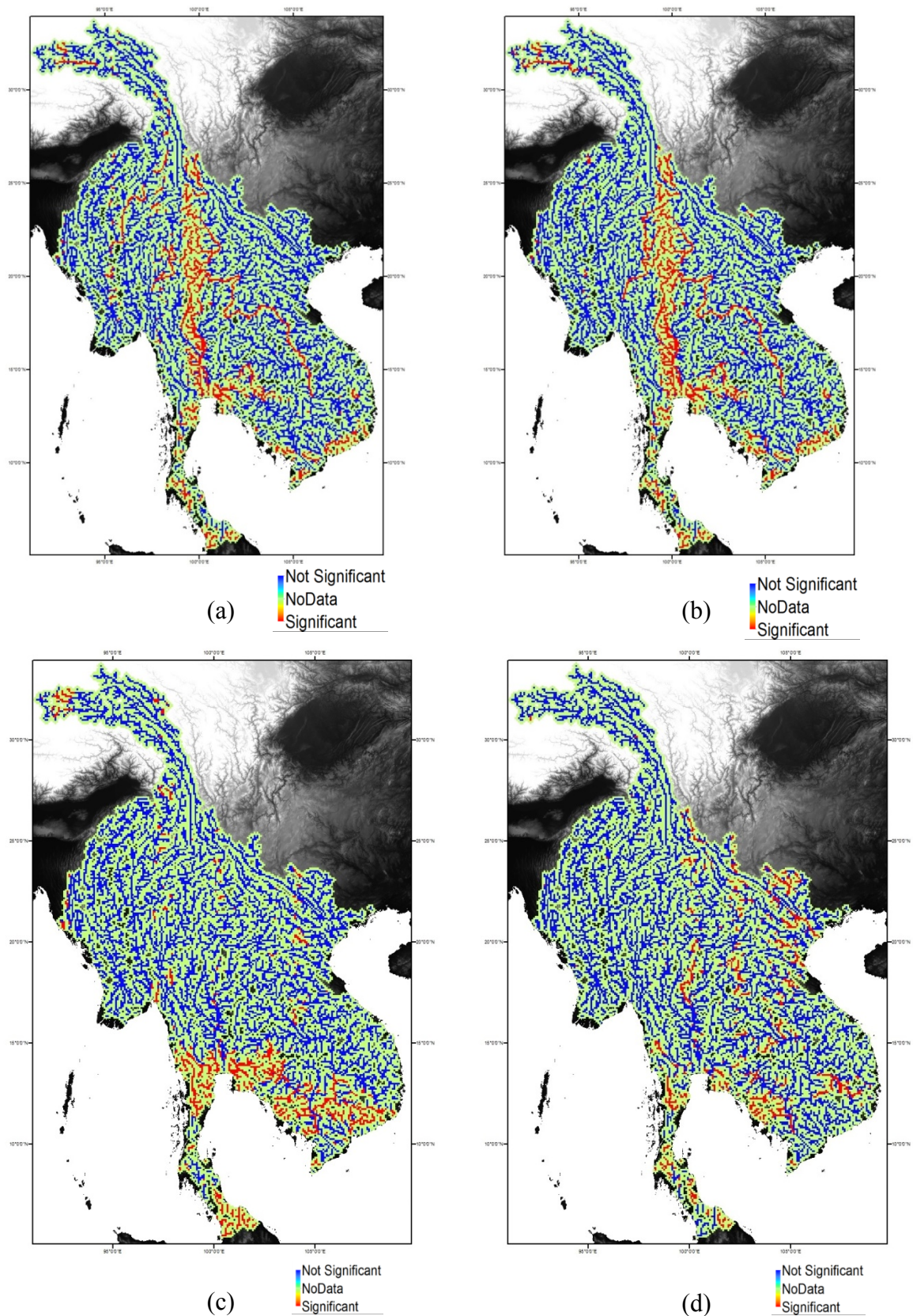


Figure 3.4 Spatial distribution showing statistical significance test using F-value of the various cloud convection schemes for (a) future 25-year maximum discharge, (b) mean of annual maximum discharge in 25 years, (c) mean of annual 25-year mean discharge, and (d) future 25-year minimum discharge

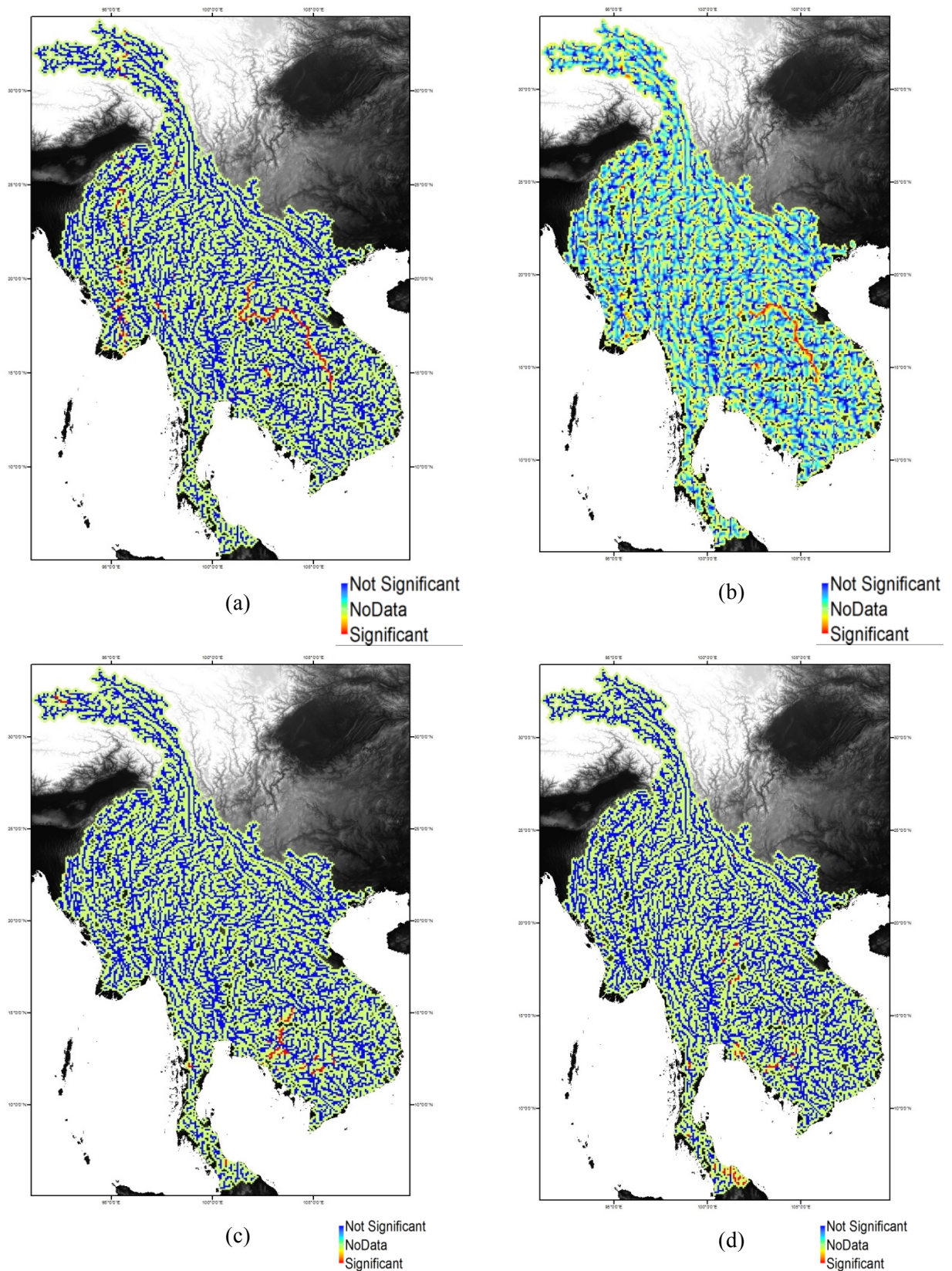


Figure 3.5 Spatial distribution showing statistical significance test using F-value of SST warming patterns for (a) future 25-year maximum discharge, (b) mean of annual maximum discharge in 25 years, (c) mean of annual 25-year mean discharge, and (d) the future 25-year minimum discharge

ensembles precipitation and tropical cyclone projections in the Asia Pacific Region. The results have revealed evidence that for extreme and average precipitation indices, variances arising from the use of the different cumulus parameterization schemes are larger than those resulting from the utilization of the different SST warming patterns in most of the Asia-Pacific, especially in the Indochinese Peninsula and mainland China. Thus, uncertainties in the projected changes in precipitation are derived mainly from differences in the cloud convection schemes employed in these areas.

Due to the nature of the runoff data used as input for the flow routing model, it is strongly related to projected precipitation data. Therefore, it should be reasonable that some significant proportions of the flow area in which the convection parameterization schemes dominate the total uncertainty of the projected daily river discharge are substantially larger than the SST-dominated area, as shown in Figure 3.4 and 3.5.

In conclusion, the analysis in this chapter helps clarify which factor of the use of different SST patterns or different cloud convection schemes contributes more to the projected uncertainty on river discharge by using the two-way analysis of variance (ANOVA) for the nine ensemble projections by the 60-km model, based on the established F-statistics criterion on accepting null hypotheses. The results reveal that the uncertainty in the future river discharge in the Indochina Peninsula derived mainly from the differences in the convection schemes.

However, further confirmation of the effect of the interaction between the multiple cloud convection schemes and SST warming conditions is still needed. Statistically, the interaction represents the combined effects of factors on the dependent measure. When an interaction effect is present, the impact of one factor depends on the level of the other factor. Part of the power of ANOVA is the ability to estimate and test interaction effects. When the interaction effects are present, it means that interpretation of the main effects is incomplete or misleading. In the next chapter, the assessment of the projection uncertainty of precipitation and runoff for the Asia Pacific Region is quantified, fully incorporated with the interaction effects. The analysis results will sufficiently provide the overview of the uncertainty of the hydrological projection in the wider region, which should strengthen the finding of the last chapter's findings on daily river discharge prediction at the Indochinese Peninsula.

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Chapter 4

Evaluation of future hydrologic projection uncertainties in the Asia-Pacific Region

4.1 Introduction

There are several methods to evaluate the source of climate change impact on hydrology and water resources in a comprehensive manner; one fundamental approach is to use outputs of general circulation models (GCMs) such as precipitation, evapotranspiration, surface runoff, subsurface runoff and so on, as an input for hydrological models. Many GCMs have been developed to simulate climate conditions, its changes, and variability over time.

In the previous chapter, the uncertainty of daily river discharge projection at the Indochinese Peninsula Region for the present climate (1979 – 2003) and the future climate (2075 – 2099), was assessed using a high-resolution, 60-km atmospheric model, MRI – AGCM 3.2H (Mizuta et al., 2006; Yukimoto et al., 2011). The total runoff outputs from the GCM was feed into a distributed flow routing model with kinematic wave approximation, 1K – FRM.

To fully illustrated the overview of the hydrological projection uncertainty in the study area, we need to evaluate its sources by using a range of parameters by examining statistical differences in precipitation, total runoff – which is the summation between the surface and sub-surface water, and river discharge projections. This chapter presents the uncertainty quantification method that is similar to the prior section, which is two-way ANOVA, but in a more generalized term at a wider region. The effect of different cumulus parameterization schemes (YS, AS, and KF), SST warming patterns (C1, C2, and C3) and the interaction effect between these two most important factors is also considered to confirm whether each factor genuinely contributes to the projection uncertainties. Two-way ANOVA *with replication* (Storch and Zwiers, 1999) was conducted for the projected precipitation and runoff data retrieved from the MRI – AGCM 3.2H with nine multi-physics experiments.

In conclusion, the objectives of this chapter are:

- 1) To provide the definitive clarification on whether the differences in cloud convection schemes or SST warming patterns are truly a major contributing factor to the projected uncertainty of future hydrological regimes in the Asia-Pacific Region, and

- 2) To perform a statistical evaluation and examine whether the means of GCM-derived hydrological datasets come from the same source or a different population.

4.2 Study area

Asia-Pacific Region (see Figure 4.1) is the part of the world in the Western Pacific Ocean. Typically includes much of East Asia, South Asia, Oceania, and Southeast Asia (including Indochinese Peninsula). The region also consists of several countries with a variable degree of population size, ranging from continental-scale such as China and India to maritime nations like American Samoa and French Polynesia. However, despite the differences, most individual countries within the zone are emerging markets experiencing rapid economic growth.

There is evidence of noticeable increases in the intensity and frequency of extreme events such as tropical cyclones, intense rainfall, thunderstorms, prolonged dry spells, and severe dust storm in the region. The future annual average surface air temperature is projected to increase in the area by order of 0.5 - 1°C by 2030 and 1 - 7°C before the end of this century. Several climate models also indicate rising precipitation concentration throughout much of the region, especially during monsoon season (IPCC, 2013; Hartmann et al., 2013). Therefore, the Asia-Pacific Region could experience a significant degree of vulnerability such climatic changes affecting millions of poor rural people. Impacts of such disasters ranging from hunger, diseases, to loss of income, property, and human livelihoods.

4.3 Methodology

The uncertainty of future hydrologic projection in the Asia-Pacific Region was assessed with two-way ANOVA *with replication* for precipitation, runoff, and river discharge for the future climate experiment. Finally, the total picture of hydrological uncertainties in the region will be analyzed and discussed

4.3.1 Analysis of variance

Two-way ANOVA *with replication* (Storch and Zweirs, 1999; Mcdonald, 2014) determines statistical differences between group means, e.g., SST patterns and cumulus convection schemes. The analysis decomposes the total variance of multi-physics projections into four components: the variance from different SST patterns, the variation from various

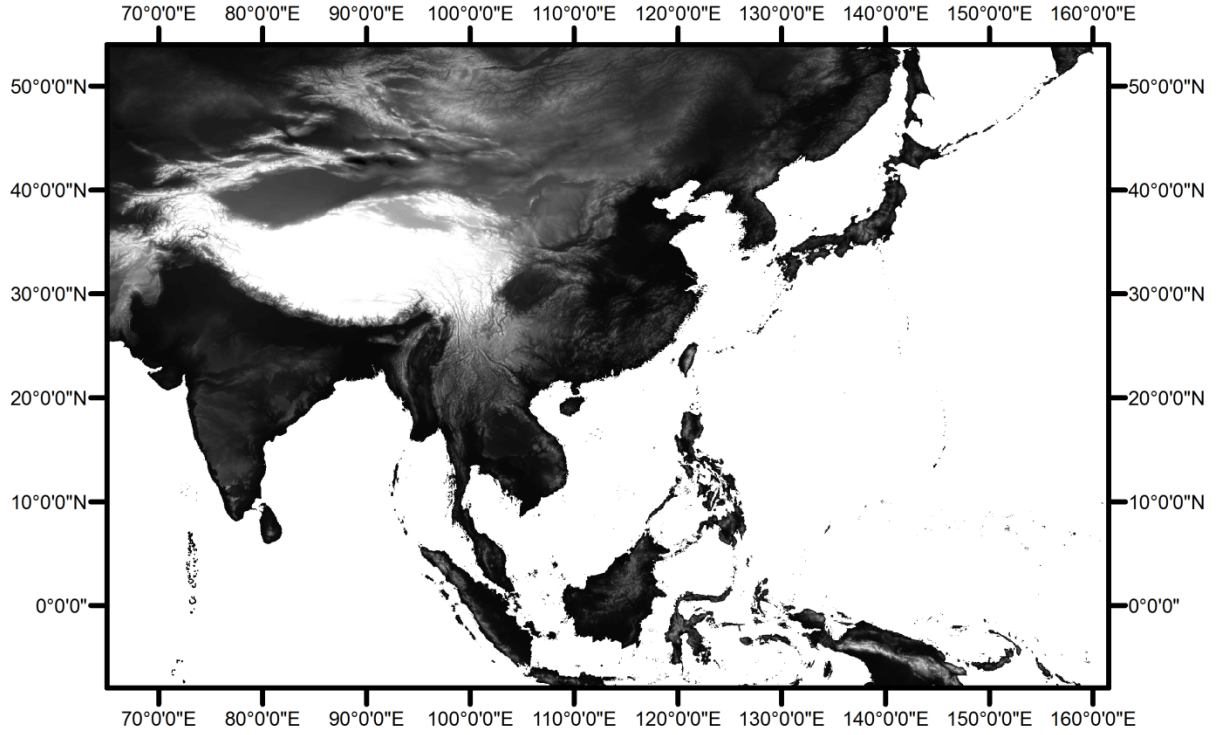


Figure 4.1 The Asia-Pacific Region

convection schemes, the variation from the interaction between the two main effects, and the mean random error (residual). Assuming the consequences of the two factors are not mutually independent, the mathematical structure of the two-way ANOVA is modeled as a linear relationship, as follows:

$$x_{ij} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \varepsilon_{ij} \quad (4-1)$$

Where x_{ij} is the sample data, μ is the overall mean; α_i and β_j are the 1st and 2nd explanatory variables; γ_{ij} is the interaction of each main effect and ε_{ij} are the independent and identically distributed $N(0, \sigma^2)$ zero-mean normal random errors. To prove whether the different means are significant with respect to the total mean, the total variation, denoted as a sum of squares (SS), is calculated using the following equation:

$$S_T = S_A + S_B + S_{AB} + S_E \quad (4-2)$$

Where S_T is the total sum of the square; S_A is the SS for the precipitation/runoff under different convection schemes, S_B is the SS for the precipitation/runoff under different SST patterns, S_{AB} is the SS of the interaction between each group, and S_W is the within group SS for the variables studied. In this study, we investigated the primary sources of uncertainties in projected future precipitation and total runoff changes from 2075–2099 to 1979–2003 through two indexes: 1) annual rainfall/runoff and 2) maximum 3-day (R3d) precipitation/runoff. We

also investigated the uncertainties in river discharge projection separately by calculating: 1) the maximum discharge, 2) the minimum discharge, and 3) the average discharge.

For the two interdependent variables under consideration, ANOVA table was constructed with a members of the 1st variable and b members of the 2nd variable, resulting in a total a times b member. Where $a = 3$ for the three parameterization schemes AS, YS and KF, and $b = 3$ for the three SST warming patterns C1, C2, and C3. F-test statistics (Fischer, 1925) were used to assess the statistical significance of the effect of each component on variations among the ensemble projections. Based on the underlying assumptions of ANOVA variables, the SS for each interdependent variable can be computed as follows:

$$S_T = \sum_{i=1}^a \sum_{j=1}^b \sum_{k=1}^r x_{ijk}^2 - \frac{(\sum_{i=1}^a \sum_{j=1}^b \sum_{k=1}^r x_{ijk})^2}{(n_{ij} \times a \times b)} \quad (4-3)$$

$$S_A = \frac{(\sum_{j=1}^b \sum_{k=1}^r x_{1jk})^2 + (\sum_{j=1}^b \sum_{k=1}^r x_{2jk})^2 + \dots + (\sum_{j=1}^b \sum_{k=1}^r x_{ajk})^2}{(n_{ij} \times b)} - \frac{(\sum_{i=1}^a \sum_{j=1}^b \sum_{k=1}^r x_{ijk})^2}{(n_{ij} \times a \times b)} \quad (4-4)$$

$$S_B = \frac{(\sum_{i=1}^a \sum_{k=1}^r x_{i1k})^2 + (\sum_{i=1}^a \sum_{k=1}^r x_{i2k})^2 + \dots + (\sum_{i=1}^a \sum_{k=1}^r x_{ijk})^2}{(n_{ij} \times a)} - \frac{(\sum_{i=1}^a \sum_{j=1}^b \sum_{k=1}^r x_{ijk})^2}{(n_{ij} \times a \times b)} \quad (4-5)$$

$$S_{AB} = \sum_{i=1}^a \sum_{j=1}^b T_{ij}^2 / n_{ij} - \frac{(\sum_{j=1}^b \sum_{k=1}^r x_{1jk})^2 + (\sum_{j=1}^b \sum_{k=1}^r x_{2jk})^2 + \dots + (\sum_{j=1}^b \sum_{k=1}^r x_{ajk})^2}{(n_{ij} \times b)} - \frac{(\sum_{i=1}^a \sum_{k=1}^r x_{i1k})^2 + (\sum_{i=1}^a \sum_{k=1}^r x_{i2k})^2 + \dots + (\sum_{i=1}^a \sum_{k=1}^r x_{ijk})^2}{(n_{ij} \times a)} + \frac{(\sum_{i=1}^a \sum_{j=1}^b \sum_{k=1}^r x_{ijk})^2}{(n_{ij} \times a \times b)} \quad (4-6)$$

$$S_W = \sum_{i=1}^a \sum_{j=1}^b \sum_{k=1}^r x_{ijk}^2 - \sum_{i=1}^a \sum_{j=1}^b T_{ij}^2 / n_{ij} \quad (4-7)$$

Where T_{ij} is the total sum of the associated variable in each factor, n_{ij} is the total number of available data for each element (25 for this study), and N is the total number of data in all nine ensembles.

From equations (4-4), (4-5), (4-6), and (4-7); we can determine the mean square of A (MS_A), the mean square of B (MS_B), the mean square of interaction between the main effects (MS_{AB}), and the within-group variance mean square (MS_W), respectively. Subsequently, the statistical significance of the difference between each group mean to the total variance was computed by conducting an F-test, which calculates the ratios of the mean square for each explanatory variable to MS_W as shown in Table 4-1. There are two separate null hypotheses when conducting a two-way ANOVA. Hence, the criterion for acceptances or rejection of the null hypothesis are shown in equations (4-8), (4-9), and (4-10), where $(a-1)$ is the degree of freedom (dF) of the variance of the convection schemes, $(b-1)$ is the degree of freedom of the variance of multiple SST patterns, $(a-1)(b-1)$ is a degree of freedom of the interaction between each main effect, and $(N-ab)$ is a degree of freedom for the within-group SS. The significance level

(α) was 0.01 in this study.

$$F_A \equiv \frac{MS_A}{MS_W} \geq F(a-1, N-ab, \alpha) \quad (4-8)$$

$$F_B \equiv \frac{MS_B}{MS_W} \geq F(b-1, N-ab, \alpha) \quad (4-9)$$

$$F_{AB} \equiv \frac{MS_{AB}}{MS_W} \geq F((a-1)(b-1), N-ab, \alpha) \quad (4-10)$$

A simple ratio of the mean variance of each main effect to the total variance was adopted to calculate the contribution of each factor as follows:

$$R_A = \frac{MS_A}{MS_A + MS_B + MS_W} \quad (4-11)$$

$$R_B = \frac{MS_B}{MS_A + MS_B + MS_W} \quad (4-12)$$

$$R_{AB} = \frac{MS_{AB}}{MS_A + MS_B + MS_{AB} + MS_W} \quad (4-13)$$

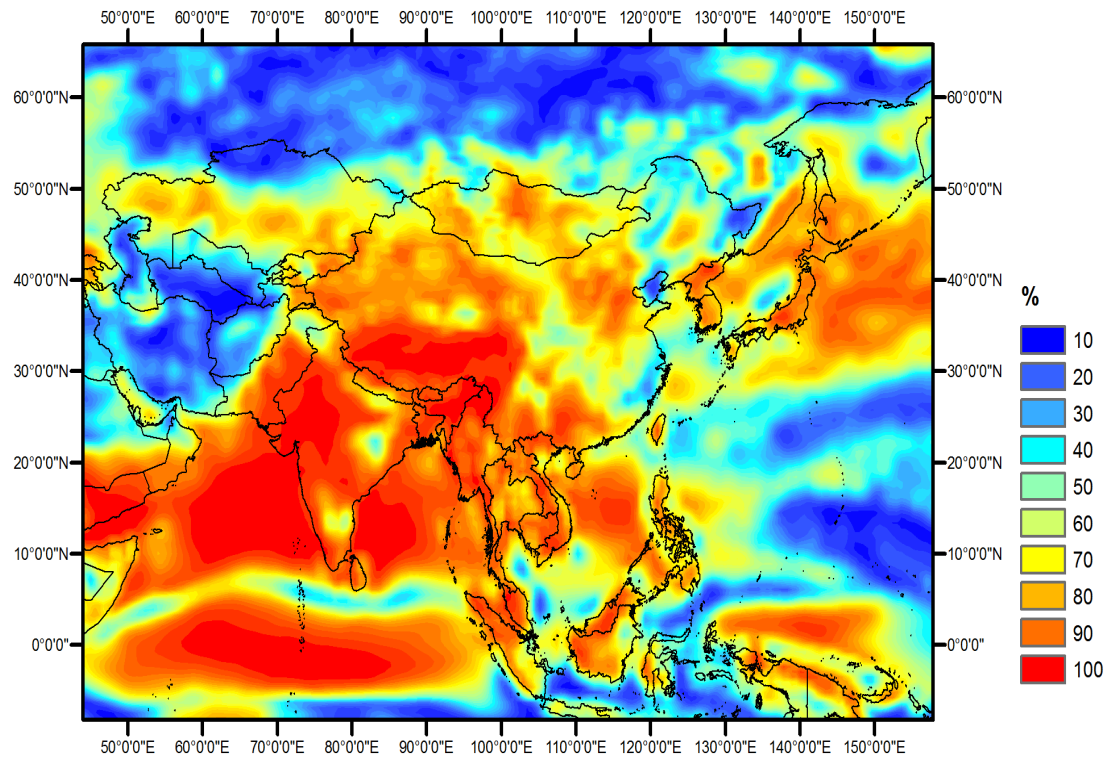
$$R_W = \frac{MS_E}{MS_A + MS_B + MS_W} \quad (4-14)$$

Where R_A , R_B , R_{AB} , and R_W are the contributing ratios of different SST patterns, different cumulus convection schemes, the interaction between main effects, and the residual errors, respectively.

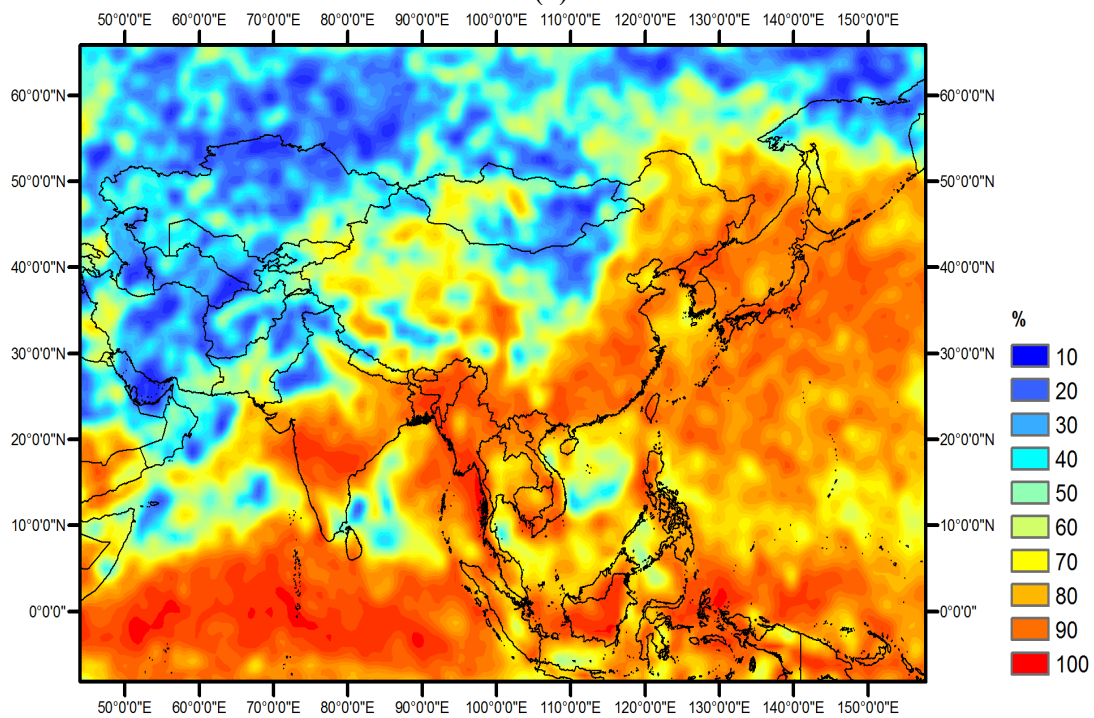
4.4 Attribution of the uncertainties of the future hydrological projections under climate change

4.4.1 Contribution of the convection parameterization schemes to the projection uncertainty of precipitation

Spatial distribution mappings of the contributing of convection schemes (YS, AS, and KF) to the total uncertainty in precipitation across the Asia-Pacific Region are illustrated for two cases: 1) annual precipitation, and 2) annual maximum 3-day precipitation (R3d) in Figure 4.2a and 4.2b. The parameterization schemes apparently made a sizable contribution to the total variance in precipitation based on the 60-km AGCM with multiple ensembles. The proportion of the total uncertainty is shown for each grid. In this figure, the greatest contribution from the convection schemes ($0.75 \leq R_A < 1.00$) to annual precipitation was commonly found in the Indian subcontinent, the Indochinese Peninsula, a maritime region of the Southeast Asia, China, the Korean Peninsula, and Japan. Noticeable exceptions were



(a)



(b)

Figure 4.2 The contributing ratio of the cloud convection parameterization schemes for (a) annual precipitation, and (b) R3d precipitation to the total projection uncertainty

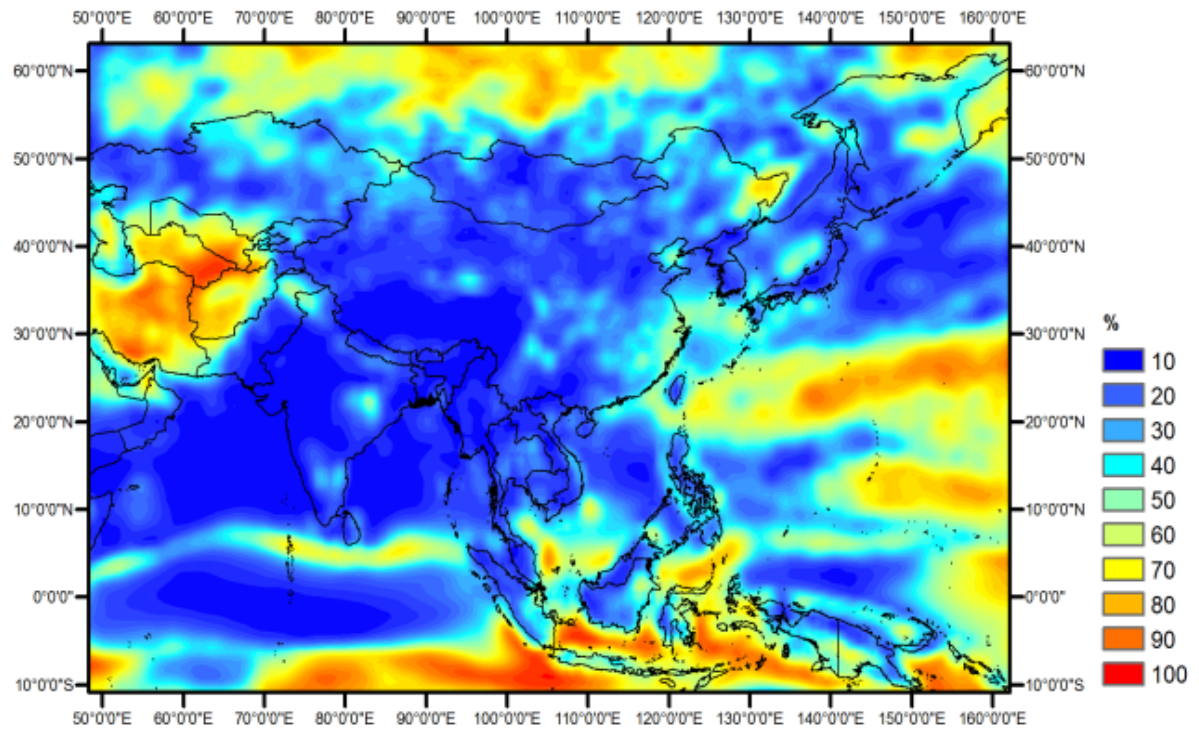
Found in the Gulf of Thailand, South China Sea, and the Java Sea. For R3d, uncertainty arises from the use of different convection schemes (shown in red color) were generally vast ($0.70 \leq R_A < 1.00$) at the middle Indian subcontinent, the Indochinese Peninsula, Eastern China, Japan, and Korean Peninsula. The region where the effect of various convection schemes is less impactful to the total uncertainty of precipitation is the Gulf of Thailand, South China Sea, and the Southern Bay of Bengal.

4.4.2 Contribution of the SST warming patterns to the projection uncertainty of precipitation

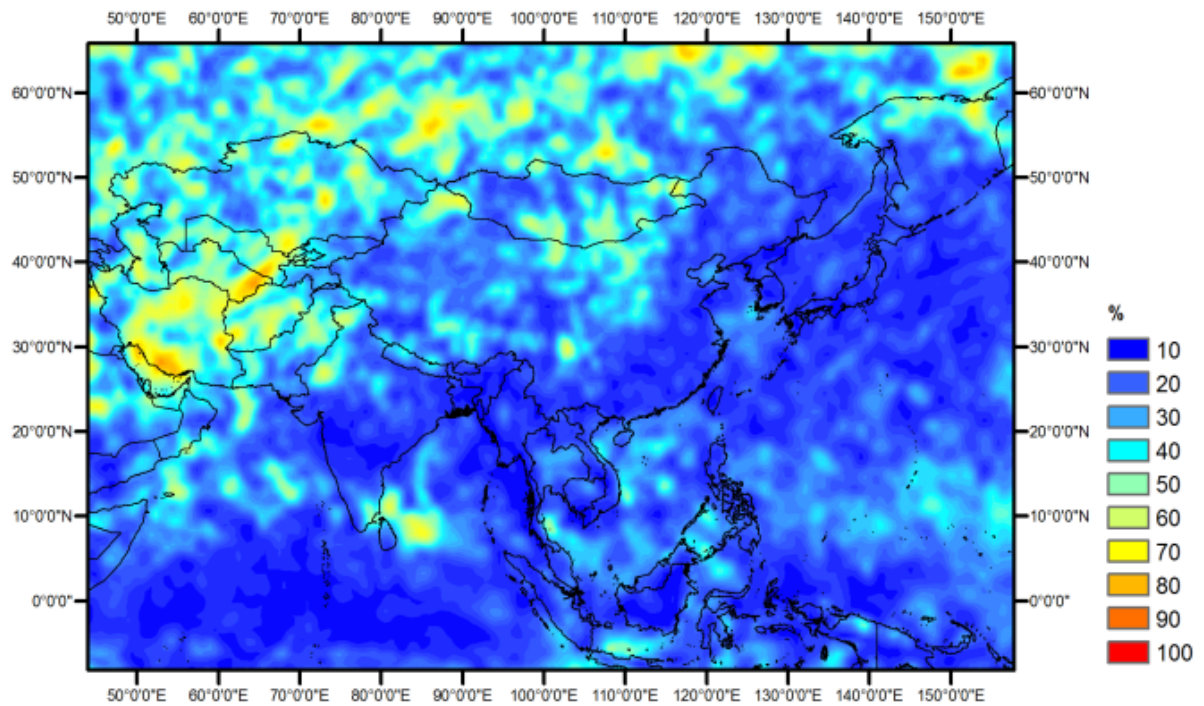
Figure 4.3a and 4.3b shows the spatial distribution of the SST arrangement contributing ratios to the variance of precipitation in the Asia Pacific, for the same cases discussed previously. The SST patterns typically contributed up to 10% of the total variance ($R_B \leq 0.10$) in the majority of the Asia Pacific landmass. The SSTs play a slightly more prominent role in the total variance in precipitation ($0.10 \leq R_B \leq 0.40$) on the east coast of China, the East China Sea and the Gulf of Thailand. The variances arising from the use of different SST patterns showed a strong effect in the maritime region of South East Asia, e.g., the Java and the Banda Seas, with a contributing ratio in a realm of 90% ($0.90 \leq R_B \leq 0.99$) for annual precipitation. In the case of R3d, the various use of SSTs has even less effect on the total variance of precipitation for the landmass and maritime regions of the Asia Pacific, with contributing ratios mostly at 10–40% ($0.10 \leq R_B \leq 0.40$). This finding points toward the major differences in SST contributions in the equatorial region between annual precipitation and R3d precipitation.

4.4.3 Contribution of the interaction between the convection schemes and SST warming patterns to the projection uncertainty of precipitation

The Interaction effects of cloud convection schemes and SST warming arrangements are summarized in Figure 4.4a and 4.4b. For the annual precipitation, the effect was found to be negligible for the entire Asia Pacific region. Contributing ratios of annual and maximum 3-day precipitation are in the ranges of 10–30% ($0.10 \leq R_{AB} \leq 0.30$). The results for R3d precipitation are largely similar to those for annual precipitation, for most of the Asia Pacific landmass and the maritime region. The findings indicated the uncertainties arising from the use of different convection schemes and SST warming patterns did have a much more



(a)



(b)

Figure 4.3 The contributing ratio of the SST warming patterns for: (a) annual precipitation, and (b) R3d precipitation to the total projection uncertainty

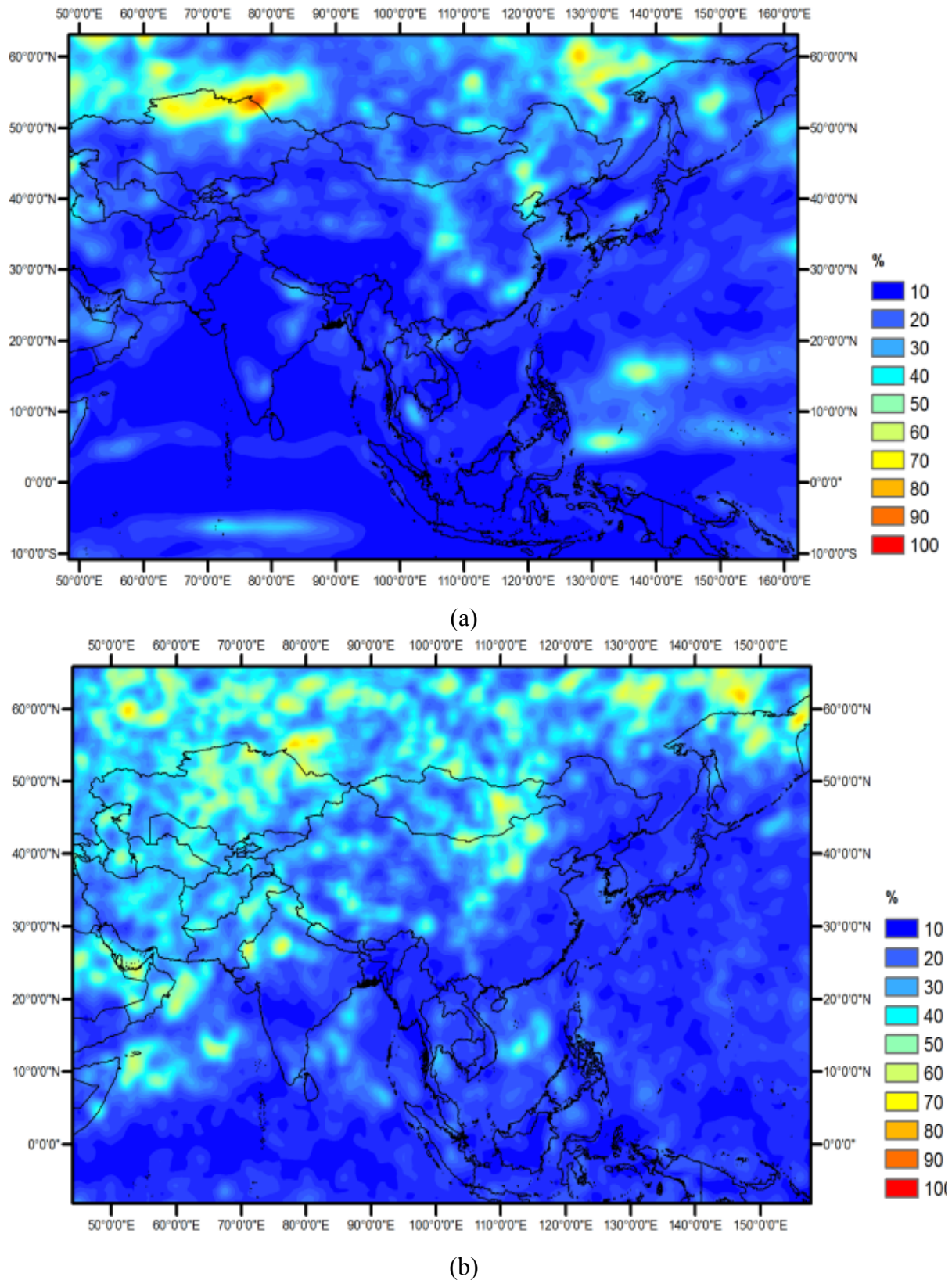


Figure 4.4 The contributing ratio of the interaction between the cloud convection schemes and SST warming arrangements for (a) annual precipitation, and (b) R3d precipitation to the total projection uncertainty

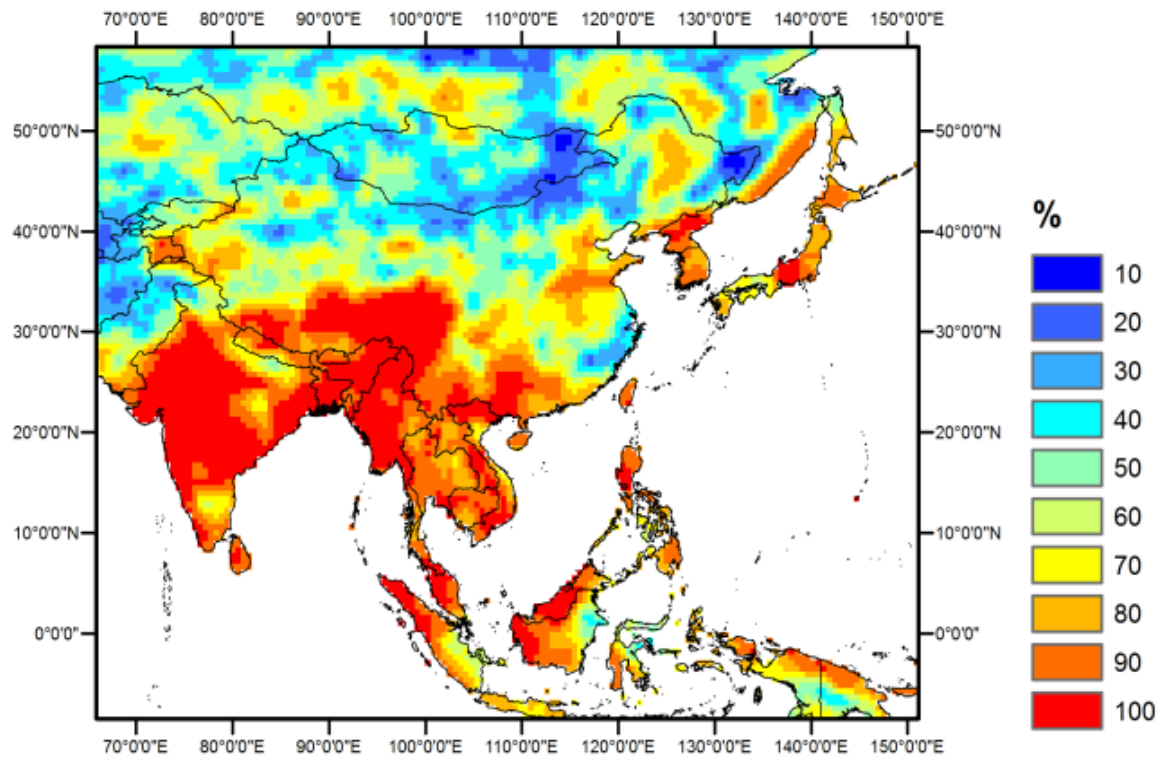
Sizable role in shaping the overall projection uncertainty of the annual and maximum 3-day precipitation for the most of Asia-Pacific Region, except for the small area in Central and Northeast Asia.

4.4.4 Contribution of the cloud convection schemes to the projection uncertainty of the total runoff generation

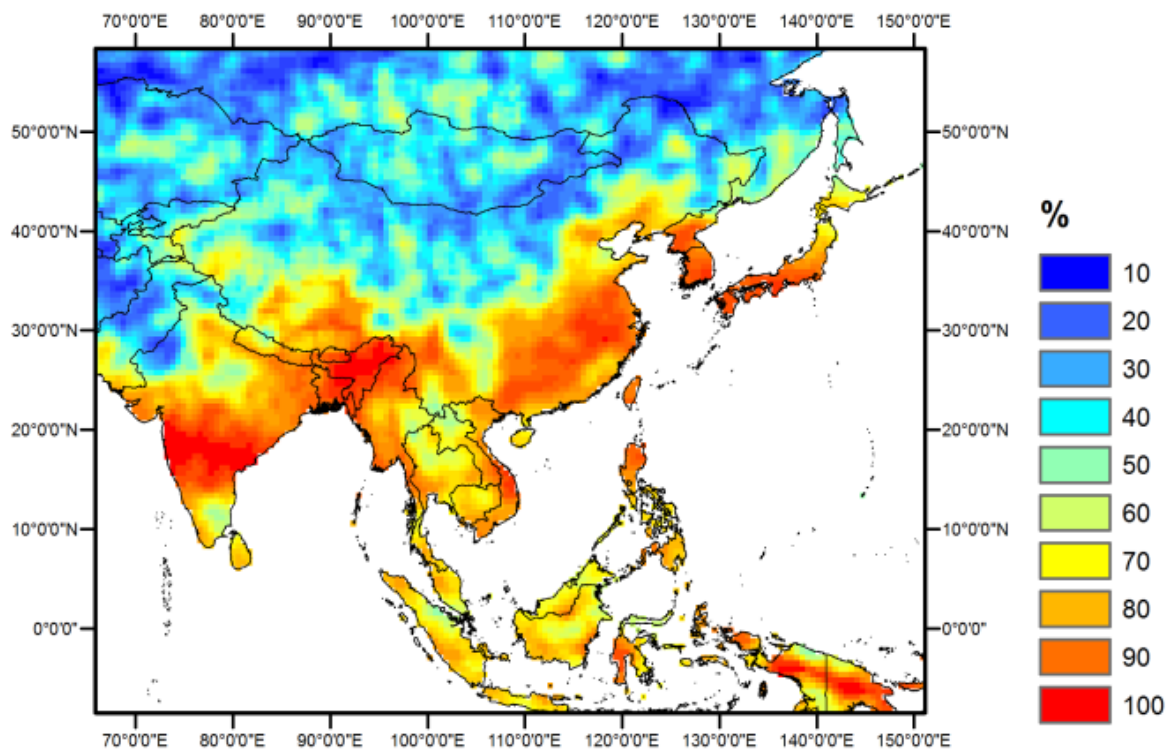
Spatial distributions of the cumulus convection schemes (YS, AS, KF), contributing ratios to the total variance of the total runoff in the Asia Pacific region, are plotted in Figure 4.5a and 4.5b for two cases: 1) annual total runoff, and 2) annual 3-day maximum total runoff (R3d). The results of the convection scheme contributions showed that the annual runoff produced distribution patterns broadly similar to the annual precipitation in the Indian subcontinent, the Tibetan Plateau, southern China, the Indochinese Peninsula, the Korean Peninsula, and Japan, with contribution between 90–98% of the total variance ($0.90 \leq R_A \leq 0.98$). R3d total runoff results also show that cloud convection schemes have a sizable impact on the total variation of the runoff in the Asia-Pacific region, but to a lesser degree relative to the effect of annual precipitation. For instance, contributing ratios between 70–80% ($0.70 \leq R_A \leq 0.80$) were observed at the inner Indochinese Peninsula, the northern Indian subcontinent, southern China, and the archipelagos region of South East Asia.

4.4.5 Contribution of the SST warming patterns to the projection uncertainty of the total runoff generation

Figure 4.6a and 4.6b shows the effect of SST patterns. In the case of an annual runoff, a contribution of less than 10% ($R \leq 0.10$) was observed in the Indian subcontinent, southern China, and the Indochinese Peninsula. There are some exceptions in parts of Eastern China and maritime regions, namely, Indonesia and Malaysia (Sarawak region), that contribute up to 40% ($0.10 \leq R_B \leq 0.40$) of the variance in the total runoff. Similarly, contributions from the different SST patterns to R3d total runoff mainly follow the annual runoff patterns in the Indian subcontinent, Eastern China, the Korean Peninsula, and Japan. However, there are several discrepancies in Eastern china and the Central Plain of Thailand, where the contributions to R3d were in the range of 30–40% of the total variance.



(a)



(b)

Figure 4.5 The contributing ratio of the convection parameterization schemes (AS, KF, YS) for the projection uncertainty of (a) annual total runoff, (b) the R3d total runoff of the Asia-Pacific Region

4.4.6 Contribution of an interaction between the cloud convection schemes and the SST warming patterns to the projection uncertainty of the total runoff generation

The interactions between the cloud convection parameterization schemes and SST warming components are summarized in Figure 4.7a and 4.7b. For the annual total runoff, the effects were found negligible for the entire Asia-Pacific Region. Contributing ratios of the annual total runoff fell into a range of 10 – 20 % ($0.10 \leq R_A \leq 0.20$) for the Indian subcontinent, the Tibetan Plateau, southern China, the Indochinese Peninsula, the Korean Peninsula and Japan. For the maximum 3-day total runoff (R3d), the contributing ratios were found to be between 20 – 30% ($0.20 \leq R_{AB} \leq 0.30$).

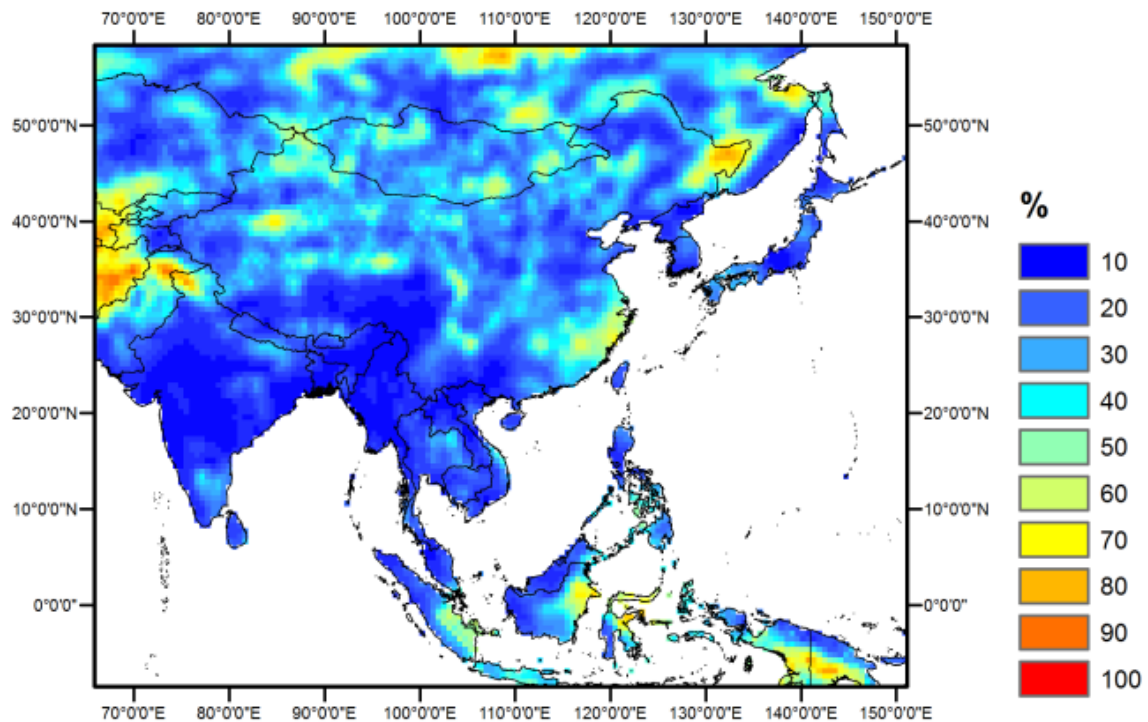
4.5 Statistical Significance on the contribution of the future hydrological projections under climate change

Here the overall contribution of each main effect and the interaction with precipitation and runoff, are confirmed by conducting statistical analyses to assess the effect of each factor on variations in multi-physics projections, using the F-test. However, due to the relatively wide range of F-statistics associated with the variable chosen in this study, the spatially-distributed F-test values are plotted separately for two cases: 1) acceptance of the null hypothesis and 2) rejection of the null hypothesis.

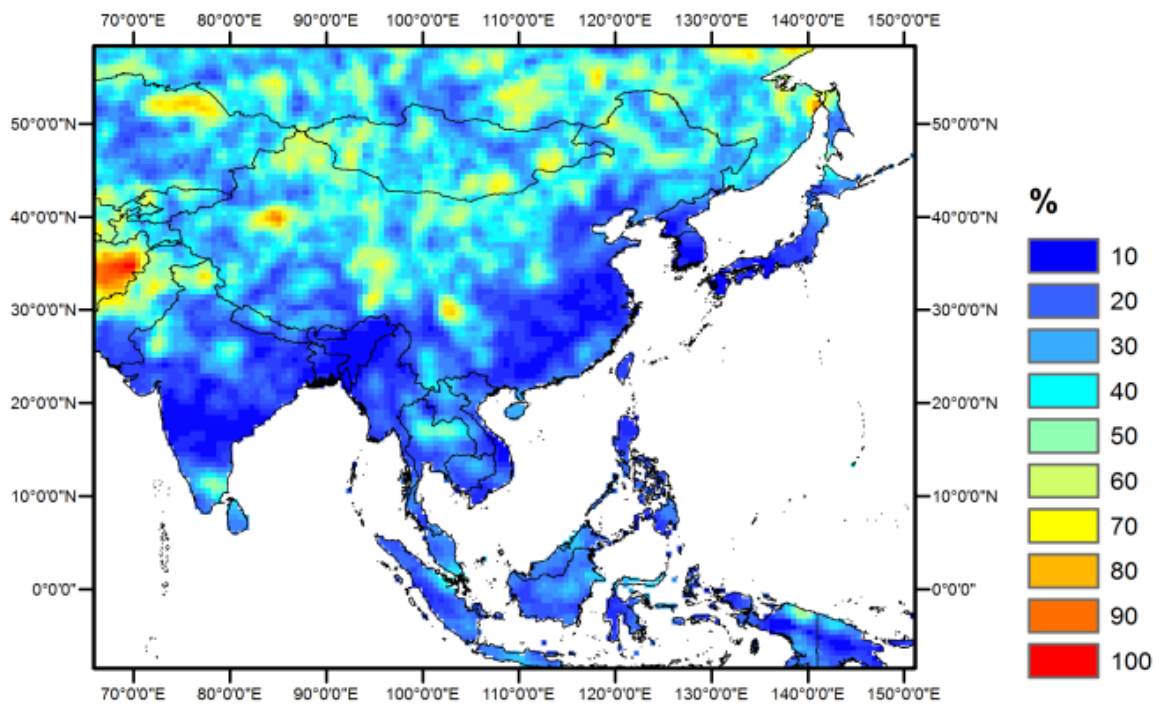
Statistically, the first instance indicates that the effects of the cloud convection schemes, SST warming systems, and their interactions with the total uncertainty in ensemble projections of precipitation/runoff are not significant at the 1% level being used in this study. In contrary, if F- values fall into the second category, the effects of the main factors and their interaction are not statistically significant with respect to the total uncertainty of projected precipitation and runoff in the Asia Pacific region.

4.5.1 Analysis on the statistical significance of cloud convection schemes to the projection uncertainty of precipitation

Figure 4.8a and 4.8b shows the effect of different cloud convection schemes on the total variance of annual and R3d precipitation. Red and blue colors indicate rejection and acceptance of the null hypothesis, respectively. For the annual indices (Figure 4.6a),



(a)



(b)

Figure 4.6 The contributing ratio of the SST warming patterns (C1, C2, C3) for the projection uncertainty of (a) annual total runoff, (b) the R3d total runoff of the Asia-Pacific Region

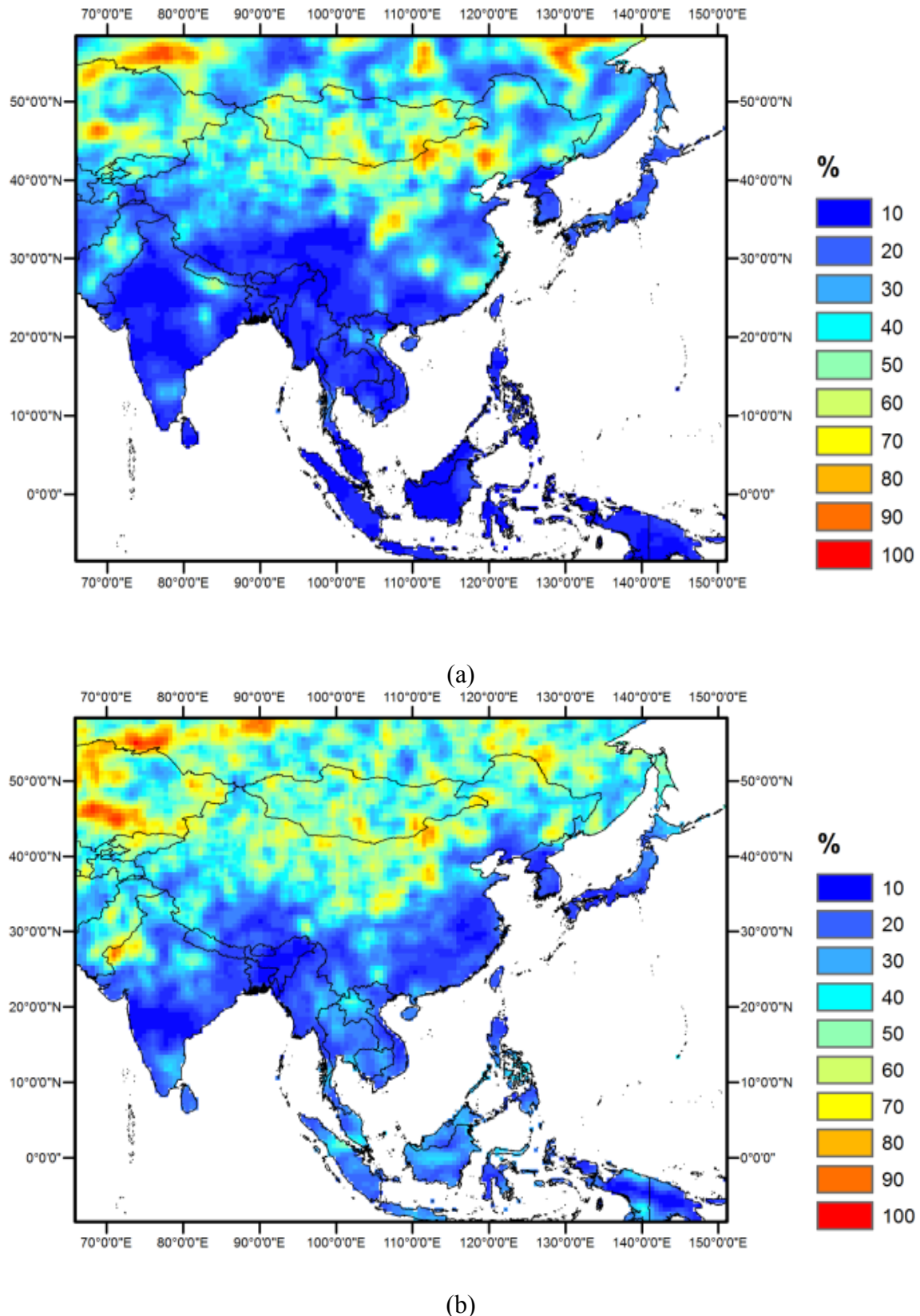


Figure 4.7 The contributing ratio of the interaction effect of the main effects for the projection uncertainty of (a) annual total runoff, (b) the R3d total runoff of the Asia-Pacific Region

the F-value analysis results entirely reject the null hypothesis pertaining to annual precipitation under different convection schemes. The signal was distributed throughout the Indochinese Peninsula, the extended region in northern Asia, South Asia, maritime countries of Southeast Asia.

Figure 4.8b is quite comparable to Figure 4.8a but instead predicts the R3d indices. The precipitation uncertainty signals point toward the same direction as the annual indices in the Indochinese Peninsula. On the contrary, its effect was much less significant in central Asia and western China, the small land area of the Gulf of Thailand, and in parts of the South China Sea, where the null hypothesis was projected to be the dominant signal of precipitation uncertainty.

4.5.2 Analysis on the statistical significance of the SST warming patterns to the projection uncertainty of precipitation

Figure 4.9a and 4.9b shows the effect of different SST patterns on the total variance of annual and R3d rainfall. In the case of annual indices (Figure 4.9a), the F-test analysis shows unusual patterns in the maritime area of southeast Asia, the Gulf of Thailand and the Indian Ocean, where different SST components had a significant effect on the total variance among the ensemble projections. However, R3d precipitation was less susceptible to the effect of different SST patterns in equatorial regions. Both indices show some similar distribution characteristics in the Asia Pacific mainland, in which different SSTs were not expected to have a statistically significant impact on total uncertainty.

4.5.3 Analysis on the statistical significance of interaction between the cloud convection schemes and the SST warming patterns to the projection uncertainty of precipitation

Figure 4.10a and 4.10b shows the interaction effect of primary factors on the total variance of the annual and R3d rainfall. The results demonstrated that the interaction effects had no significant impact on the annual precipitation for the clear majority of the Asia Pacific region, except for the western border between Thailand and Myanmar, a large cluster in the Indian Ocean, and in several spots near the Sumatra Islands. The R3d rainfall results also showed that the interactions between the main effects were not expected to cause significant impact on

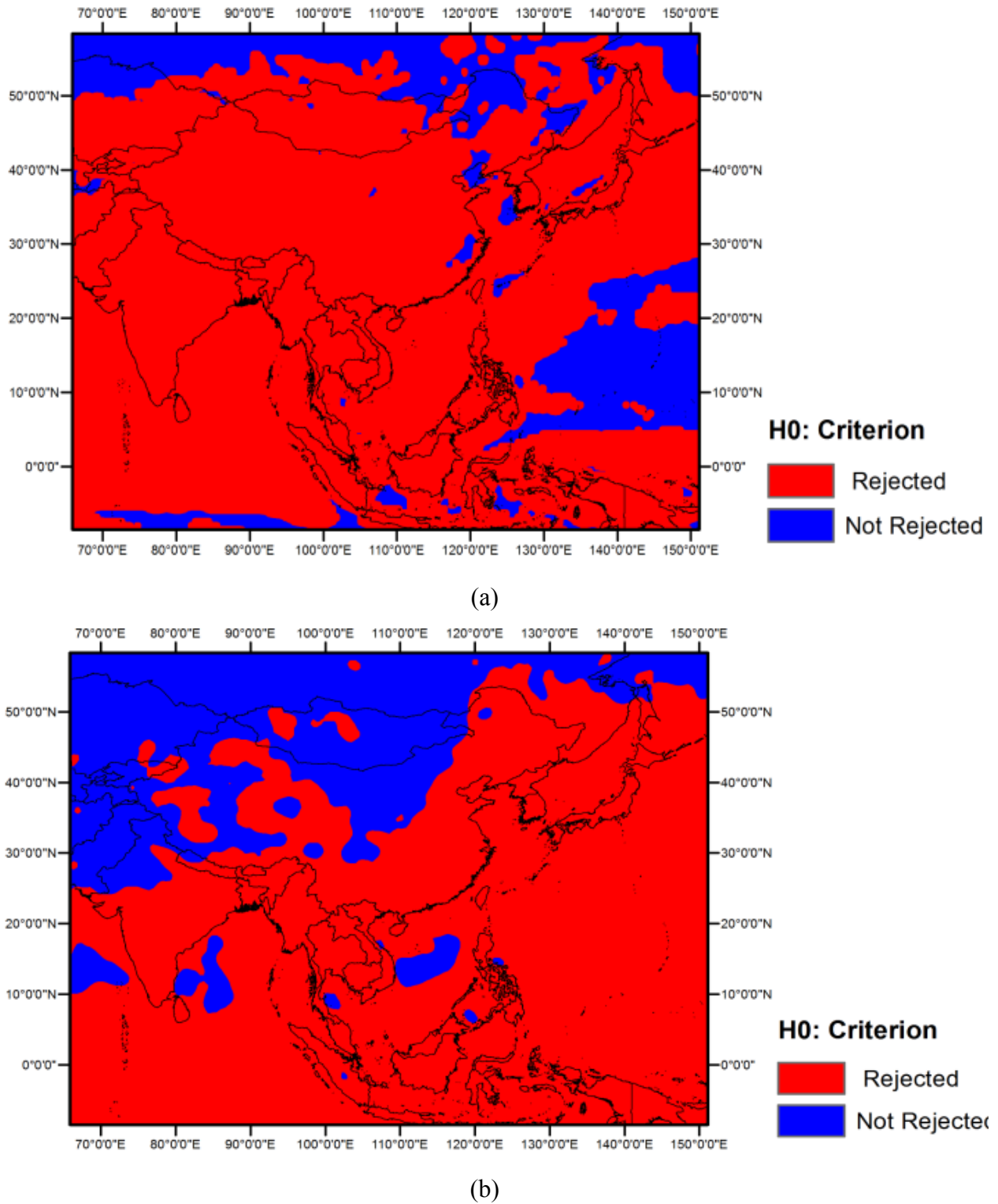


Figure 4.8 Analysis on the statistical significance of using F-test of different use of the convection parameterization schemes for (a) annual precipitation and (b) R3d precipitation for the Asia-Pacific Region

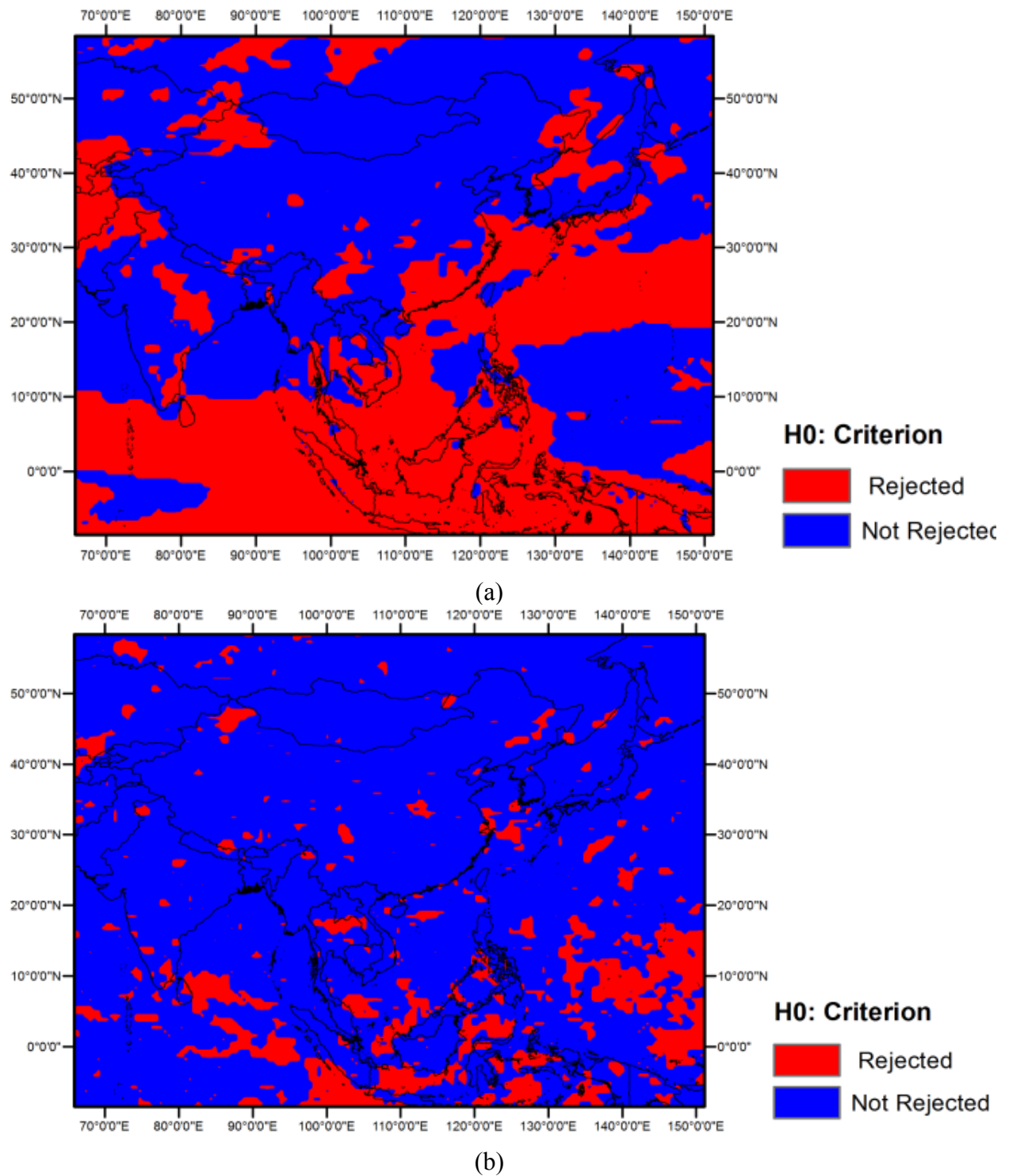


Figure 4.9 Analysis on the statistical significance of using F-test of different use of the SST warming patterns for (a) annual precipitation and (b) R3d precipitation for the Asia-Pacific Region

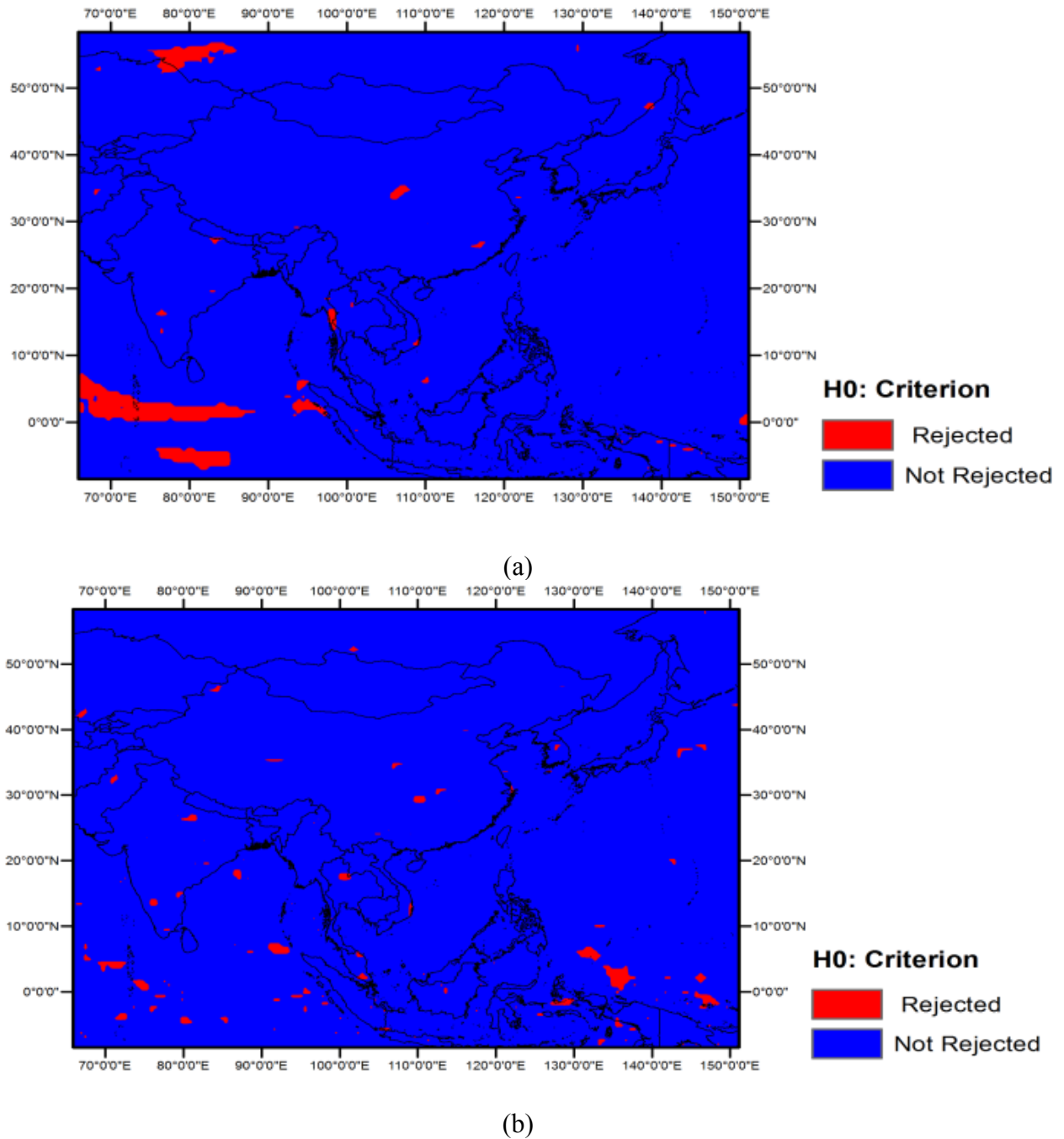


Figure 4.10 Analysis on the statistical significance of using F-test of an interaction between for the convection parameterization schemes and the SST warming patterns: (a) annual precipitation and (b) R3d precipitation for the Asia-Pacific Region

the total uncertainty in annual and maximum 3-day precipitation. The results imply that the main effect, e.g., a combination of different cloud convection schemes and the various SST warming patterns is the primary source of uncertainties regarding ensemble projection of precipitation in the region. Therefore, there is negligible evidence to indicate an interdependency of one factor compared to other factors as indexed by the F-statistics analysis signal.

4.5.4 Analysis on the statistical significance of the cloud convection parameterization schemes to the projection uncertainty of the total runoff generation

The results of an uncertainty analysis in total runoff generation based on the use of various cloud convection systems and the different source of SST warming scenarios are shown in Figure 4.11, 4.12, and 4.13, respectively.

Figure 4.11a and 4.11b presents spatial distributions of the effects of different convection schemes to the total variance in annual total runoff and R3d total runoff in the Asia Pacific region. In both cases, the cloud convection schemes contribute significantly to the total runoff variance in the Indian subcontinent, the Tibetan Plateau, the central and southern China, the Indochinese Peninsula, a maritime region of the Southeast Asia, the Korean Peninsula and Japan. The differences in these runoffs in the south of China, where the annual runoff was predicted to be a significant contributor to the total variance, but not the R3d runoff. Furthermore, the R3d total runoff did not contribute equally to the annual runoff in terms of the projected total variance in the northern Indian subcontinent. The presented results are generally correlated well with the annual and maximum 3-day precipitation.

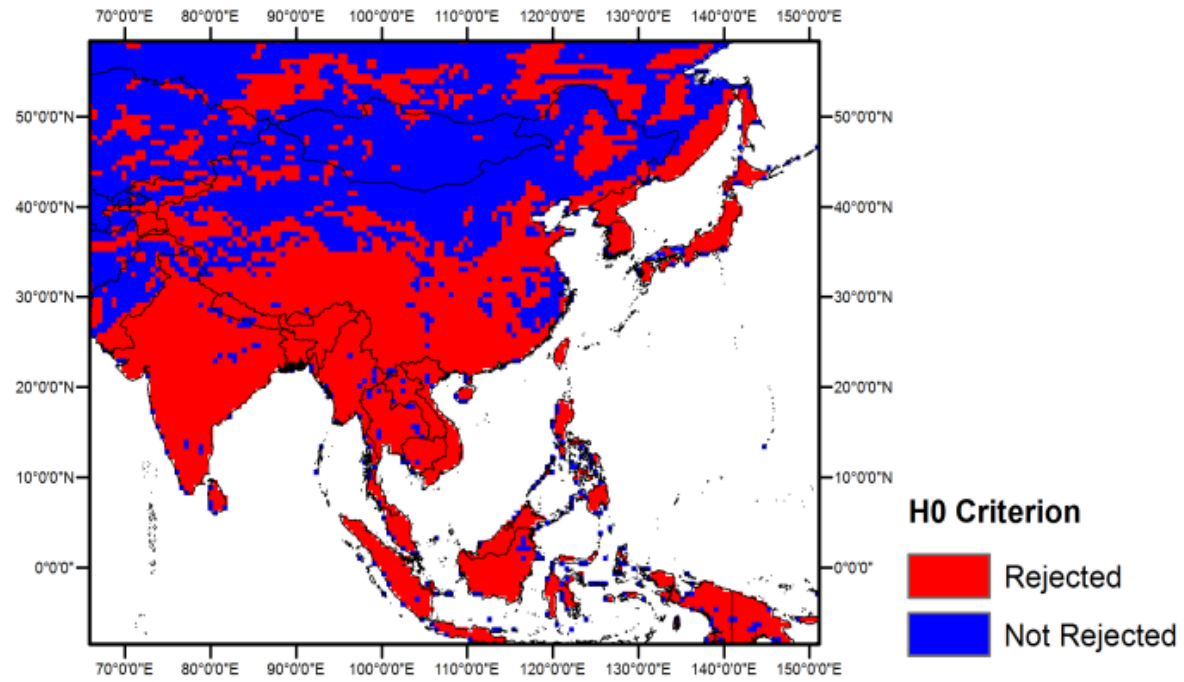
4.5.5 Analysis on the statistical significance of the SST warming patterns to the projection uncertainty of the total runoff generation

Meanwhile, an effect of the SST warming patterns to the total runoff projection uncertainty are presented in Figure 4.12a and 4.12b. Figure 4.12a showed that the effect of different SST scenarios on the annual total runoff in most of the Indian subcontinent, western China, northeast China, the Korean Peninsula and Japan were found not to be statistically significant. However, the SST warming patterns were projected to contribute significantly to the annual runoff uncertainties in

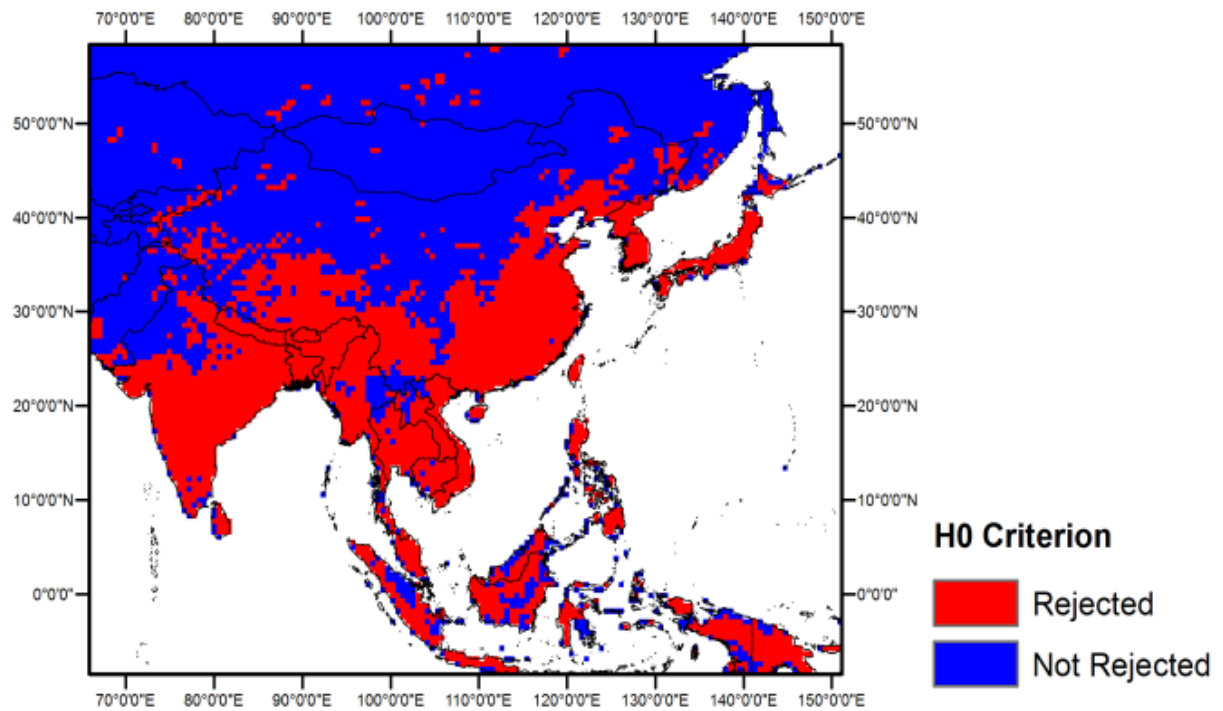
regions near the tropical sea, e.g., the Gulf of Thailand, the South China Sea, and the Java Sea. In addition, there are several Indochina river basins such as Chao Phraya, Mekong, and the southern basin of Thailand that are profoundly affected by SST warming scenarios. The total uncertainty of R3d runoff is shown in Figure 4.12b and was projected to be much less sensitive to the different use of SST patterns, and most signals in the Asia-Pacific indicated acceptance of the null hypothesis; which means that datasets pick from each SST warming pattern could originate from same populations.

4.5.6 Analysis on the statistical significance of interaction between the cloud convection schemes and the SST warming patterns to the projection uncertainty of the total runoff generation

Figure 4.13a and 4.13b shows the effect of interaction on the overall uncertainty in annual and R3d total runoff. The results demonstrated that the consequences of the interaction were negligible with respect to the annual runoff of the Asia-Pacific region, except for the western border between Thailand and Myanmar, and in several small areas in the Indian subcontinent. The R3d total runoff generation results also confirmed that the interaction between the main factors did not significantly impact on the total variance. The results imply that the main effects are the dominant sources of uncertainty in ensemble projections of total runoff in the region. Therefore, negligible evidence regarding a dependency of one factor compared to the levels of others factor was found in the F-statistics analysis of the total runoff.

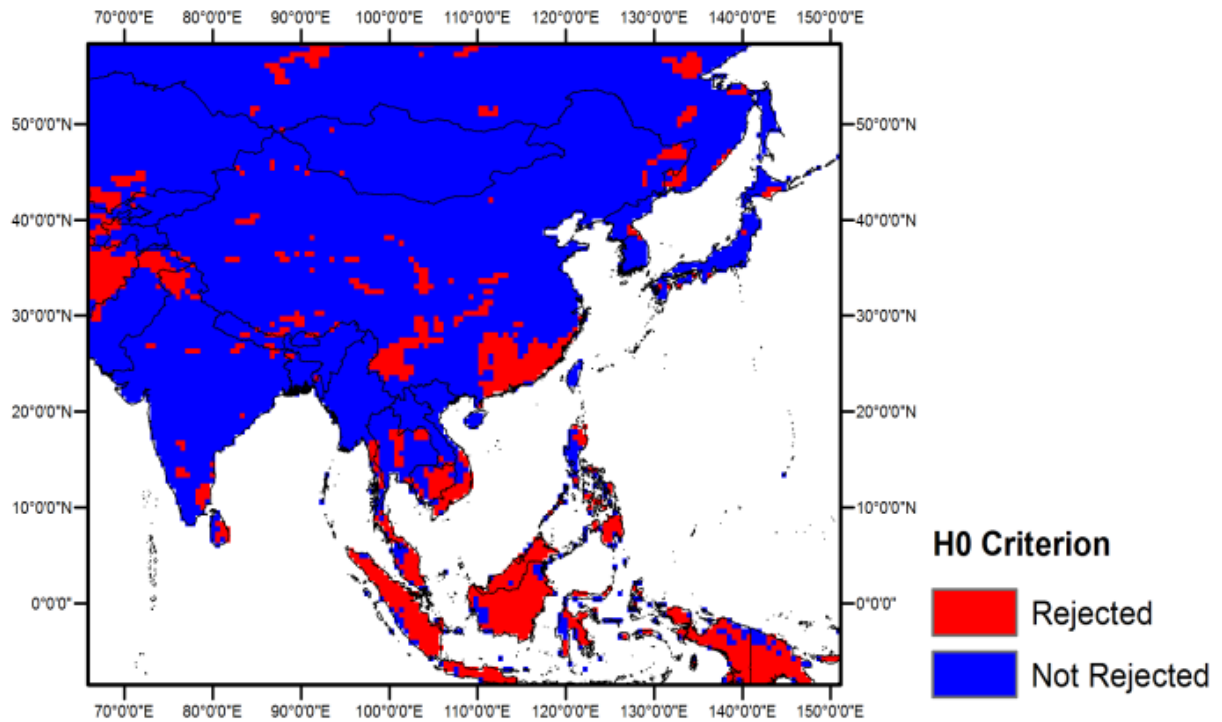


(a)

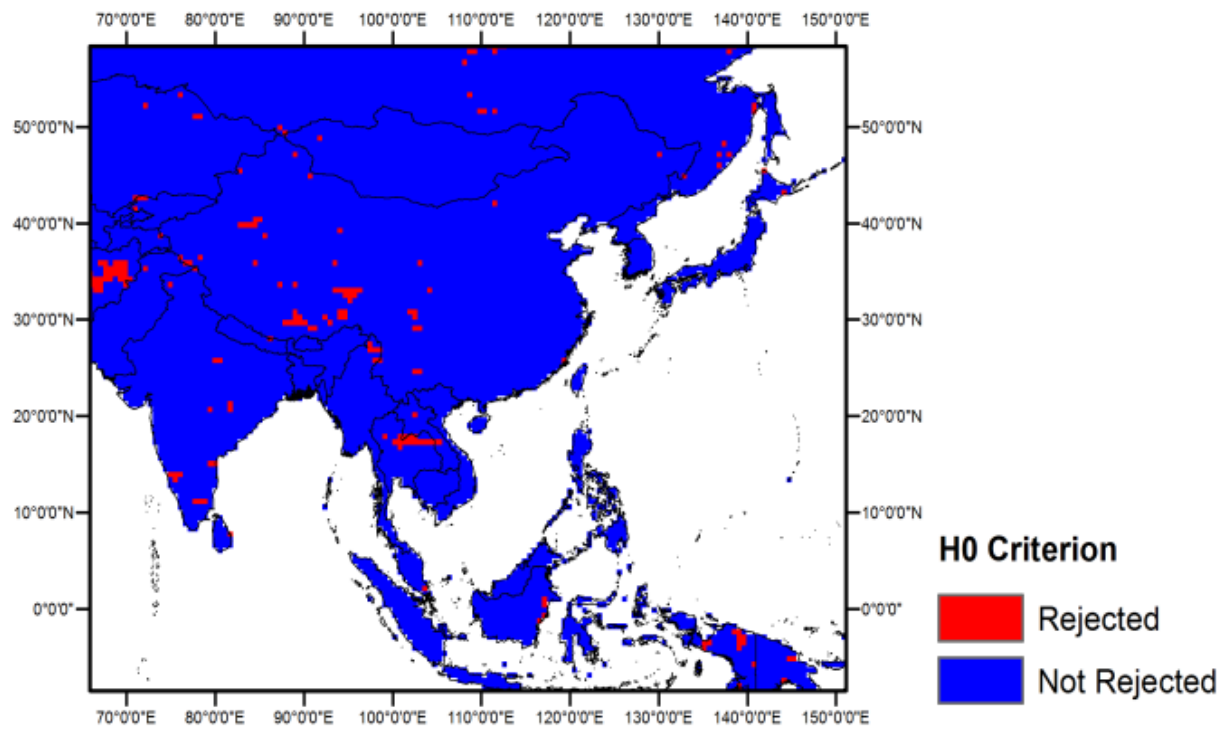


(b)

Figure 4.11 Analysis on the statistical significance of using F-test of different use of the convection parameterization schemes for (a) annual total runoff and (b) R3d total runoff for the Asia-Pacific Region

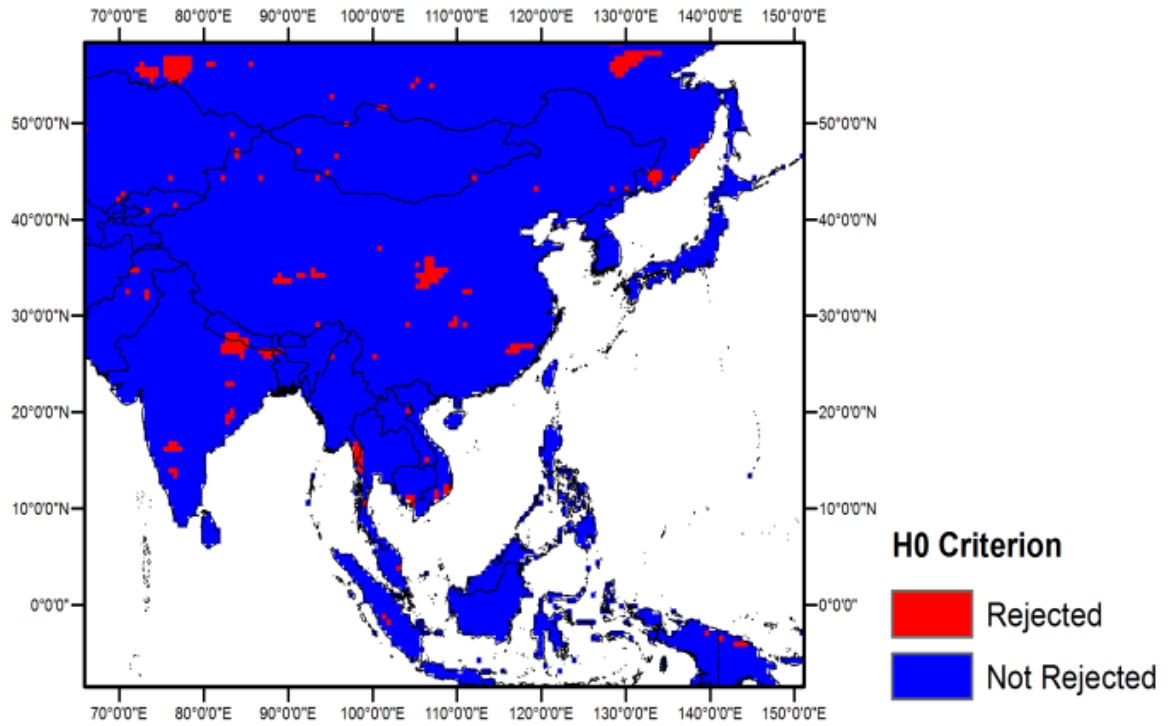


(a)

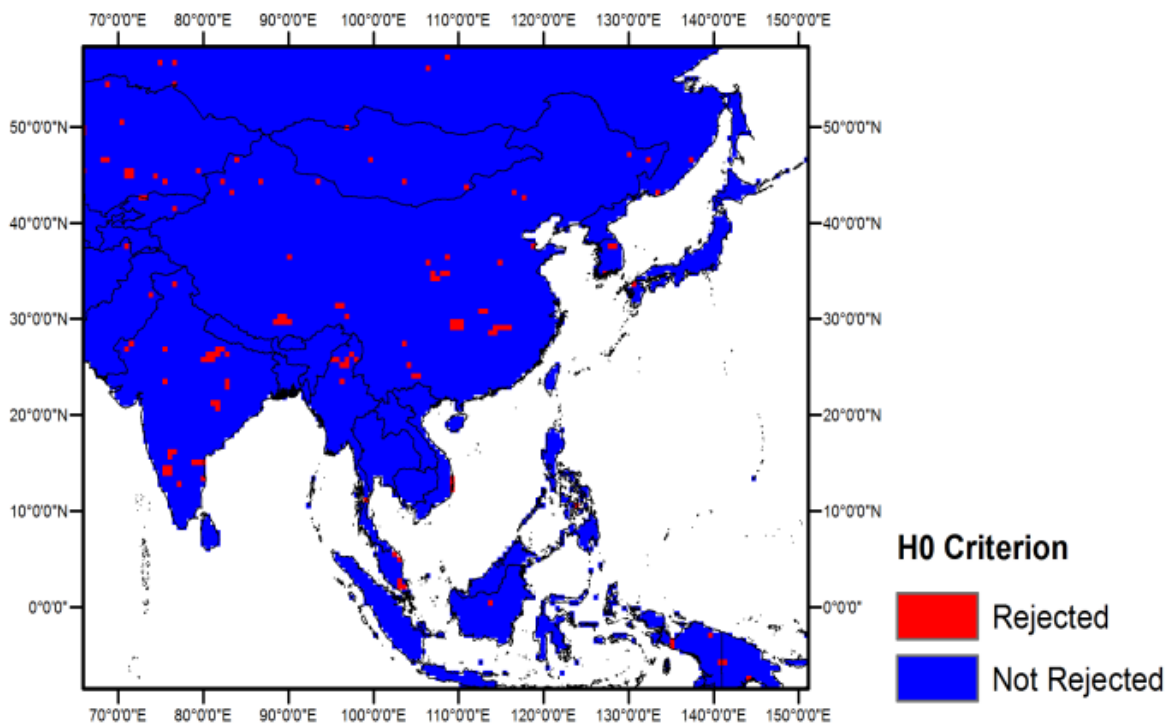


(b)

Figure 4.12 Analysis on the statistical significance of using F-test of different use of the SST warming patterns for (a) annual total runoff and (b) R3d total runoff for the Asia-Pacific Region



(a)



(b)

Figure 4.13 Analysis on the statistical significance of using F-test of an interaction between for the convection parameterization schemes and the SST warming patterns: (a) annual total runoff and (b) R3d total runoff for the Asia-Pacific Region

4.6 Statistical Significance of the contribution of the future river discharge projection under climate change

4.6.1 Analysis on the statistical significance of the cloud convection schemes and the SST warming patterns to the projection uncertainty of the river discharge

In this part, confirmation of the effect of using different SST settings, cloud convection schemes and the interaction between these two effects on the projected uncertainties in the future maximum, minimum, and average river discharge in the 25-year period from 2075–2100, using F-test, was made. Figure 4.14a, 4.14b, and 4.14c present the distribution of the projected maximum river discharge variances in the Indochinese Peninsula under various physics ensembles and its interaction. For the first cases (see Figure 4.14a), the results clearly indicate that the effects of different cloud convection schemes are not statistically significant in several river basins, namely, the Irrawaddy Basin, Salween Basin, Northern Mekong River Basin in China, Middle Mekong Basin in Laos, Mekong Delta, and Red River Basin in Vietnam. However, significant variance, indexed by hypothesis rejection of null hypothesis is clearly detected at the eastern side of the upper Chao Phraya Basin (Nan Basin), propagating to the lower Chao Phraya Basin.

In addition, other small areas of significant discharge variance in the southern Indochinese Peninsula and a small area in the Mekong Basin in Laos and Vietnam were observed. The results in Figure 4.14b are also remarkably similar to those of the first few cases, indicating that different SST patterns will have a significant effect on total uncertainty in the minimum river discharge in the Chao Phraya Basin. The interaction between the two main effects is non-existent because the signals from the most regions indicate that the null hypothesis should be accepted. Figure 4.14d, 4.14e, and 4.14f presents a similar spatial distribution but for the projected minimum river discharge. The results show that different cloud convection schemes do not contribute significantly to the total variance in any area, except the Upper Chao Phraya Basin and the middle part of the Mekong Basin in southern China and Laos. The effect of the interaction between different SST and cloud convection schemes is small across the entire

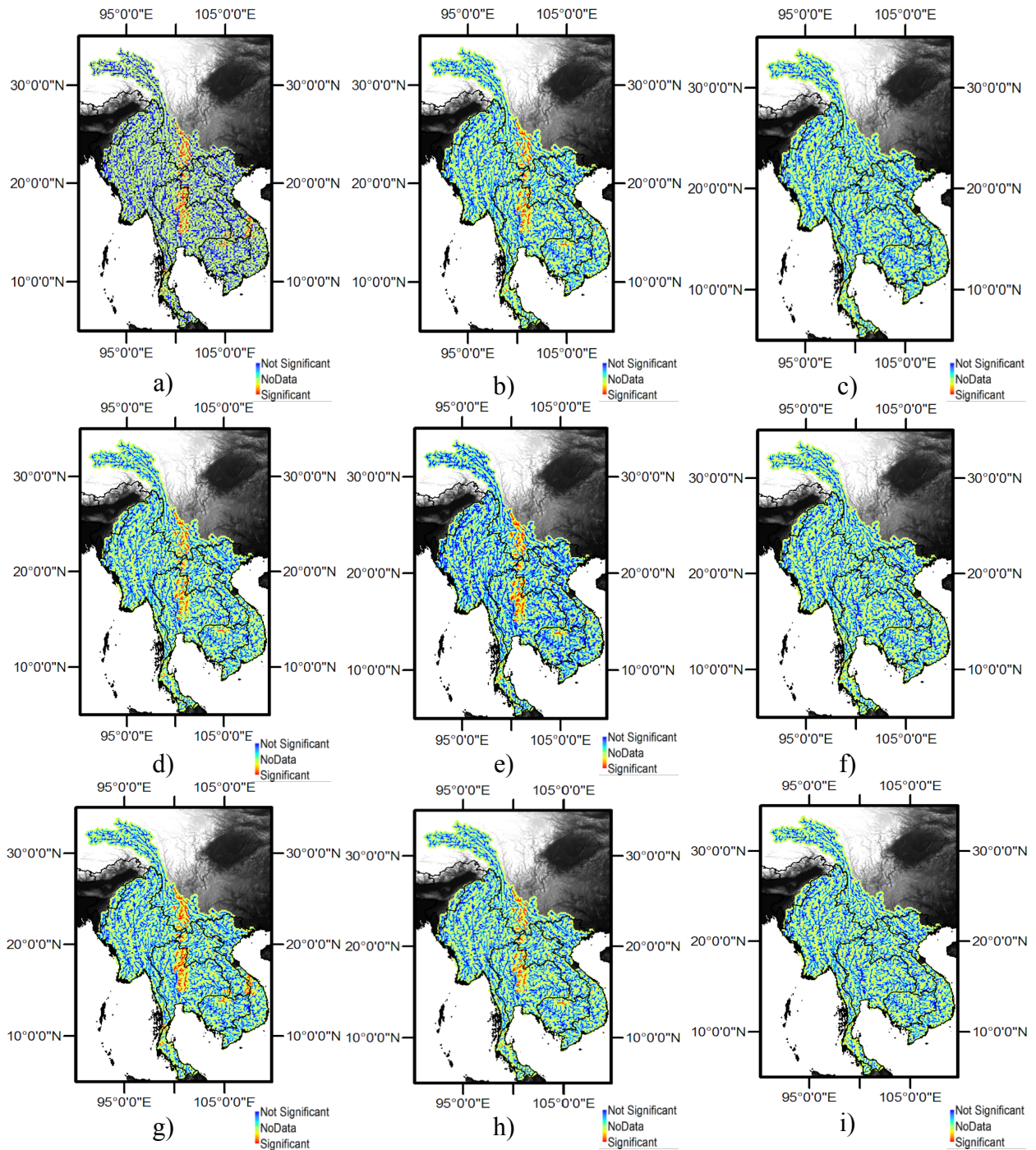


Figure 4.14 The first row presents statistical significance test using F-value of maximum river discharge under a) different convection schemes, b) different SST and c) its replication. Same for the second and the third row but for minimum and average daily river discharge

region. The total variance in mean river discharge also has a similar response to the effect of different convection schemes and various SST patterns (see Figure 4.14g and 4.14h) with Figure 4.14a, 4.14b, 4.14d, and 4.14e, respectively.

4.7 Conclusion

The implications for the hydrological extreme-event analysis of the presented figures can be summarized as follows:

- 1) The region in which the uncertainty arises from either cloud convection schemes or SST patterns represents a dominant source of uncertainty, as indicated by the rejection of the null hypothesis of F-statistics analysis. This suggests that precipitation and runoff analyzed according to combinations of these factors are derived from different mother populations. Therefore, extreme event analysis based on combinations involving significant amounts of sample in any arrangement would yield misleading results for probabilistic projections and, in turn, inaccurate assessment of water resources under a changing climate. Based on the results of annual precipitation/runoff analysis, we can conclude that, at least, these hydrological datasets retrieved from different cloud convection schemes should not be combined into a much larger sample in most of the regions of the Indochinese Peninsula. In the case of maximum precipitation and runoff, the only area that clearly prohibited any kind of large-scale combination of datasets is the Upper Chao Phraya Basin.
- 2) In locations where uncertainty arises from either multiple convection schemes or sea surface temperature warming patterns is not a primary source of projection uncertainty, as indicated by acceptance of the null hypothesis of F-statistics analysis. The study showed that precipitation and runoff analyzed under various combinations of these factors are derived from same populations. Therefore, hydrological analysis based on a pool of large samples in any arrangement can still produce a reliable probabilistic projection and assessment of water resource availability under climate change. Based on the overall results of annual precipitation/runoff analysis, we can also conclude that hydrological datasets originated from the different SST patterns could potentially be combined into a much larger sample in most of

the northern region of the Indochinese Peninsula, e.g., Ayeyarwaddy Basin and Salween Basin, the middle part of the Mekong Basin in Cambodia and Laos, and the Red River Basin. Nevertheless, notable exceptions are the Chao Phraya Basin and the Mekong Delta, regions with relatively close proximity to the gulf of Thailand, equatorial regions such as the Southern Indochinese Peninsula, and maritime countries such as Indonesia.

3) For the case of maximum, minimum, and average discharge projections, the primary source of uncertainty arises from the use of multiple convection schemes or SST patterns, reflected in rejection of the null hypothesis. As a result, the conclusion can be made with a confidence level of 0.01 that it is plausible to combine river discharge datasets retrieved from different SST patterns for most of the Indochinese Peninsula, except for the Chao Phraya River Basin. Meanwhile, the signal from different cloud convection schemes indicated the possibility of combining extensive PPE datasets.

Nonetheless, identification of the mother population origins alone may not be adequate to combine the river discharge datasets from different SST patterns reliably. In the next chapter, another important criterion before consideration of datasets combination, which is the prior distributions function between two or more datasets, are investigated by using the non-parametric approach – two-sample Kolmogorov-Smirnov and Anderson-Darling tests.

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Chapter 5

Evaluation of the difference between probability distribution of the annual maximum river discharge derived from multiple SSTs of the d4PDF datasets

5.1 Introduction

It is widely acknowledged that warming of climate systems will have impacts on global hydrological cycle (Kundzewicz et al., 2007), with implications for the drainage basin that vary in scale from small to medium-sized catchments (Chun et al., 2009; Thompson et al., 2012); local to regional river basins (Conway and Hulme, 1996; Arnell and Osborn, 2006), and global scales (Nohara et al., 2006; Gosling et al., 2010; Nakaegawa et al., 2013; Hirabayashi et al., 2013).

General Circulation Models (GCMs) are served as fundamental tools in future projections and expand the current understanding of the effect of climate change on hydrology and water resources. Despite continuing improvements in recent years, there is a range of uncertainties that are cascaded throughout these hydrological impact assessments.

First, uncertainty related to the definition of the greenhouse gasses emission scenarios used to force the GCMs. Secondly, uncertainties associated with the internal variability, which represents the natural fluctuation of climate at daily to multi-decadal time scale (Karoly and Wu, 2005). Structural model uncertainty caused by difference use of the GCMs and leads to various projections presents a third source of uncertainty.

Typically, the use of multi-model ensemble in conjunction with the exploration of single GCM is required to investigate climate projection uncertainty extensively. However, in practice, the single projection of climate response to increasing greenhouse gasses emission are far more useful to practitioners and policymakers when they are accompanied by some measures of the associated uncertainty (Tebaldi and Knutti, 2007). By using the sets of simulations within single GCM but different choices for various perturbed parameters; vast and diverse sets of realizations to generate empirical probability density function of extreme hydrological events could possibly be made.

Fortunately, there is a way to overcome these fundamental impediments in climate change

projection using GCM outputs and increase the reliability of probabilistic analysis of hydrological variables, which involves a combination of projections given by multi-physics ensembles. However, relying only on a large number of samples could give misleading results because the data from different perturbed ensembles might not originate from an identical source of population and could also have different prior distribution functions.

The focus of the previous chapter is the former point, which found and concluded that uncertainty in extreme hydrological events such as precipitation, total runoff, annual maximum daily discharge in the mainland Southeast Asia and South Asia, are primarily derived from differences in the convection parameterization schemes rather than the different SST warming patterns. The analyzed outcomes are also corresponding well with several past studies (Endo et al., 2012; Murakami et al., 2012; Hanittinan et al., 2016).

The aim of this chapter is to address the latter part of the question. Therefore, we proceed to analyze the change of the probability distribution function of annual maximum daily discharge projections, derived from the latest 60-km extremely large multi-SST ensembles of MRI-AGCM 3.2H under a single cumulus parameterization scheme (Yoshimura et al., 2011) – database for Policy Decision-making for Future climate change (d4PDF), to examine the statistical difference on a shape and tail of its prior empirical distribution function, two-sample Kolmogorov - Smirnov test and Anderson-Darling test were conducted with the projected discharges in the Indochinese Peninsula.

5.2 Methodology

5.2.1 Kolmogorov-Smirnov test

The Kolmogorov – Smirnov test (K-S test) was first introduced by Kolmogorov (1933, 1941) and Smirnov (1939). It is a non-parametric test of the equality of continuous, one-dimensional cumulative probability distribution that can be used to compare a sample with a postulated distribution (one-sample K-S test) or to compare two samples (two-sample K-S test). The null distribution of the statistics is calculated under the null hypothesis that the sample is drawn from the reference distribution in the one-sample case or that the samples are taken from the same prior distribution in the two-sample case.

The empirical distribution function F_n for n independent and identically distributed observation X_i is defined as:

$$F_n(x) = \frac{1}{n} \sum_{i=1}^n I_{[-\infty, x]}(X_i) \quad (5-1)$$

where $I_{[-\alpha, x]}(X_i)$ is the indicator function, equal to unity if $X_i \leq x$ and equal to zero otherwise. Next, the K-S statistics for a given theoretical cumulative distribution $F(x)$ is:

$$D_n(x) = \sqrt{n} \sup_x |F_n(x) - F(x)| \quad (5-2)$$

where $\sup_x$ is the supremum of the set of distances between the cumulative probability distributions; $F(x)$ is the theoretical cumulative distribution value at x , and $F_n(x)$ is the empirical cumulative distribution value for a sample size of n . The null hypothesis that $F_n(x)$ come from the postulated distribution $F(x)$ is rejected if $D_n(x)$ is larger than the critical value K_α at a given confidence level α , where KS_α is found from:

$$\Pr(K \leq K_\alpha) = 1 - \alpha \quad (5-3)$$

where K is the cumulative distribution function of Kolmogorov distribution and given by

$$\Pr(K \leq x) = 1 - 2 \sum_{k=1}^{\infty} (-1)^{k-1} e^{-2k^2 x^2} \quad (5-4)$$

In the case of the two-sample version of the K-S test generalizes to

$$KS_{nn'} = \sqrt{\frac{nn'}{n+n'}} \sup_x |F_n(x) - F_{n'}(x)| \quad (5-5)$$

where $F_n(x)$ and $F_{n'}(x)$ are two empirical cumulative distribution value at time point x , based on the datasets of size n and n' . The null hypothesis that $F_n(x)$ and $F_{n'}(x)$ come from the same prior distribution is rejected at level α if

$$D_{n,n'} > c(\alpha) \sqrt{\frac{n+n'}{nn'}} \quad (5-6)$$

where the value of $c(\alpha)$ is given in generalized form provided by

$$C(\alpha) = \sqrt{-\frac{1}{2} \ln \left(\frac{\alpha}{2} \right)} \quad (5-7)$$

The main advantages of the K-S test are its sensitivity to a shape of the prior distribution due to its ability to detect differences everywhere along the scale (Darling, 1957). It is also applicable and dependable for small sample size (Lilliefors, 1967; Engmann and Cousineau, 2011). In this chapter, the two-sample K-S test approach was adopted to evaluate the difference between the cumulative distribution of the future annual maximum daily discharge (2051 – 2100) from each possible group of the 15-cluster, 6-SST warming patterns with 60-member ($6 \times 60 \times 15 = 900$) samples of the d4PDF datasets. The null hypothesis H_0 for the test of the difference in empirical cumulative distributions assumed to be statistically insignificant.

5.2.2 Anderson-Darling test

The Anderson-Darling test (AD test) is a statistical test developed in 1952 by T.W. Anderson and D.A. Darling (Anderson and Darling, 1952) as an alternative to other statistical tests for detecting departure from an underlying probability distribution (one-sample AD test), especially powerful for detecting most departures from normality (Stephen, 1974), or comparison between k-samples (K-sample AD test) whether several collections of observations can be modelled as coming from the same prior distribution.

Anderson and Darling (1952, 1954) introduced the goodness-of-fit statistic

$$AD_m^2 = m \int_{-\infty}^{\infty} \frac{\{F_n(x) - F_0(x)\}^2}{F_0(x)\{1 - F_0(x)\}} dF_0(x) \quad (5-8)$$

to test the hypothesis that a random sample $X_1, X_2, \dots, X_n$, with sample distribution function $F_n(x)$, comes from a continuous population with distribution function $F_0(x)$. The function $F_n(x)$ is defined as a proportion of the random sample $X_1, X_2, \dots, X_n$ which is not greater than x . If there are two random samples $X_1, X_2, \dots, X_n$ and $Y_1, Y_2, \dots, Y_m$ are subjected to the null hypothesis that the samples come from same continuous populations, then the corresponding two-sample version was proposed by Darling et al. (1957) and studied further by Pettitt (1976).

$$AD_{mn}^2 = \frac{mn}{N} \int_{-\infty}^{\infty} \frac{\{F_n(x) - G_m(x)\}^2}{H_N(x)\{1 - H_N(x)\}} dH_N(x) \quad (5-9)$$

where $F_n(x)$, $G_m(x)$, and $H_N(x)$, which $N = m + n$, are the empirical distribution functions of the X-sample, Y-sample, and the combined sample, that is

$$H_N(x) = \{nF_n(x) + mG_m(x)\}/N \quad (5-10)$$

The above integrand in (5-9) does not have any meaning when $H_N(x) = 1$. Therefore, for A_{mn}^2 to exist the integrand is defined to be zero at the largest observation. Then, the integrand in (5-9) could be simplified to

$$AD_{mn}^2 = \frac{1}{mn} \sum_{i=1}^{N-1} \frac{(M_i N - ni)^2}{i(N-i)} \quad (5-11)$$

where M_i is defined as the number of X that less than or equal to the i th smallest in the pooled sample of X_n and Y_m with the size of N . The null hypothesis that X_n and Y_m come from the same continuous prior distribution is rejected if AD_{mn}^2 is larger than the correspondent critical value, which depends on confidence level α and sample size (Pettitt, 1976).

The AD test has the similar advantages as mentioned in the KS test, e.g., sensibility toward scale and shape of the distribution, applicability to a small sample, etc. In addition, the primary two distinct benefit of using AD test are its sensitivity toward differences at the tails of distribution and its ability to detect a subtle difference between the two empirical cumulative

distributions, even between large sample sizes at the tails of the distribution.

5.3 Comparison of the empirical probability distribution of the annual maximum daily discharge derived from the d4PDF datasets at the Indochinese Peninsula

5.3.1 Two-sample Kolmogorov-Smirnov test statistics

Figure 5.1 and 5.2 present geographical distribution of the Kolmogorov-Smirnov statistics (D_n) from 15 groups of the 900-member annual maximum daily discharge of the Indochinese Peninsula of each SST warming pattern. Statistically significant changes in the probability distribution for each cluster were calculated at each grid. For the entire Indochinese Peninsula standpoint, there are only two cases where most of the river basins signal rejection of the null hypothesis. However, on the basin scale, the explicit rejections of the null hypothesis were found at the Ayeyarwaddy, Chao Phraya, and the Mekong River Basin with remarkably similar patterns in 12 of 15 groups of SST patterns. Meanwhile, the K-S statistics is also found to be high at the Salween River Basin but only reject the null hypothesis in 8 of 15 cases, with the other are all indicated the acceptance of the null hypothesis. For several parts of the Mekong Delta and the southern Indochinese Peninsula, the changes in an empirical cumulative probability distribution are found to be statistically insignificant in most of the cluster of the d4PDF SST patterns (13-14 cases).

The characteristics of change in the probability distribution in the Red River Basin in Vietnam was found having a unique pattern, which the change of the empirical probability distribution is statistically significant in 7 out of 15 cases. Figure 5.3a and 5.3b summarize K-S statistical evaluation consistency of the change in the probability distribution of SST-derived annual maximum daily discharge of the Indochinese Peninsula. For the case of hypothesis acceptance, most of the region, except the middle part of Mekong Delta and the southern Indochina, are predicting the significant difference of only 3 to 7 cases out of total 15. In contrast, the case of hypothesis rejection is broadly consistent across the Ayeyarwaddy Basin, the middle part of Mekong Basin, and Chao Phraya River Basin.

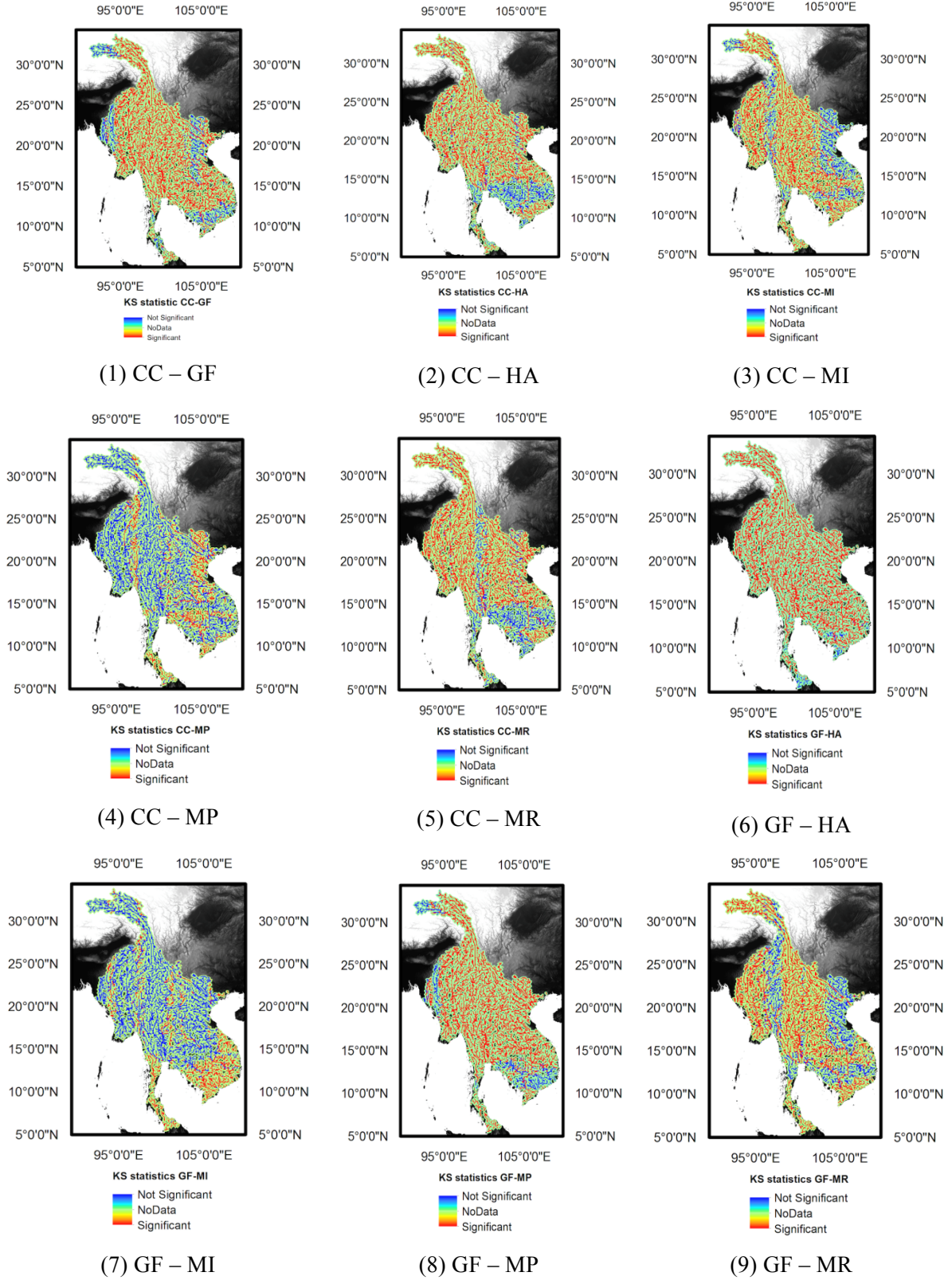


Figure 5.1 Geographical distribution of the two-sample Kolmogorov-Smirnov test statistics of annual maximum daily discharge for each pair of the d4PDF SST patterns

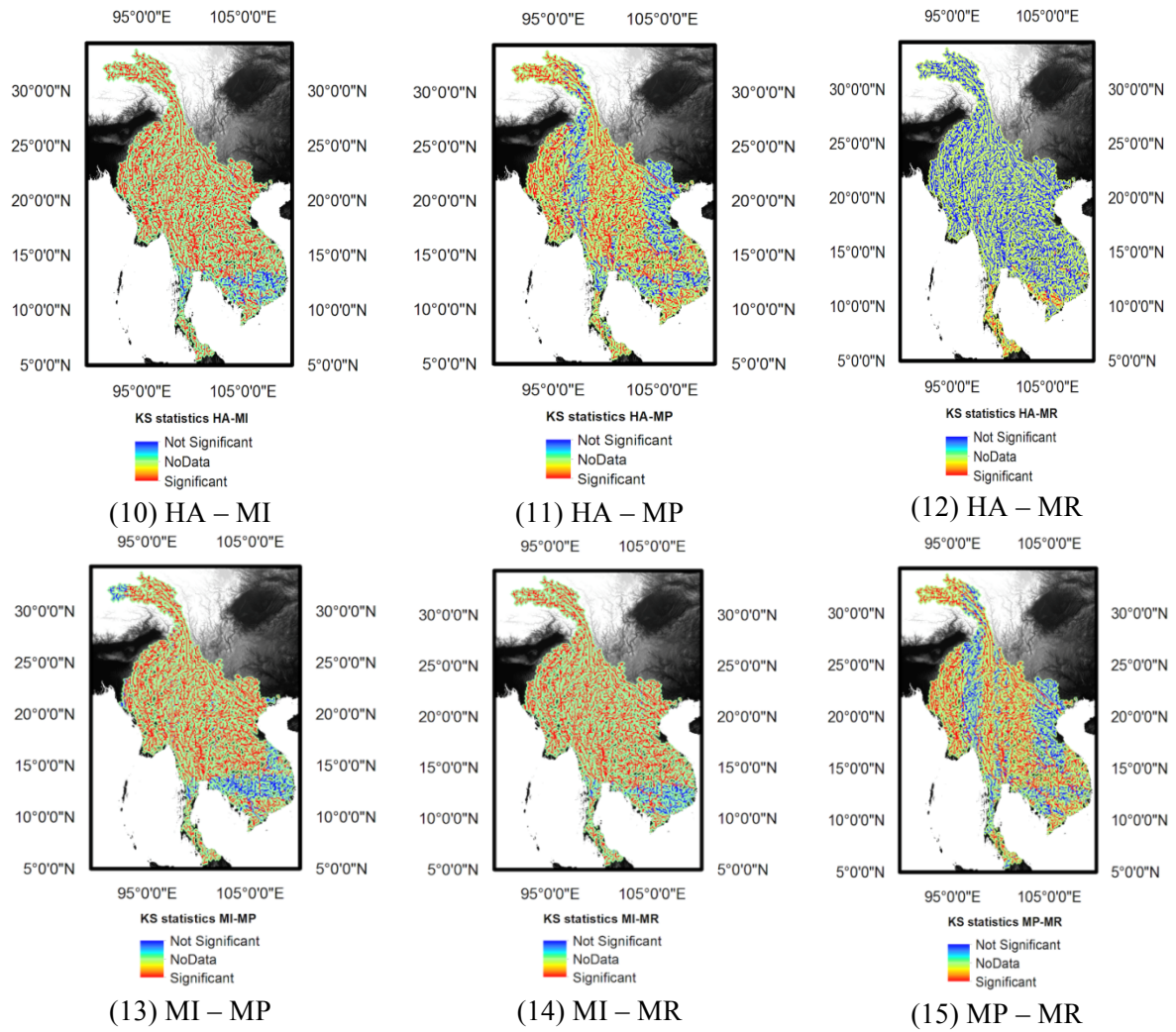


Figure 5.2 Same as Figure 5.1 but for the remaining groups of annual maximum daily discharge from d4PDF SST patterns (group 10 – 15)

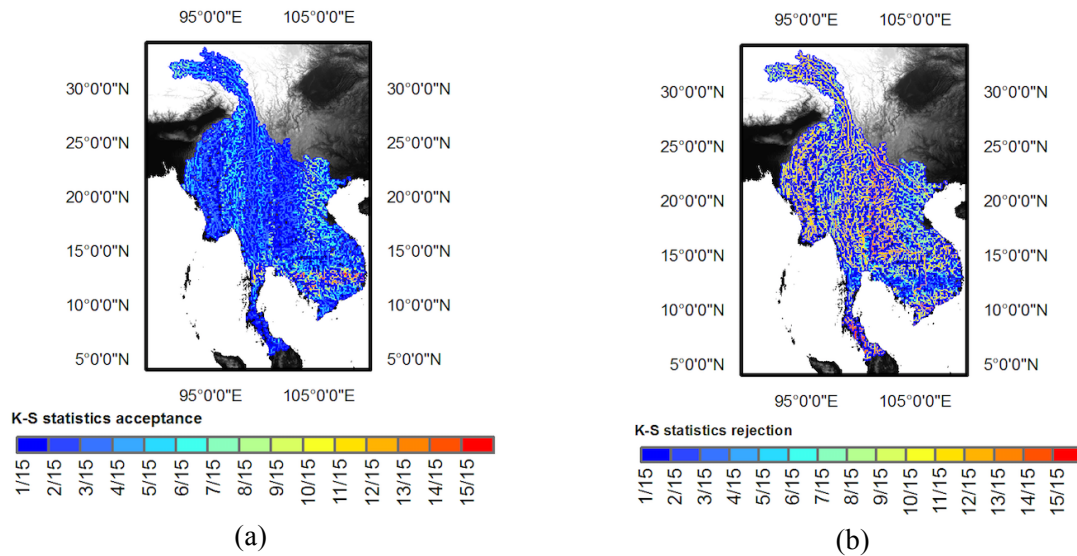


Figure 5.3 The two-sample KS statistics evaluation consistency (a) the case of KS statistics null hypothesis acceptance and (b) the case of KS statistics null hypothesis rejection

The implication of hydrologic analysis for the results in Figure 5.1, 5.2 and 5.3 can be summarized as follows:

- 1) In the region where the null hypothesis is *rejected* imply that the difference in the prior probability distribution function between the two SST-derived annual maximum daily discharge is significant. The combination of the two rejected datasets could increase the river discharge projection uncertainty for each grid points.
- 2) In the region where the null hypothesis is *not rejected* imply the opposite outcome, which means that the difference in the prior probability distribution between the two SST-derived annual maximum daily discharge is not statistically significant. Therefore, the combined ensemble in the non-rejected region should bring more reliable probabilistic projection of the changes in probability density function (PDF) of the annual maximum daily discharge of the Indochinese Peninsula.

5.3.2 Two-sample Anderson-Darling test

Figure 5.4 shows the geographical distribution of the two-sample Anderson-Darling test statistics (AD^2) from 15 groups of the 900-member annual maximum daily discharge of the Indochinese Peninsula of each SST warming pattern. Statistically significant changes in the probability distribution for each cluster were calculated at each grid for the entire of the Indochinese Peninsula. The characteristics of the Anderson-Darling statistics across several cases of SST couples are broadly similar to the spatial distribution of the two-sample KS test. For instance, the explicit rejections of the null hypothesis were found at the Ayeyarwaddy, Chao Phraya, and the Mekong River Basin with remarkably similar patterns in 12 of 15 groups. The results also showed that there is a relatively high probability of the null hypothesis rejection by the two-sample AD test at the Salween River Basin for 8 out of 15 possible SST groups. For several parts of the Mekong Delta and the southern Indochinese Peninsula, the changes in an empirical probability distribution in each SST group is found to be statistically insignificant in most of the possible cases (13-14 cases).

The patterns of AD value distribution also found to be unique to the test cases, which shows that the difference between the empirical allocation of each pair is predicted to be significant in 7 out of 15 cases.

Figure 5.6a and 5.6b illustrates the consistency of AD test statistics for the entire Indochinese Peninsula. The results showed that most of the region, except the Mekong Delta and the southern Indochinese Peninsula, are predicted the rejection of the null hypothesis

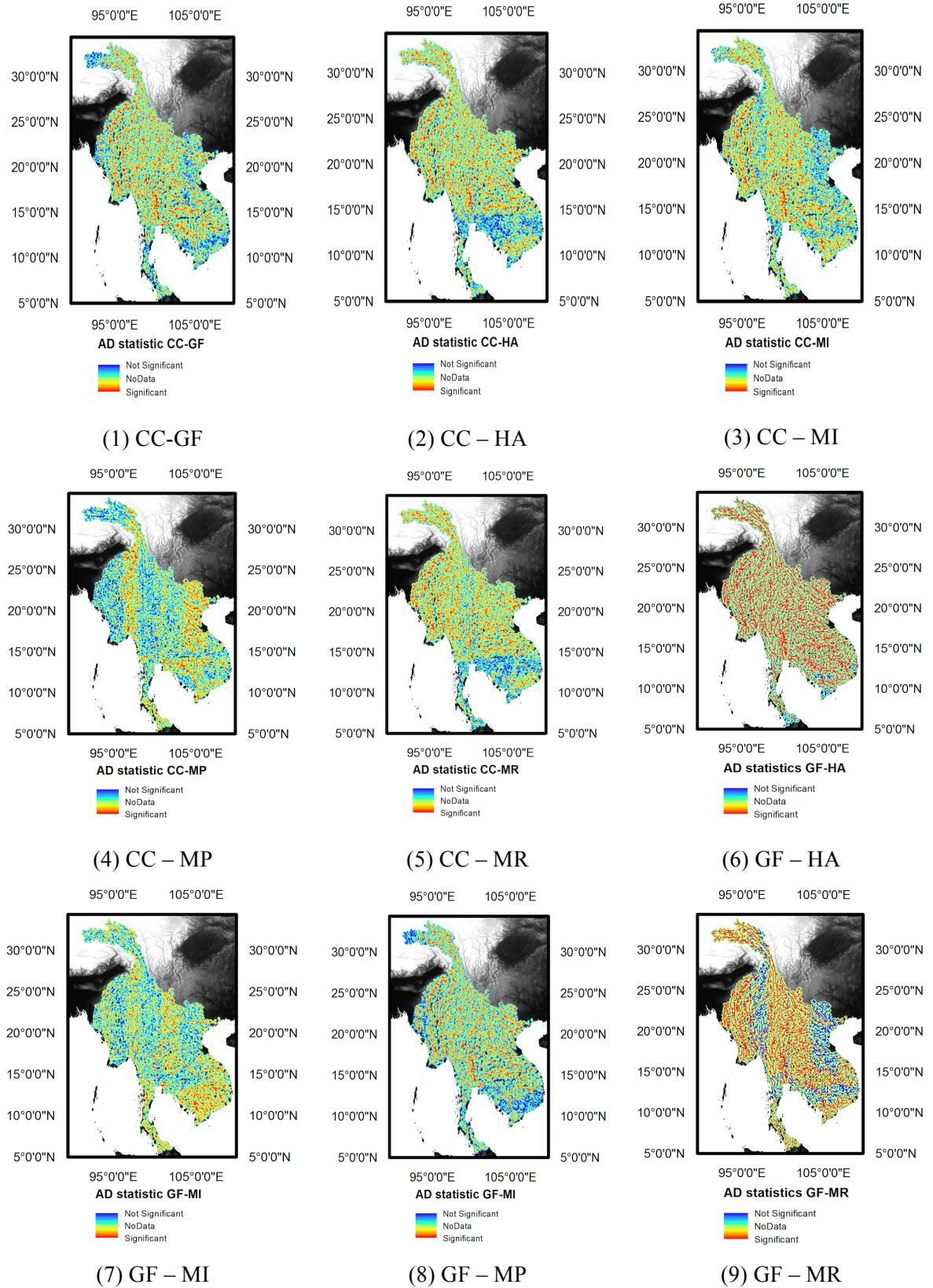


Figure 5.4 Geographical distribution of the two-sample Anderson-Darling test statistics of annual maximum daily discharge for each pair of the d4PDF SST patterns

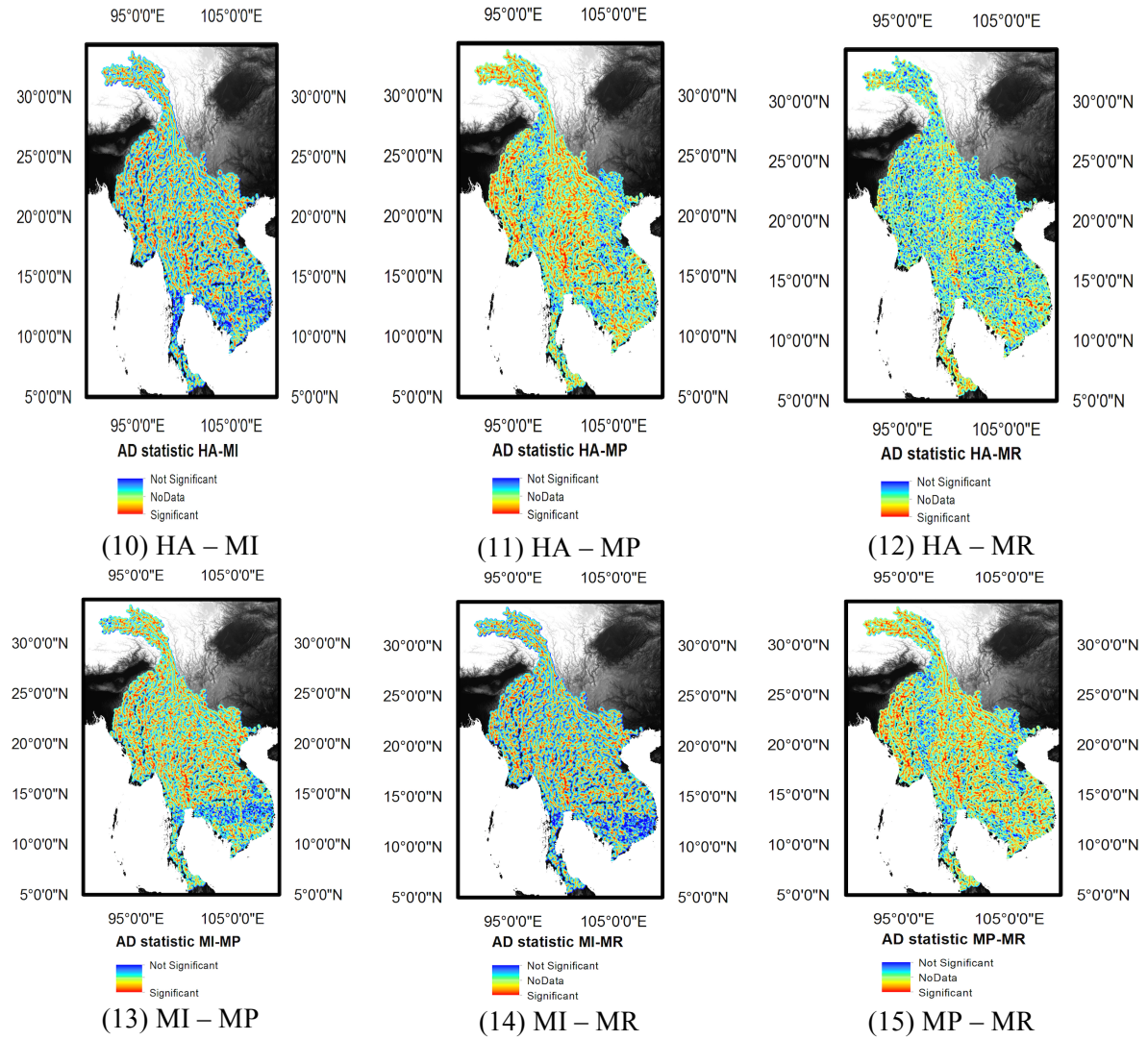


Figure 5.5 Same as Figure 5.4 but for the remaining groups of annual maximum daily discharge from d4PDF SST patterns (group 10 – 15)

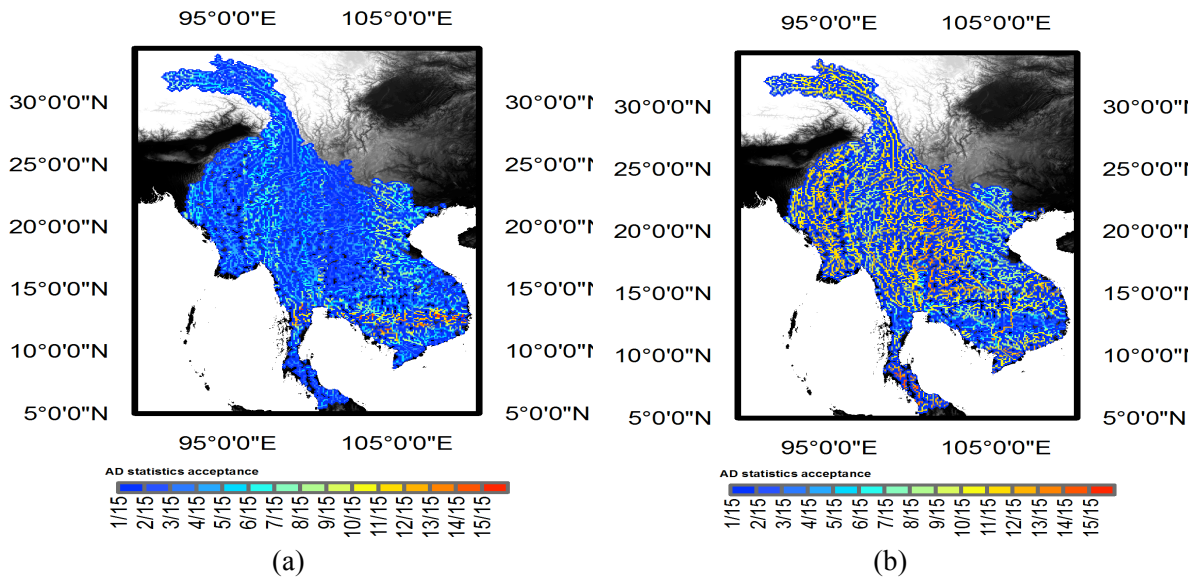


Figure 5.6 The two-sample AD statistics evaluation consistency (a) the case of AD statistics null hypothesis acceptance and (b) the case of AD statistics null hypothesis rejection

For 3 to 7 cases of the total of 15, which is exactly similar to the two-sample KS statistics. Meanwhile, the signal of the AD statistics is much more uniformly detected at the Ayeyarwaddy Basin, the middle part of Mekong Basin, and Chao Phraya River Basin.

The implication of hydrologic analysis for the results in Figure 5.4, 5.5 and 5.6 can be summarized as follows:

- 1) In the region where the null hypothesis is ***rejected*** imply that the difference in the tail of the underlying probability distribution function between the two SST-derived annual maximum daily discharge is significant. Therefore, the combination of the two rejected datasets could possibly increase the river discharge projection uncertainty for each grid points.
- 2) In the region where the null hypothesis is ***not rejected*** indicates that the difference in the upper and lower tail of the underlying probability distribution between the annual maximum discharge samples are not statistically significant. Therefore, it is possible to combine the samples in the non-rejected region for the analysis of changes in the empirical probability distribution of the annual maximum daily discharge under climate change.

5.4 Conclusion

This chapter investigated the difference in the empirical cumulative distribution of the annual maximum daily discharge of the Indochinese Peninsula under the future climate. The non-parametric two-sample Kolmogorov-Smirnov test and the two-sample Anderson-Darling test were utilized for the evaluation between the possible fifteen groups of SST-derived annual maximum discharge datasets retrieved from the d4PDF database.

Application of the two-sample K-S and the AD tests to the studied area showed that there is significant difference between cumulative probability distribution of the annual maximum daily discharge in most of the SST combinations (12 cases out of 15) at the Ayeyarwaddy River Basin, Chao Phraya River Basin, the middle part of Mekong River Basin, and 8 out of 15 combinations at the Salween Basin. The finding also showed that the difference of the probability distribution at the Mekong Delta and the southern Indochinese Peninsula are not statistically significant in most of the SST warming patterns combinations, with only 1 – 3 cases that the null hypothesis has been rejected. These findings also help to clarify that it is possible to increase a total number of sample in the future annual maximum discharge up to

multi-thousands, which theoretically, should better derive the empirical probability distribution and could be useful for the hydrological frequency analysis of extreme floods.

The end results in this chapter could potentially be served as a complimentary to the past research (Nakaegawa et al., 2006; Endo et al., 2012; Murakami et al., 2012; Hanittinan et al., 2016), which indicated that the uncertainty of hydro-meteorological data, e.g., precipitation, runoff, and river discharge in terms of total variance due to non-uniform population and should underpin the case to combine the data sets that met the criteria established by the cited articles and the one proposed in this study.

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Chapter 6

Hydrological projections at the Indochinese Peninsula under climate change using the d4PDF datasets

6.1 Introduction

The Indochinese Peninsula, comprising Thailand, Myanmar, Laos, Vietnam, Malaysia, and the southern portion of China, is known to be one of the most disaster-prone areas in the world. This is a developing region with a large and growing population bases that heavily reliant on agricultural sectors. The region has a diverse geographic landscape from mountainous area and plateau to low-lying areas such as swamp and grasslands. Therefore, the region is at risk and confronting significant challenges from the impact of climate change.

According to the fifth report of the Intergovernmental Panel on Climate Change (IPCC, 2013), warming of the climate is unequivocal, and many observed changes are unprecedented over several millennia. Recent climate changes have had widespread impacts on human, natural systems, hydrological cycle, and associated extremes such as floods and droughts.

To better manage the risk of water-related disaster induced by climate change, information based on river discharge projections is essential. In this regard, hydrological modeling plays a significant role in transferring input climatic information into runoff or discharge outputs.

Currently, most studies about analyzing hydrological projections employ either direct or bias-corrected input forcing datasets from GCMs, to simulate river discharge and assess its impact on hydrology and water resources.

This chapter focus on the determination of the impact of climate change on daily extreme river discharge and to locate possible hotspot areas in the Indochinese Peninsula by conducting the statistical significant analysis on the changes in the mean, mean of the annual maximum, standard deviation, and the 95th percentile of the annual maximum daily discharge for the entire study area. The kinematic-wave based, distributed flow routing model 1K-FRM was fed with the forcing datasets from the latest vast ensemble, 60-km-mesh, MRI – AGCM 3.2H archived under the d4PDF datasets. There are two periods of the simulations: the present climate (1951 – 2010) with

100 perturbed ensembles and the future climate (2051 – 2100) with 90 perturbed ensembles from the various sea surface temperature warming patterns, e.g., CCSM4 (CC), GFDL-CM3 (GF), HadGEM2-AO (HA), MIROC5 (MI), MPI-ESM-MR (MP), and MRI – CGCM3 (MR), under the single cumulus cloud parameterization scheme –Yoshimura scheme (Yukimoto et al., 2011; Yoshimura et al., 2015). Simulated river discharge in the present climate and the future climate were compared to investigate the changes in the river discharge under climate change. The ratio of the mean, standard deviation, and the 95th percentile of the annual maximum daily discharge in the future climate to the one in the present climate experiment was calculated and analyzed.

The statistical significance of the changes in river discharge at the Indochinese Peninsula was further assessed with a comparison of means, standard deviation, and the 95th percentile of the maximum projected annual maximum daily discharge for the future and present climate experiments. The primary purpose of this analysis is to evaluate whether the changes in river discharge are statistically significant or just occur by chance.

In this study, the approach for comparing those statistics is based on the non-parametric assumptions of the annual maximum daily discharge datasets. Generally, when the assumptions are correct, statistical analysis based on the parametric methods will produce more accurate and precise estimate than non-parametric one with more statistical power. Therefore, we need a larger sample size to draw conclusions from the data with the same degree of confidence. However, as non-parametric methods make fewer assumptions; their applicability is much wider than the corresponding parametric methods. In particular, they may be applied in situations where less is known about the application in question.

Fortunately, a uniquely large ensemble of climate simulations with a 60-km atmospheric general circulation model has been performed to obtain probabilistic projections of low-frequency and high-impact events, at the regional-scale. One of the major advantages of using the d4PDF datasets is the large number of ensembles available, which allows a direct utilization of the future changes in extreme events without given any prior assumptions. In addition, the results will enable the assessment of probabilistic change in localized hydrological extreme events that have significant uncertainty emanated from the internal variability.

Finally, this chapter also presents the future projections of the hydrologic variables such as precipitation and total runoff, to provide support for the finding related to the river discharge.

This chapter is organized as follows. “Methodology” describes datasets configuration and

research implementation. “Results and Discussions” provides statistical comparisons of the changes between simulated future with respect to present river discharges in the Indochinese Peninsula region under climate change. Finally, the “Conclusion” section provides the summary of the findings.

6.2 Methodology

6.2.1 Test for statistically significant differences between two mean of the annual maximum discharge (Mann-Whitney U test)

The statistical significant of the changes in the average of the annual maximum daily discharge was assessed by conducting the non-parametric Mann-Whitney U-test. The null hypothesis of the method states that it is equally likely that a randomly selected value from one sample will be less than or greater than a randomly selected value from a second sample. This test is a non-parametric test, so it does not require the assumption of normal distribution

Here are the underlying assumptions of the analysis (Mann and Whitney, 1947; Nachar, 2008)

- 1) All the observations from both groups are independent of each other,
- 2) The responses from both groups are ordinal.
- 3) Under the null hypothesis H_0 , the probability of an observation from the population X exceeding an observation from the population Y equals the probability of an observation from Y greater than an observation from X
- 4) The alternative hypothesis H_1 is the probability of an observation from the population X greater than the second population Y is different from the probability of an observation from Y larger than an observation from X

The procedure to calculate U-test statistics are listed below:

- 1) Rearrange the data from the lowest to highest score while keeping track of both group membership, and then assign a rank to each score. If there is a tie, all the tied scores instead receive the average rank of that set of scores,
- 2) Compute the sum of the ranks for one of the samples. For example, for each member of group 2, count the number of data in group 1 that have a smaller rank. The sum of these counts is called R_I

- 3) For each member of group 1, count the number of the data in group 2 that have a smaller rank. The sum of the count is called R_2
- 4) Compute U-statistics using the following formula

$$U_1 = R_1 - \frac{n_1(n_1+1)}{2} \quad (6-1)$$

$$U_2 = R_2 - \frac{n_2(n_2+1)}{2} \quad (6-2)$$

When n_1 is the number of observations for sample 1, and R_1 is the sum of the ranks in sample 1; n_2 is the number of observations for sample 2, and R_2 is the sum of the ranks in sample 2.

The U-statistics is then determined from the smallest value between U_1 and U_2 , $\min(U_1, U_2)$. The sum of the two values is given by:

$$U_1 + U_2 = R_1 - \frac{n_1(n_1+1)}{2} + R_2 - \frac{n_2(n_2+1)}{2} \quad (6-3)$$

In the Mann-Whitney U test, the null hypothesis H_0 will be rejected if the U-statistics is smaller than the critical value at a significance level α (U_α).

6.2.2 Test for homogeneity of variance between the annual maximum daily discharges of the present and future climate experiments (Levene's test)

The Levene's test for a homogeneity of variance (L-test) proposed by Levene (1960). It is an inferential statistic used to assess the equality of variances for a variable calculated for two or more groups. This test has a particular importance for detecting changes in extreme events by the measure of differences in the variance of the datasets. The F-test is the most widely used technique if the standard deviation of the two populations is equal and approximately normal distribution. However, most of the extreme-event hydrological data such as precipitation or streamflow almost always violate the normality assumption (Wang et al., 2008). Therefore, in the present study, L – test, which is much less sensitive than the F-test and Barlett test to departure from normality to detect whether the variance of k groups is identical or not (Conover et al., 1981; Snedecor and Cochran, 1989, p. 252).

The L-test is based on computing absolute deviations from the group mean within each cluster. Given that a variable Y with sample size N divided into k subgroups, the L-test statistic is defined as follows:

$$W = \frac{(N-k)}{(k-1)} \frac{\sum_{i=1}^k N_i (\bar{z}_i - \bar{Z})^2}{\sum_{i=1}^k \sum_{j=1}^{N_i} (z_{ij} - \bar{z}_i)^2} \quad (6-4)$$

Where N_i is the sample size of the i^{th} subgroup; the within-group absolute deviations $z_{ij} = |x_{ij} - \bar{x}_i|$, $i = 1, 2, \dots, k$, $j = 1, 2, \dots, N_i$ $\bar{x}_i$ is the mean of the i^{th} subgroup; $\bar{z}_i$ is the group mean of z_{ij} ; and $\bar{Z}$ is the overall mean of the z_{ij} .

The L-test rejects the null hypothesis (H_0) which states that the two datasets have equal variances if $W > F(\alpha, k-1, N-k)$. Where $F(\alpha, k-1, N-k)$ is the upper critical value of the F distribution with degrees of freedom $k-1$ and $N-k$ at a significance level α .

6.2.3 Test for the shift of the upper tail between the annual maximum daily discharges of the present and future climate experiments (Two-sample Anderson-Darling test)

Several statistical methods designed to detect a shift in the empirical probability distribution of group 1 relative to group 2. For instance, the KS test is well known for its sensitivity to the shape of the distribution which makes it more capable of detecting a shift in the center of the distribution than at the tails (Filliben and Heckert, 2006; Engmann and Cousineau, 2011). However, when detecting changes in extreme events, significant interest in the variance and the tail of the data. Therefore, in addition to the Levene's test, the two-sample Anderson-Darling test (AD-test) was chosen to detect a shift in the upper tail of the distribution of the present and future climate experiments. The AD-test has an exceptional ability to identify some subtle differences between the large sample sizes and its sensitivity towards differences at the tails of distributions.

The two-sample AD-test are simplified as follows (Pettitt, 1976):

$$AD_{mn}^2 = \frac{1}{mn} \sum_{i=1}^{N-1} \frac{(M_i N - ni)^2}{i(N-i)} \quad (6-5)$$

where M_i is defined as the number of X that less than or equal to the i^{th} smallest in the pooled sample of X_n and Y_m with the size of N . The null hypothesis that X_n and Y_m come from the same continuous prior distribution is rejected if AD_{mn}^2 is larger than the correspondent critical value, which depends on confidence level α and sample size.

6.3 Future changes in river discharge at the Indochinese Peninsula under climate change

6.3.1 Changes in mean of the annual maximum daily discharge

Figure 6.1 presents change ratio of the average of the annual maximum discharge in the Indochinese Peninsula. The changes in annual maximum daily discharge primarily showed a similar trend regardless of SST patterns. The slightly decreased trend with change ratio of 0.90 can be found at the Chao Phraya and the northern part of the Mekong River Basin (in Laos). The positive trend was found to be slightly at upstream of the Mekong, the central part of the Irrawaddy, Salween and the Red River Basin at northern Vietnam in 4 of 6 SST warming patterns of the future climate experiments (CC, HA, MP, and MR) with the change ratio up to 1.10. The results also show the ratio at the Mekong Delta was projected to be between 1.5 – 2.0 for all the d4PDF SST warming scenarios. The change ratio was expected to be between 2.5 – 3.0 at the southern Indochinese Region (in Thailand) for all the d4PDF SST patterns, which means that the risk of flooding in those areas is likely to be increased by the end of the 21st century. The results also showed that the changes in the mean of the annual maximum daily discharge near the Red River Basin delta are projected to sizable increase for the entire SST settings, with a particular degree of variation (2.00 – 2.50).

6.3.2 Changes in the variability of the future annual maximum daily discharge

The change ratio of the annual maximum daily discharge variability for the future climate with respect to the present climate experiment is shown in Figure 6.2. For the future climate analysis, the standard deviation was found to be remarkably consistent across the d4PDF SST settings in the Mekong Delta and the Southern Indochinese Peninsula. The standard deviation was projected to increase slightly at the Chao Phraya River Basin, Ayeyarwaddy River Basin and central part of the Mekong River Basin (in Laos) for the 4 out of 6 SST scenarios. Meanwhile, the increases in standard deviation with the change ratio up to 1.50 – 2.00 were detected at the Red River Basin. From Fig. 6.2a – 6.2f, the increasing trend of standard deviation were found to be the most extreme at the Mekong Delta and the southern Indochinese Peninsula, where its change ratio was projected to be between 2.50 - 3.00 in all the future climate experiments, which

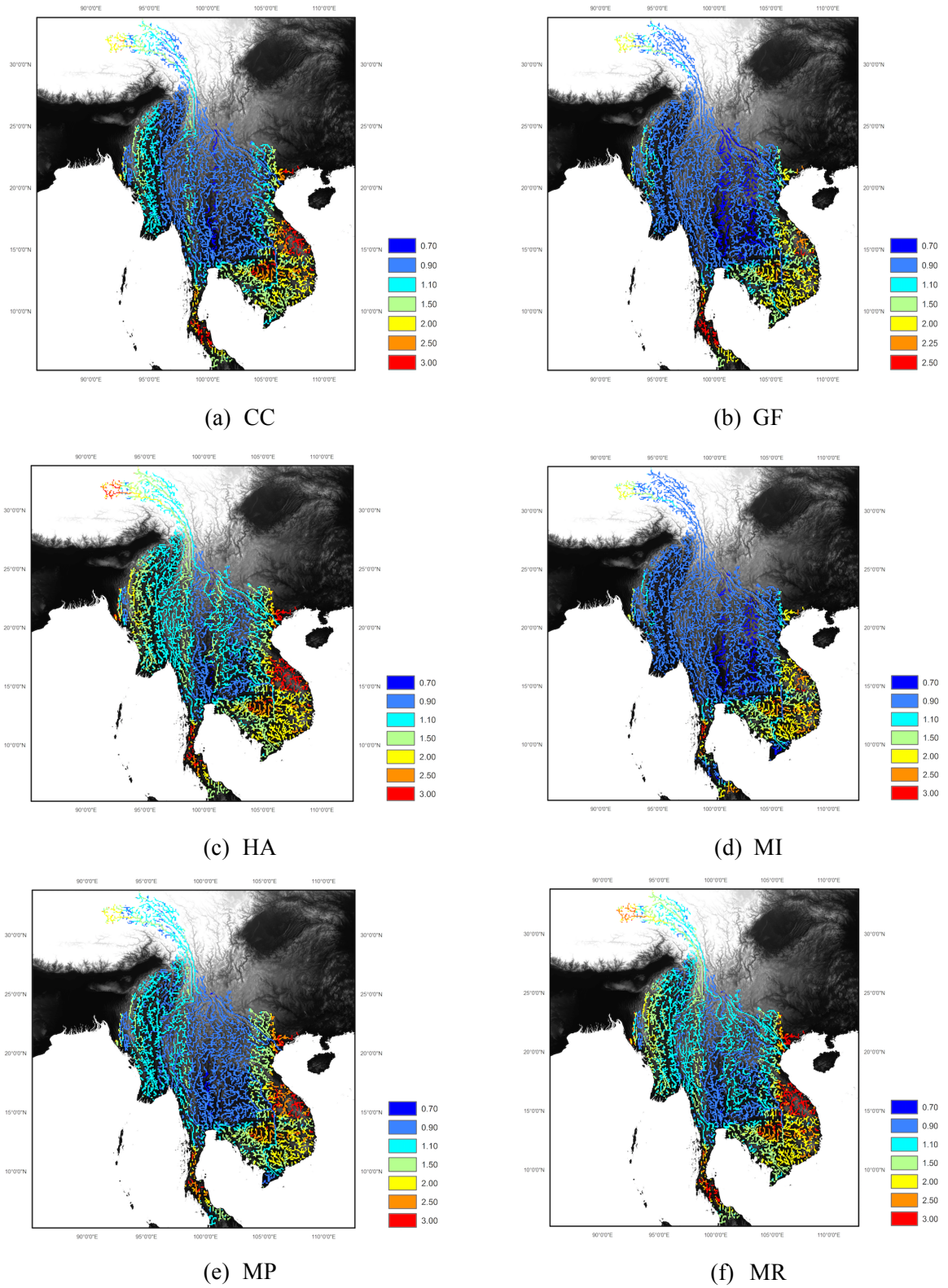


Figure 6.1 Change ratio of mean of the annual maximum river discharge of the future climate to present climate of six different SST patterns under the d4PDF MRI-AGCM 3.2H (a) CC, (b) GF, (c) HA, (d) MI, (e) MP, (f) MR

global scale. The results showed that a substantial increase in multi-model mean and median floods indicates that the region is likely facing more fluctuation in annual maximum discharge or floods in the future. The change ratios of the standard deviation were broadly similar but generally more intense than the mean of annual maximum daily discharge at the most region in the Indochinese Peninsula except for Ayeyarwaddy and Salween River Basin in the CC, HA, MP and MR scenarios.

6.3.3 Changes in the future extreme discharge at the Indochinese Peninsula under climate change

Figure 6.4 shows the change ratio of the 95th percentile of the annual maximum river discharge for the future climate of six different SST warming patterns to present climate experiment. From figure 6.4a – 6.4e, there are not so many changes in the annual maximum discharge in some of the major river basins in the Indochinese Peninsula such as Irrawaddy, Chao Phraya, Salween Basin with values of ratio were slightly less than unity. However, the increases in the ratio larger than 1.5 were detected at the Mekong Delta in 5 of 6 SST patterns of the future climate. The changes ratio up to 3.00 were found at the southern Indochina Peninsula and the Red River Basin in the northwestern part of Vietnam for the HA and MP future SST warming patterns.

Due to the sizable discrepancy in the number of samples of the annual maximum daily discharge between the future experiments on each SST (15 ensembles x 60 years/ensemble = 900 samples) and the present climate (100 ensembles x 60 years/ensemble = 6,000 samples), outcomes of the analysis should have uncertainty. Hereafter, despite unknown differences on the prior distribution function of the annual maximum daily discharge from different SST settings, we proceed to combine the datasets from the six experiments into a large ensemble of 5,400 samples (900 samples/SST x 6 SSTs). Results showed similar outcome with HA and MP scenarios, where the most extreme changes in the 95th percentile of the annual maximum river discharge were detected at the Red River Basin with the ratio up to 3.50.

6.3.4 Discussions on the river discharge projections

Several studies attempt to analyze the trend of change of extreme discharge and its frequency of occurrence. For instance, Hirabayashi et al. (2013) simulated daily river

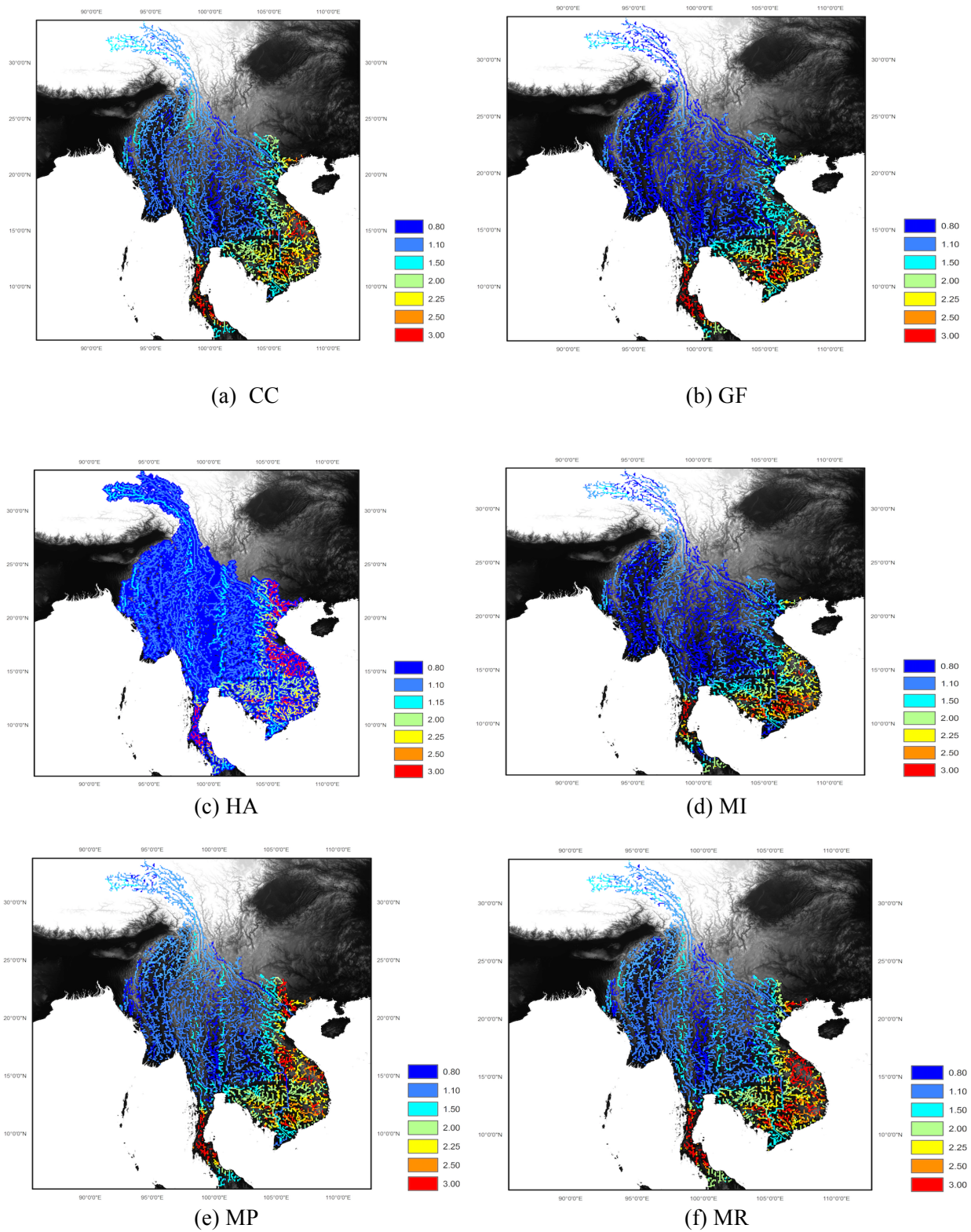


Figure 6.2 Change ratio of standard deviation of the annual maximum daily discharge of the future climate to present climate of six different SST patterns under the d4PDF MRI-AGCM 3.2H (a) CC, (b) GF, (c) HA, (d) MI, (e) MP, (f) MR

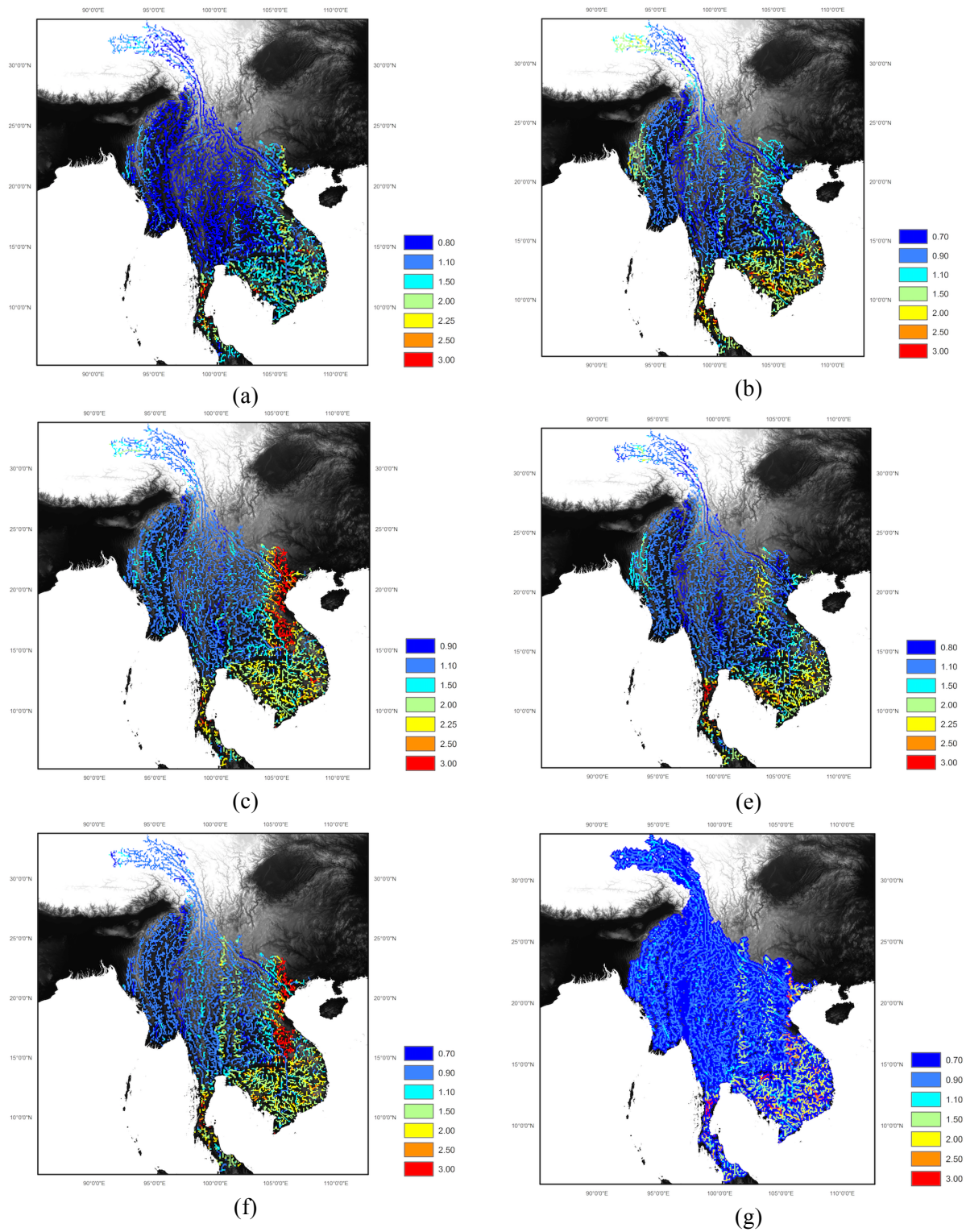


Figure 6.3 Change ratio of the 95th percentile of the annual maximum river discharge of the future climate to present climate of six different SST patterns under the d4PDF MRI-AGCM 3.2H (a) CC, (b) GF, (c) HA, (d) MI, (e) MP, (f) MR

discharge derived from the CMIP5 multi-model ensemble to project the changes in floods on a frequency at the Indochinese Peninsula, particularly at the Mekong and Red River Basin for the 11 ocean-coupled GCMs. Duong et al. (2013) performed river discharge projection at the Indochinese Peninsula using 20-km and 60-km atmospheric models, which showed that the mean of annual maximum daily discharge was projected to increase meaningfully at the Irrawaddy Basin. It was also expected to increase at the Mekong and the Red River Basin. However, the results showed some difference with this study in the Chao Phraya Basin, which in Duong *et al.* was detected an increase but was shown as a slight decrease in 4 of 6 of the future d4PDF SST scenarios in this study. Champathong et al. (2013) also performed a similar analysis but only focus at the Chao Phraya River Basin using four different types of the future SST scenarios. The results showed that the future climatological mean of the runoff and river discharges were projected to decline between 10 – 30 %, which was within the range of this research.

6.4 Analysis on the statistical significance of the difference between the annual maximum daily discharge between present and future climate experiments

6.4.1 Changes in mean of the annual maximum daily discharge at the Indochinese Peninsula under climate change

The results of the statistical significance test of the shifts in the average of the annual maximum daily discharge are shown in figure 6.4.

According to the figure 6.4, which illustrates the results of a future climate experiments, the change in the mean of the annual maximum discharge is entirely projected to be statistically significant in all the SST warming patterns at the middle and the lower Mekong Basin (Mekong Delta) in Cambodia, Laos PDR, and Vietnam; the Southern Indochinese Peninsula; and the mouth of the Red River Basin in Vietnam.

On the contrary, the significance of the change along the Ayeyarwaddy River Basin is not projected to be significant for all the SST scenarios as well as the changes at the Chao Phraya River Basin and the Salween River Basin in Myanmar.

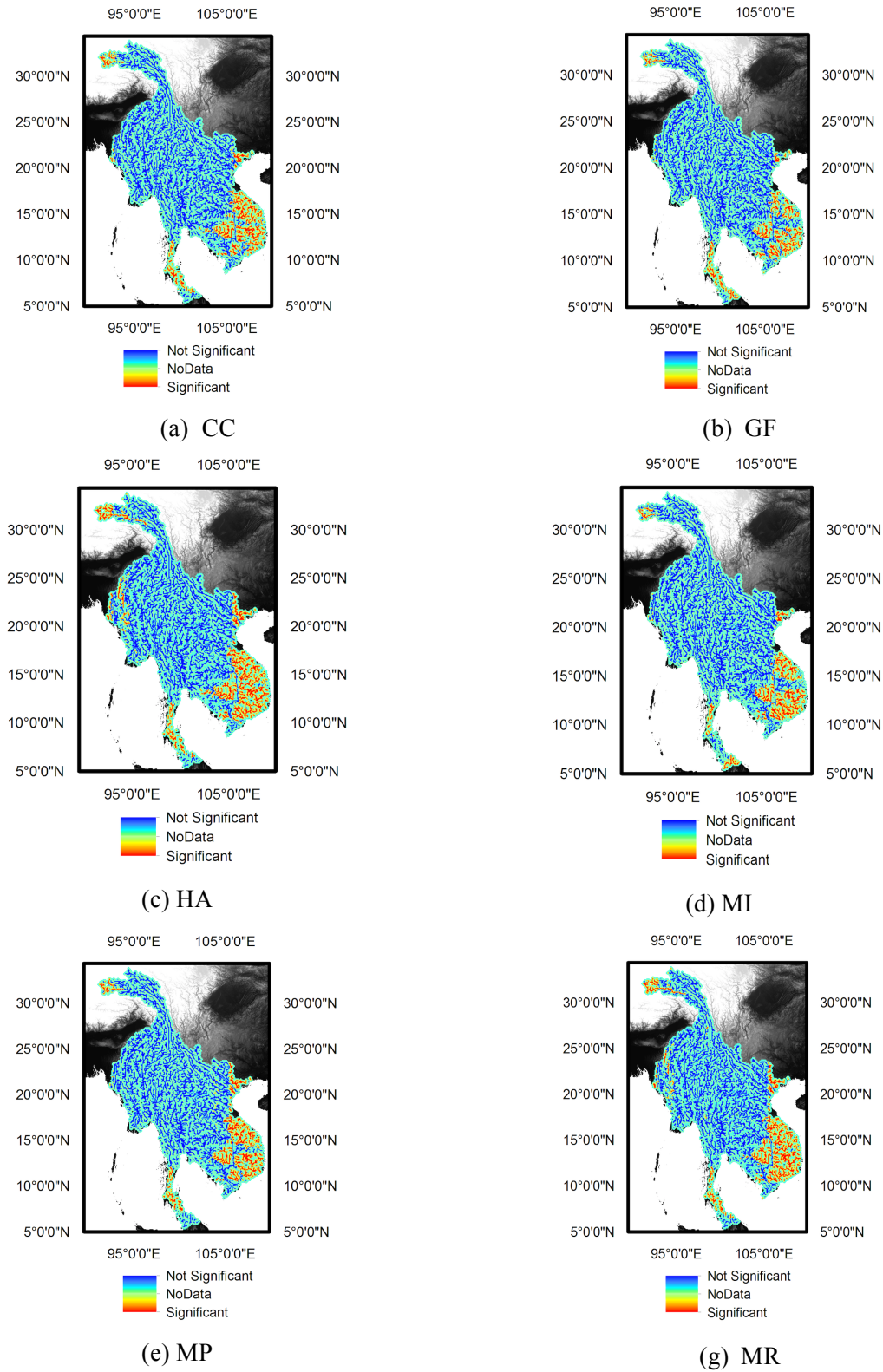


Figure 6.4 Statistical significance of the difference between mean of annual maximum daily discharge for the future and present climate under six SST scenarios (a) CC, (b) HA, (d) MI, (e) MP, and (f) MR

6.4.2 Changes in the variability of the future annual maximum daily discharge at the Indochinese Peninsula under climate change

The results of the statistical significance test of the shifts in the variability of the annual maximum daily discharge at the Indochinese Peninsula, which represented as its standard deviation for the present and future climate experiments, are shown in figure 6.5.

According to the figure 6.5 in the future climate, the change in the variability of the annual maximum discharge is found to be statistically significant in all the SST warming patterns; for the lower Mekong Basin to the Mekong Delta, the central part of the Chao Phraya Basin in Thailand, the lower Ayeyarwaddy Basin, and the Southern Indochinese Peninsula. However, the significance of the change along the middle Mekong Basin are showed a less consistent results, where most of the main channel of the Mekong river was projected to affected by the increase of the standard deviation of the future annual maximum river discharges, but some signal of insignificant changes was emerged at the Che and Mun sub-basin in at least two SST patterns (HA and MR).

Meanwhile, the changes in the Salween Basin was found to be mixed, which most of the changes may just occur by chance for four SST warming scenarios (GF, HA, MP, and MR). The significance of the future change in the variability of extreme river flows may also occur near the mouth of the Red River Basin's main channel for the four SST scenarios (GF, HA, MI, and MR).

6.4.3 Changes in the future extreme discharge at the Indochinese Peninsula under climate change

The results of the statistical significance of the future changes in the daily extreme river discharge are represented as a 95th percentile of the annual maximum daily discharge of both the present and the future climate are shown in figure 6.6.

The findings reveal that there are two major spatial structures of change in the 95th percentile of the annual maximum daily discharge. The first pattern was found at the SST scenarios CC, GF, and MI, where the differences in the river discharge are significant in virtually all the river basins at the Indochinese Peninsula. The second pattern was detected at the scenarios HA, MP, and MR, where the statistically insignificant changes were found along the main tributary of the Salween River Basin, parts of the Red River Basin of Vietnam, and at the Mekong sub-basin

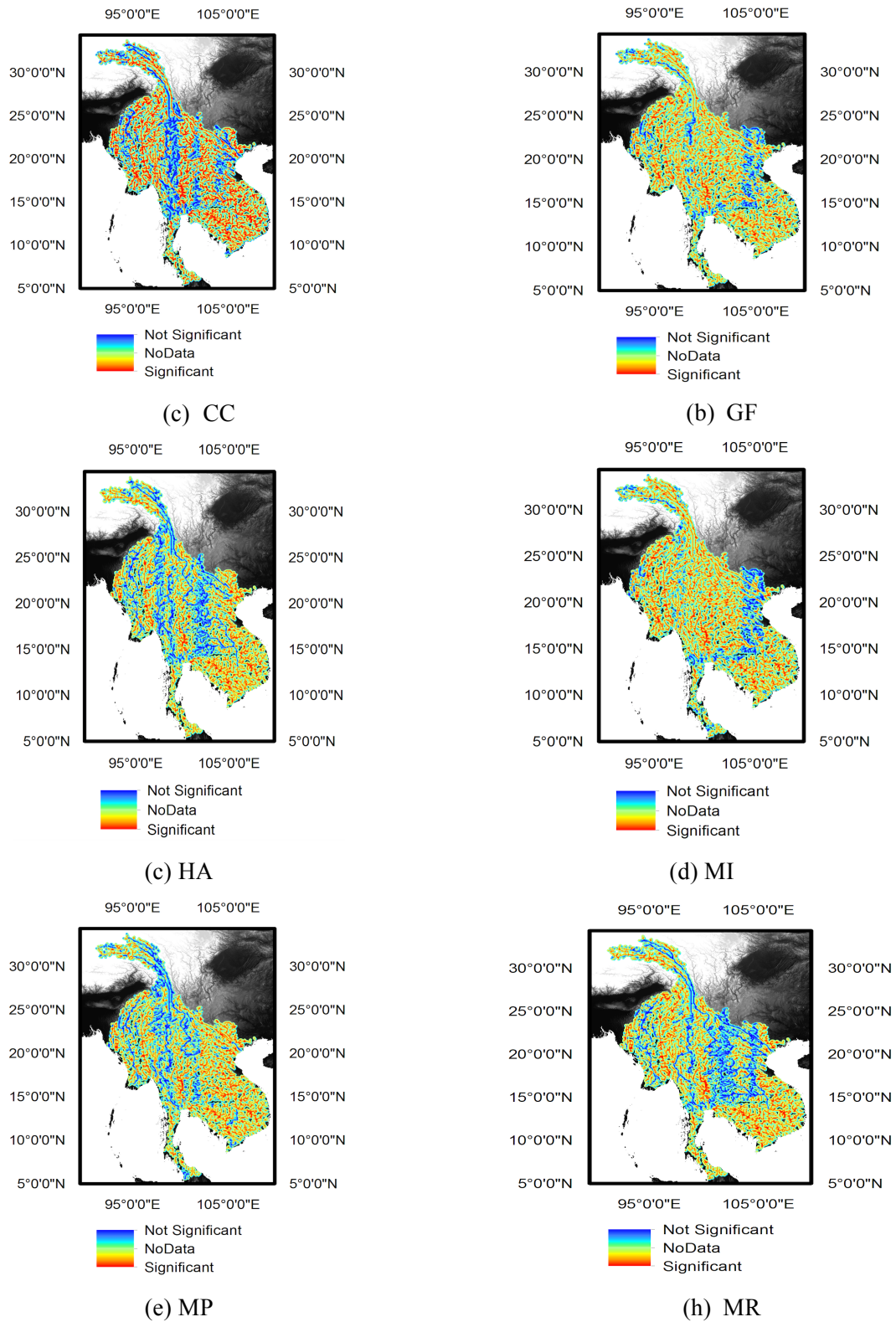


Figure 6.5 Statistical significance of the difference between the variability of the annual maximum daily discharge for the future and present climate under six SST scenarios (a) CC, (b) GF, (c) HA, (d) MI, (e) MP, and (f) MR

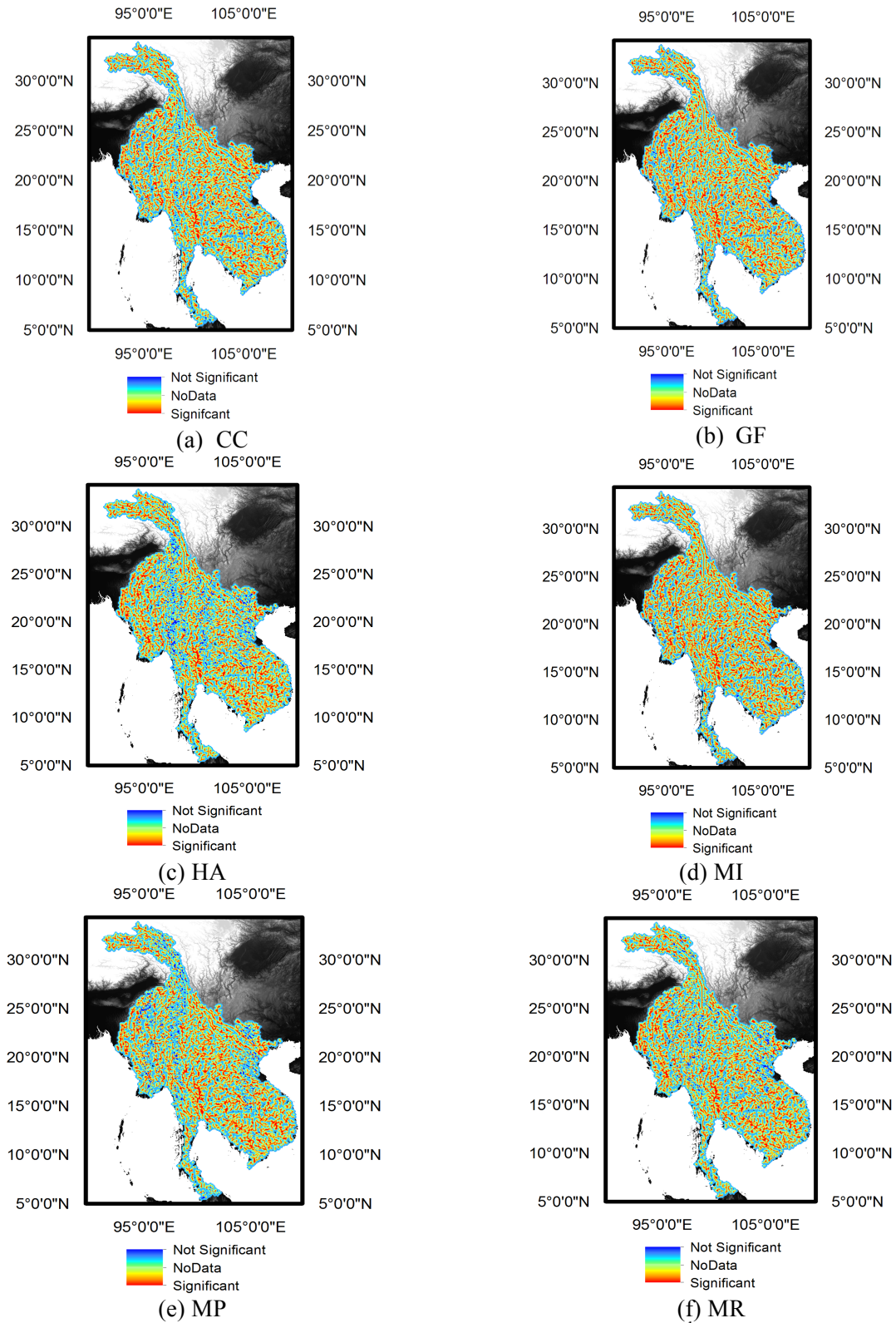


Figure 6.6 Statistical significance of the difference between the 95th percentile of the annual maximum daily discharge for the future and present climate experiments under six SST scenarios (a) CC, (b) GF, (c) HA, (d) MI, (e) MP, and (f) MR

Therefore, the significant changes in extreme river discharges indicated that the future flood risks in according regions would increase. Consequently, floods adaptation strategies should be developed in a systematic way to reduce the vulnerability of those who projected to be affected in this area in the future.

6.5 Analysis and comparison of the empirical probability density function of the annual maximum daily discharges between the present and future climate at the selected hotspot areas within the Indochinese Peninsula

In this section, the outcomes of the changes in mean, standard deviation, and the 95th percentile of the annual maximum daily discharge were used to select the hotspot area, where the peak discharge is projected to increase significantly in the future climate with respect to the present climate condition. The results of the two-sample, non-parametric methods such as KS-test and AD-test were used to complement the finding related to the statistical analysis, by providing a way to help to screen the annual hydrologic time series for the statistical compatibility between multiple datasets. In this regard, derivation of the empirical probability distribution of the extreme hydrological events with larger ensemble members is possible and could be applied for the frequency analysis of severe floods under climate change.

6.5.1 Identification of the hotspot areas

Table 6.1 summarizes the findings from sections 5.3, 6.3, and 6.4. The results of statistical analysis are first presented in each river basin (Ayeyarwaddy, Chao Phraya, Mekong, Mekong Delta, Salween, Red River, and Southern Indochinese Peninsula). Most of the measure shown in table 6.1 indicates a significant shift in the mean, standard deviation, and the 95th percentile of the annual maximum discharge, at the Mekong Delta and Southern Indochinese Peninsula. Future changes in the annual maximum discharge variability and its 95th percentile at the Chao Phraya River Basin are projected to be significant in all the SST warming patterns. In the meantime, the changes in the mean of the annual maximum discharge are also found to be significant near the

mouth of the Red River Basin and at a middle section of the Mekong Basin. The rest of the basins such as Ayeyarwaddy and Salween have also expected a significant shift in the future annual maximum discharge variability and its 95th percentile in some of the SST patterns.

Table 6.2 presents the potential number of samples that could be analyzed in the major river basins at the Indochinese Peninsula. The total number of samples at each catchment is calculated from the SST couple that did not reject the null hypothesis of the two-sample KS and AD tests. According to the results, the Mekong Delta and Southern Indochinese Peninsula are expected to generate various possible future ensemble combinations of the annual maximum discharge datasets with at least 1,800 samples such as CC-GF, CC-HA, CC-MP, CC-MR, GF-MP, HA-MI, HA-MP, HA-MR, MI-MP, and MI-MR. Furthermore, the results also suggest that larger number of samples at these two regions up to 2,700 samples is attainable through the merger of the particular SST arrangements such as HA-MI-MP and HA-MI-MR.

Table 6.1 Summary of the statistical analysis of the annual maximum daily discharge

Methods	River Basins						
	Ayeyarwaddy	Chao Phraya	Mekong	Salween	Red River	Mekong Delta	Southern Indochina
U-test	HA, MR (Partially)	-	CC, GF, HA, MI, MP, MR (middle section)	-	CC, GF, HA, MI, MP, MR	CC, GF, HA, MI, MP, MR	CC, GF, HA, MI, MP, MR
Levene's test	CC, GF, MI	CC, GF, HA, MI, MP, MR	CC, GF, MI, MP, MR (middle section)	CC, GF, MI, MR	CC, HA, MP, MR	CC, GF, HA, MI, MP, MR	CC, GF, HA, MI, MP, MR
AD-test	HA, MP, MR	CC, GF, MI, MP, MR	HA, MP, MR	GF, MP	HA, MP, MR		GF, HA, MP, MR

Table 6.2 Potential number of sample to be analyzed at the principal river basins at the Indochinese Peninsula

River Basins	Potential combination	Number of annual maximum samples
Ayeyarwaddy	CC-MP, GF-MI, HA-MR	$900 \times 2 = 1,800$
Chao Phraya	CC-MP, GF-MI, HA-MR	$900 \times 2 = 1,800$
Mekong	CC-MI, CC-MP, GF-MI, HA-MP, HA-MR, MP-MR	$900 \times 3 = 2,700$
Salween	CC-MI, GF-MI, GF-MR, HA-MP, HA-MR, MP-MR	$900 \times 3 = 2,700$
Red River	CC-GF, CC-MI, GF-MI, GF-MR, HA-MP, HA-MR, MP-MR, CC-GF-MI	$900 \times 3 = 2,700$
Mekong Delta	CC-GF, CC-HA, CC-MP, CC-MR, GF-MP, HA-MI, HA-MP, HA-MR, MI-MP, MI-MR	$900 \times 3 = 2,700$
Southern Indochinese Peninsula	CC-GF, CC-HA, CC-MP, CC-MR, GF-MP, HA-MI, HA-MP, HA-MR, MI-MP, MI-MR	$900 \times 3 = 2,700$

By consider all the results, two major river gauging stations were chosen as a representative of the hydrological hotspot regions due to the significant of changes in future annual peak flows and the potential number of sample to be analyzed, which are:

- 1) Kampong Chhnang station (12°16'17" N, 104°40'60" E) at the Mekong Delta with proximity with the Ton Le Sap sub-basin.
- 2) B.10 station (12°58'24" N, 99°53'10" E) at the southern Indochinese Peninsula

In addition, the others flow observation station in the primary catchment of the study area were also included in this chapter:

- 3) C.2 station (15°40'14" N, 100°6'35" E) at the Chao Phraya River Basin, Thailand
- 4) Pakse station (15°7'0" N, 105°47'60") at the central Mekong Basin, Laos PDR
- 5) Monywa station (22°6'0" N, 95°7'60" E) at the Ayeyarwaddy River Basin, Myanmar
- 6) Hanoi station (105°52'00" N, 21°02'00" E) at the Red River Basin, Vietnam

The detailed analysis such as the comparison of an empirical probability distribution of the annual maximum discharges of the present and future climate experiments and the relationship between annual peak discharge and the associated return periods were shown.

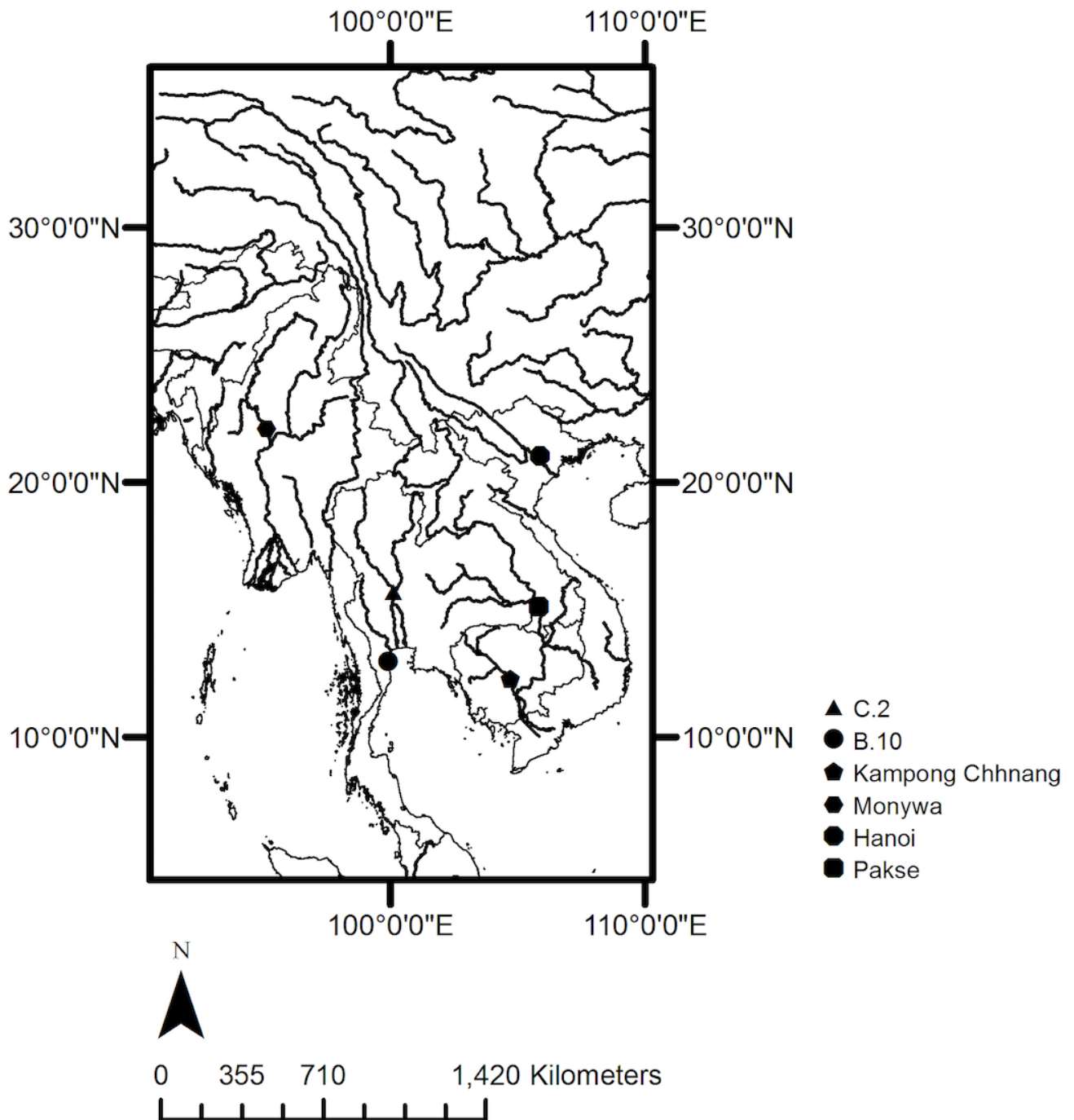


Figure 6.7 Hydrological hotspot areas at the Indochinese Peninsula

6.5.2 Comparison of the empirical probability distribution of the annual maximum daily discharge under the future and present climate experiments

Kampong Chhnang station (Mekong Delta)

The changes in the empirical distribution of the annual maximum daily discharge in the future climate with respect to the present climate at the Kampong Chhnang station ($12^{\circ}16'17''$ N, $104^{\circ}40'60''$ E), under different number of annual maximum samples, e.g., 900, 1800, and 2700, are shown in figure 6.8, 6.9, and 6.10

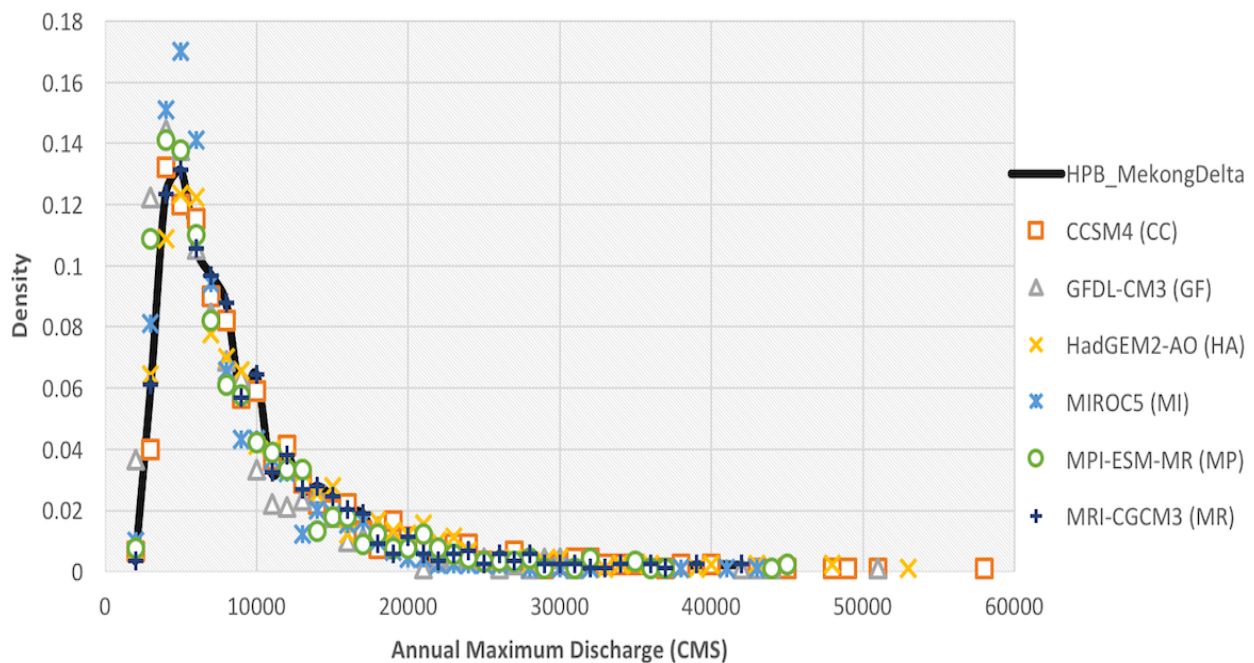


Figure 6.8 The empirical probability distribution represents the comparison between the annual maximum daily discharge of the present climate versus the future climate under the six SST warming patterns (CC, GF, HA, MI, MP, and MR) at Kampong Chhnang station. The total number of sample in the future climate is 900 for each scenario

Figure 6.8 displays the empirical probability distribution of the Kampong Chhnang station in the Mekong Delta. The thick black curve represents the peak discharge of the present climate, and six other plots are coming from the SST patterns under the +4K scenario. The x-axis shows the annual maximum daily discharge, and the y-axis is the empirical density. The future distribution generally shifts rightward relative to the present conditions at most of the quantile, which projects more frequent occurrence of average up to the extreme discharge events into the future.

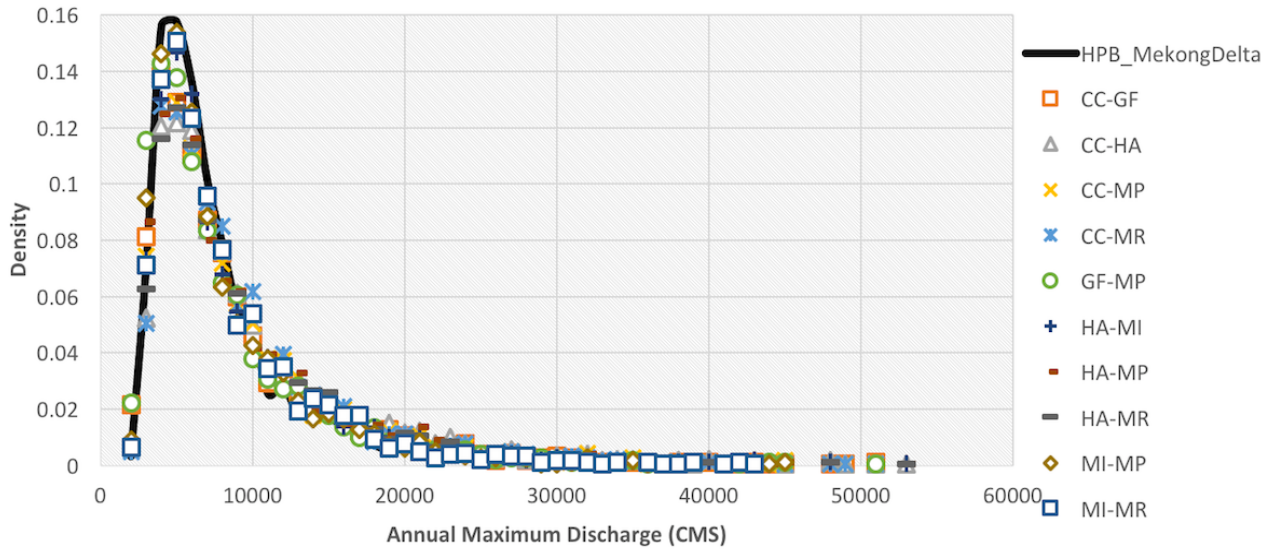


Figure 6.9 The empirical probability distribution represents the comparison between the annual maximum daily discharge of the present climate (HPB) versus the future climate (HFK) under the ten SST combination patterns at Kampong Chhnang station. The total number of sample in each of the future SST-combined scenario is 1,800

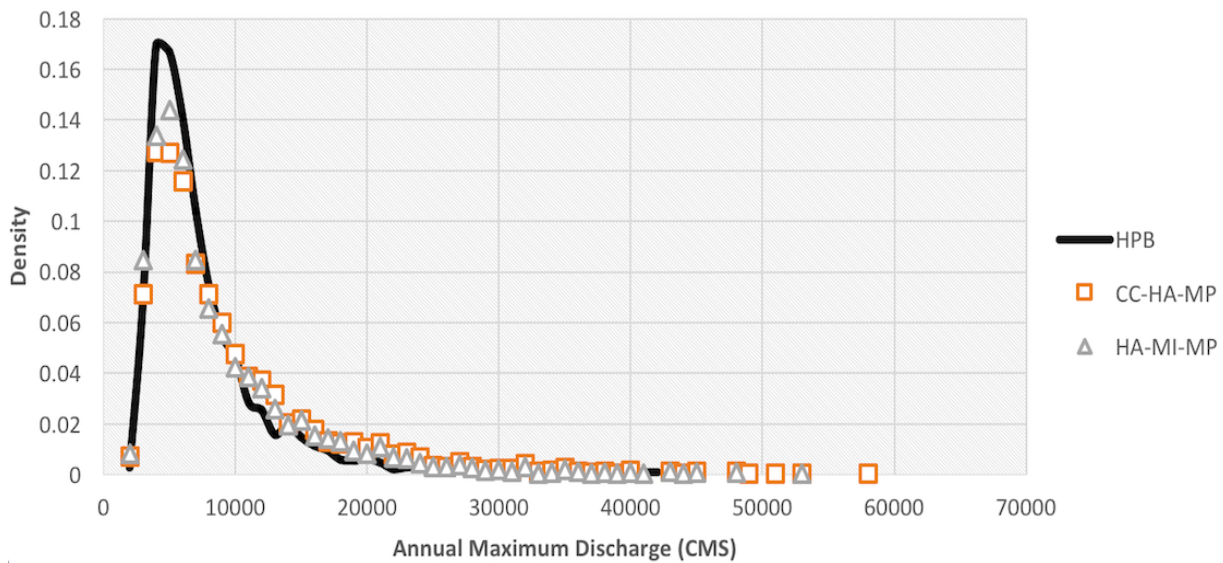


Figure 6.10 The empirical probability distribution represents the comparison between the annual maximum daily discharge of the present climate (HPB) versus the future climate (HFK) under the SST combination pattern at Kampong Chhnang station. The total number of sample in each of the future SST-combined scenario is 2,700

The changes in the 95th percentile flow regime (Q_{95}) significantly increase from the present climate from 14.86% (MIROC5) to 39.45% (CCSM4). The mean of the annual maximum discharge also increased across the SST warming scenarios from 1.02% (GFDL-CM3) to 21.68% (CCSM4).

The effect from increased number of samples is investigated in figure 6.9 and 6.10. In the first case, there are ten patterns of the 1,800-member ensemble from the combination of possible SST scenarios. The results showed the peak discharge at each quantile is projected to increase remarkably from the present climate experiment (HPB) for all the SST patterns. The growth rate at the larger return period is found to be more robust than the lower flow regime, with a rise from 23.28% (MI-MP) to 37.00% (CC-HA) at 5-year return period, and from 26.91% (MI-MP) to 40.95% (CC-MP) at 50-year return period. The projected range is expected to widen further to the largest quantile.

The second case displays the comparison of the empirical probability distribution of the 2,700-member ensemble from the combination of the plausible SST scenarios in two cases. The results preserve the past trend with the increase of the annual maximum discharge across the combined SST patterns, but no significant change in the degree of the increase of peak discharge at each return period was detected.

B.10 station (Southern Indochinese Peninsula)

The shifts in the empirical distribution of the annual maximum daily discharge in the future climate with respect to the present climate at the B.10 station ($12^{\circ}58'24''$ N, $99^{\circ}53'10''$ E), under different number of annual maximum samples, e.g., 900, 1800, and 2700, are shown in figure 6.11, 6.12, and 6.13.

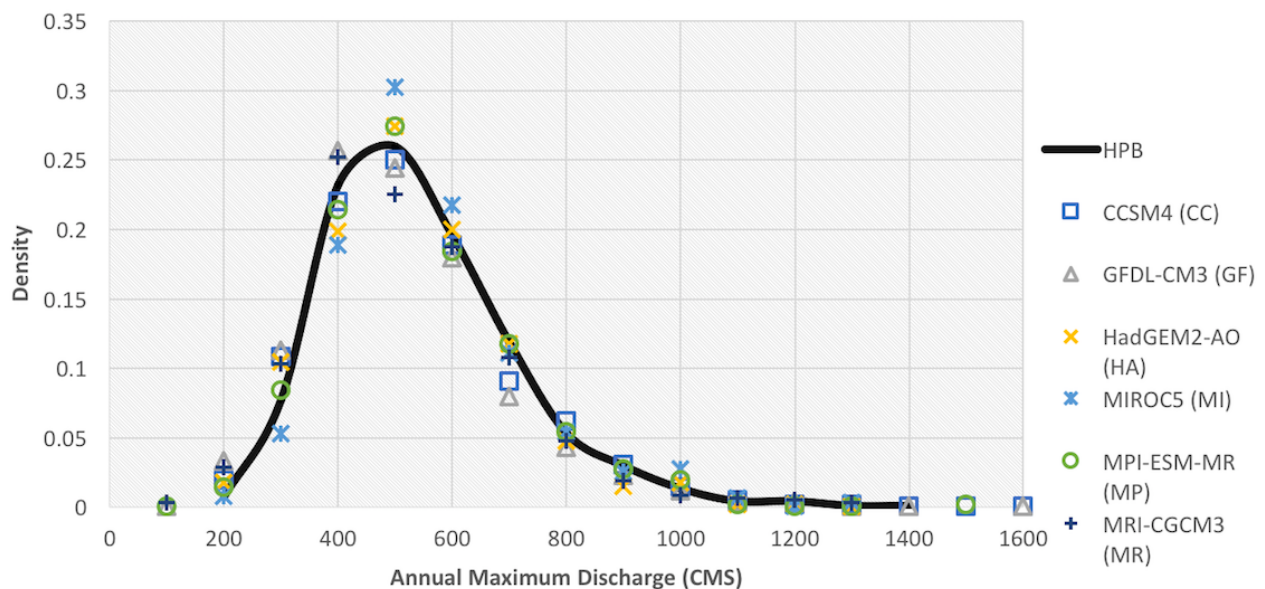


Figure 6.11 Same as Figure 6.8 but for B.10 station

Figure 6.11 displays the empirical probability distribution of the B.10 station in the southern Indochinese Peninsula. The shift rightward in the future annual maximum discharge distribution was clearly observed in the d4PDF SST CCSM4 (CC), GFDL-CM3 (GF), and MIROC5 (MI) settings at the return period larger than 100 years, which the projected annual maximum discharge is expected to increase by 0.84% to 2.75%. However, the changes in the empirical maximum discharge distribution at the median quantile suggests a diverging trend, where the river discharge under the HA, MI, and MP are projected to be more frequent, while the changes under the CC, GF, and MR could happen less frequently in the future climate.

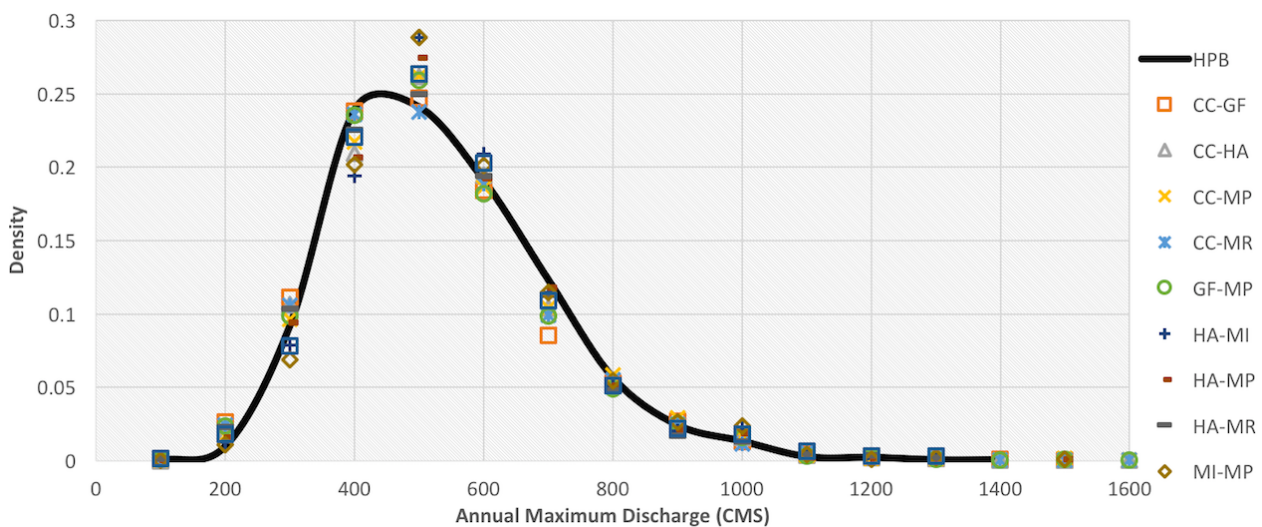


Figure 6.12 Same as Figure 6.9 but for B.10 station

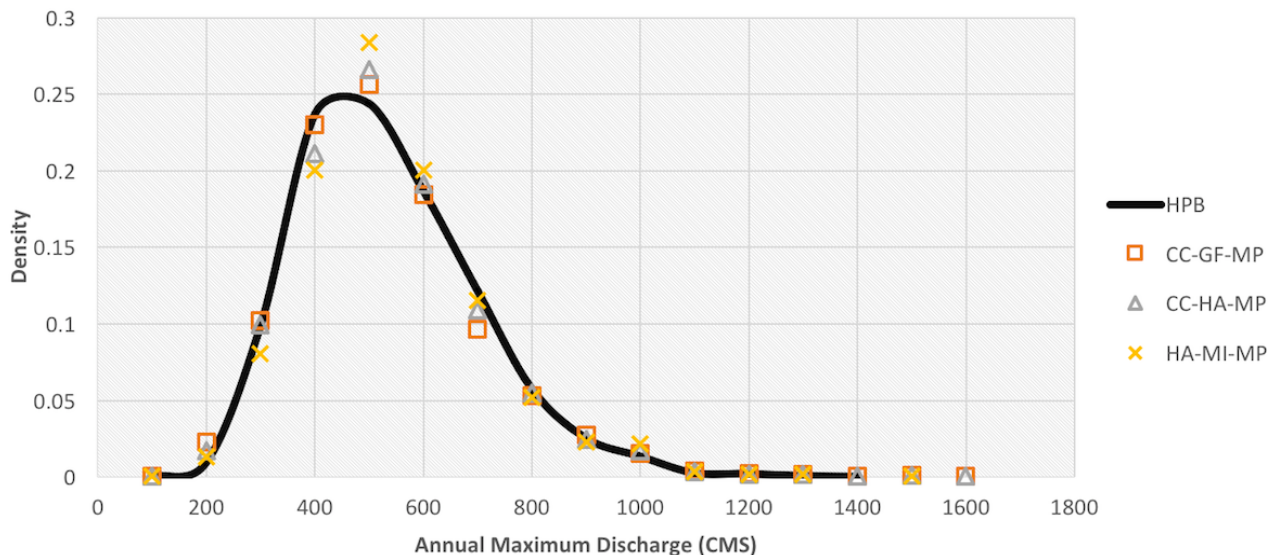


Figure 6.13 Same as Figure 6.10 but for B.10 station

Figure 6.12 illustrates the comparison with the number of combined sample at each future SST scenario at 1,800. The result shows a clear rightward shift in the shape and tail of the empirical distribution, where the peak flow at Q_{95} and the 100-year return period is universally increased across all the combined SST warming scenarios from 3.44% (CC-MP) and 6.50% (MI-MR) for the Q_{95} case; and from 2.67% (CC-HA) and 12.69% (CC-MR) for the latter case, respectively. The results also showed that the positive trend in the future annual maximum river discharge is projected to be unevenly distributed at the lower than 30-year return period, where the decline at 5 – 25 years return periods were expected between 0.47% (MI-MR) and 3.42% (CC-GF).

The results of the larger ensemble at 2,700 is shown in figure 6.13, where the generally rightward shift in the empirical distribution of the annual peak flow was evidently demonstrated. Most of the increases in the future pooled SST scenarios were detected at the larger quantile equivalent to the 8-year return period, where the peak flow at Q_{95} and the 100-year return period are projected to increase from 2.17% (CC-HA-MP) to 3.07% (HA-MI-MP); and 2.62% (HA-MI-MP) to 6.28% (CC-GF-MP), respectively.

C.2 station (Chao Phraya River Basin)

The changes in the empirical distribution of the annual peak discharge in the future climate relative to the present climate at the C.2 station (15°40'14" N, 100°6'35" E), under a different number of annual maximum samples, e.g., 900 and 1,800, are shown in figure 6.14 and 6.15.

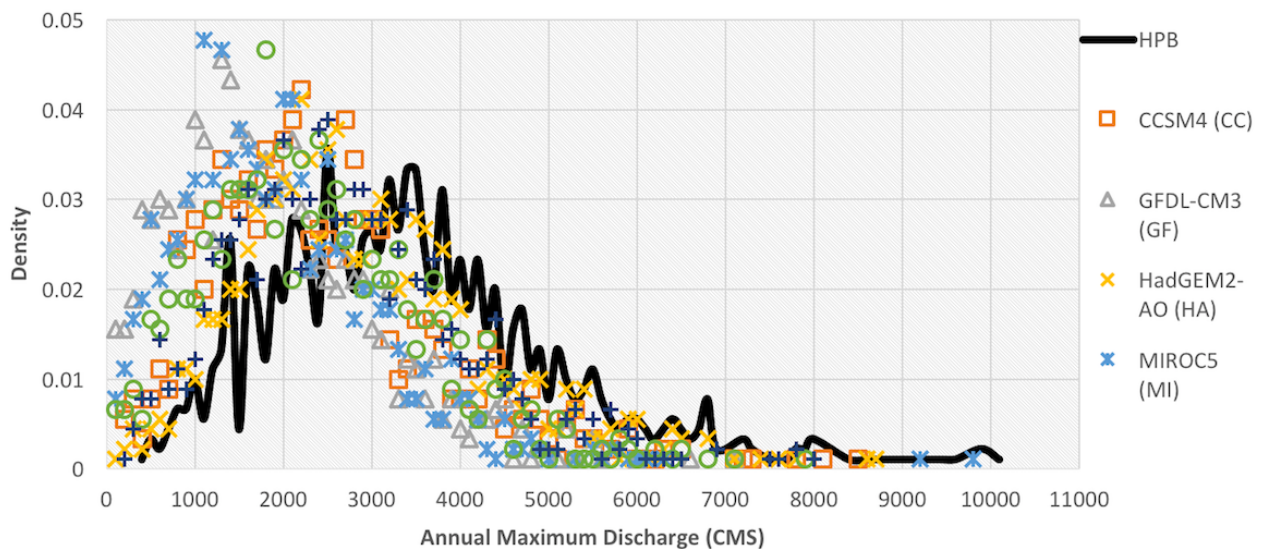


Figure 6.14 Same as Figure 6.9 but for C.2 station

Figure 6.14 displays the empirical probability distribution comparison between the future and present climate at C.2 station in the Chao Phraya River Basin, Central region of Thailand. The simulated future distribution shows the leftward shift compared with the current climate experiment. The Q_{95} is projected to drop by 16.18% (HadGEM2-AO) to 35.92% (GFDL-CM3). Similarly, the 100-year peak discharge also follows the same direction, where the annual associated peak flow is projected to drop by 19.26% (HadGEM2-AO) to 37.83% (GFDL-CM3). The comparison further revealed that the future discharge at the lower flow regime such as mean, median are also projected to be declined for each quantile.

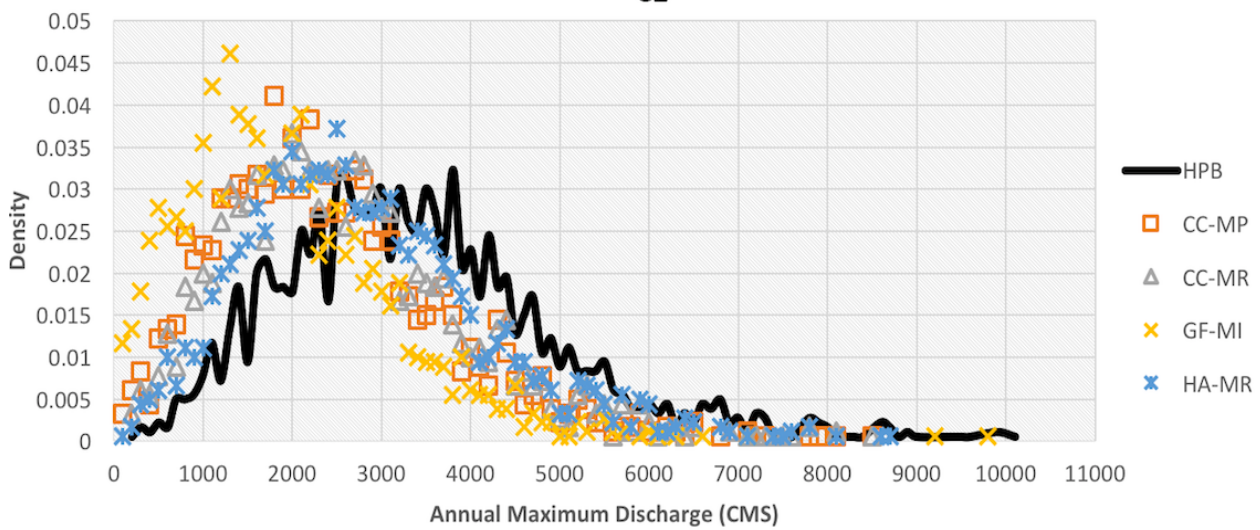


Figure 6.15 Same as Figure 6.10 but for C.2 station

Figure 6.15 shows the similar comparison of the empirical probability distribution comparison between the future and present climate, with a larger, three SST patterns of 1,800-member ensemble. The simulated future distribution shows the leftward shift compared with the current climate experiment. The Q_{95} is projected to drop by 27.35% (HadGEM2-AO) to 38.14% (GFDL-CM3). Similarly, the 100-year peak discharge also follows the same direction, where the annual associated peak flow is projected to drop by 19.26% (HadGEM2-AO) to 37.83% (GFDL-CM3). The comparison further revealed that the future discharge at the lower flow regime such as mean, median are also projected to be declined in each quantile.

Pakse station (Mekong River Basin)

The changes in the empirical distribution of the annual maximum daily discharge in the future climate with respect to the present climate at Pakse station ($15^{\circ}7'0''$ N, $105^{\circ}47'60''$), under different number of annual maximum samples, e.g., 900, 1800, and 2700, are shown in figure 6.16, 6.17, and 6.18

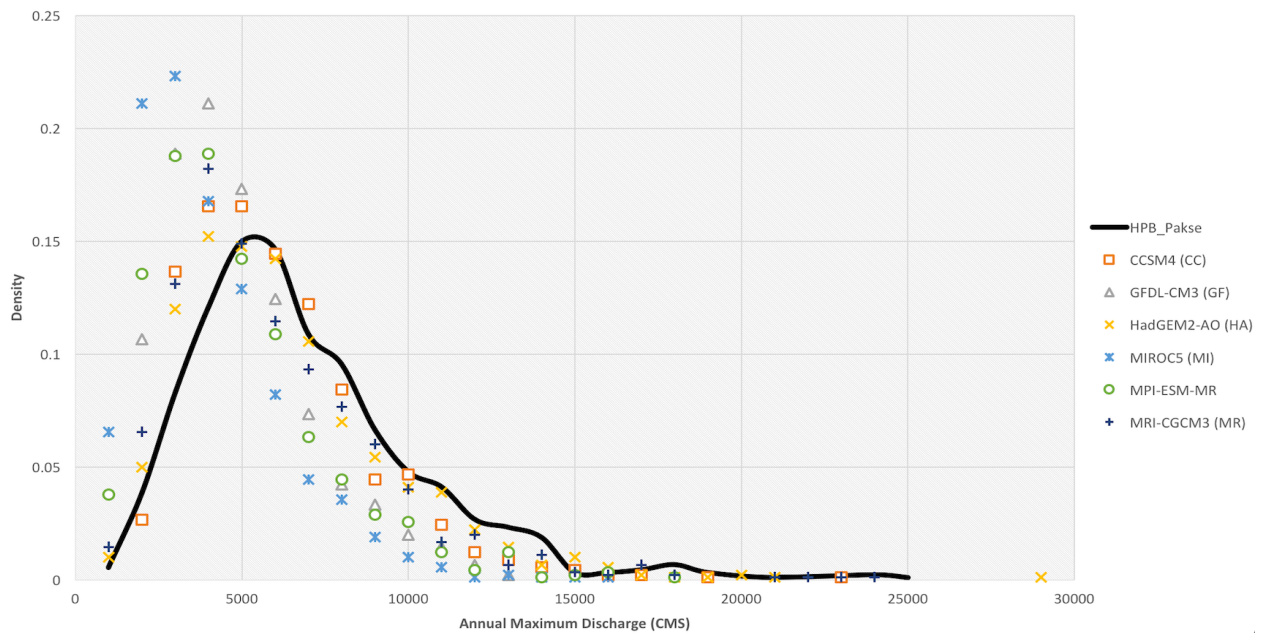


Figure 6.16 Same as Figure 6.9 but for Pakse station

The results of the 900-member case at Pakse station, Mekong Basin, is shown in figure 6.16. The simulated future distribution shows the leftward shift compared with the present climate experiment. The Q_{95} is projected to drop by 8.72% (HadGEM2-AO) to 38.39% (GFDL-CM3). Coincidentally, the 100-year peak discharge also follows the same direction, where the annual associated peak flow is projected to drop by 10.80% (HadGEM2-AO) to 40.38% (GFDL-CM3). The comparison further revealed that the future discharge at the lower flow regime such as mean, median are also projected to be declined for each quantile.

Figure 6.17 presents the comparison with the number of combined sample at each future SST scenario at 1,800. The result also confirms the earlier finding of leftward shift in the shape and tail of the empirical distribution, where the peak flow at Q_{95} and the 100-year return period is universally decreased across all the combined SST warming scenarios from 10.11% (HA-MR) to

39.09% (GF-MI) for the Q_{95} case; and from 9.66% (HA-MR) to 42.09% (GF-MI) for the latter case, respectively.

The results of the larger ensemble at 2,700 is shown in figure 6.18, where the generally rightward shift in the empirical distribution of the annual peak flow was evidently demonstrated. Most of the decrease in the future pooled SST scenarios were detected at the larger quantile equivalent to the 8-year return period, where the peak flow at Q_{95} and the 100-year return period are projected to drop by 14.32% and 14.20%.

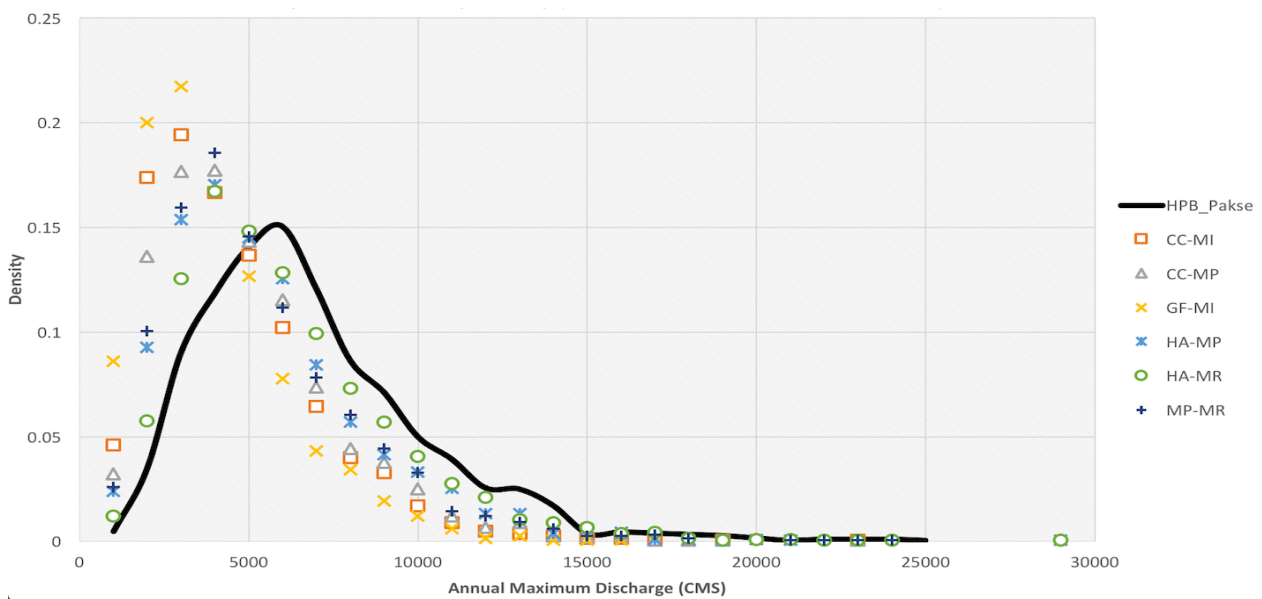


Figure 6.17 Same as Figure 6.10 but for Pakse station

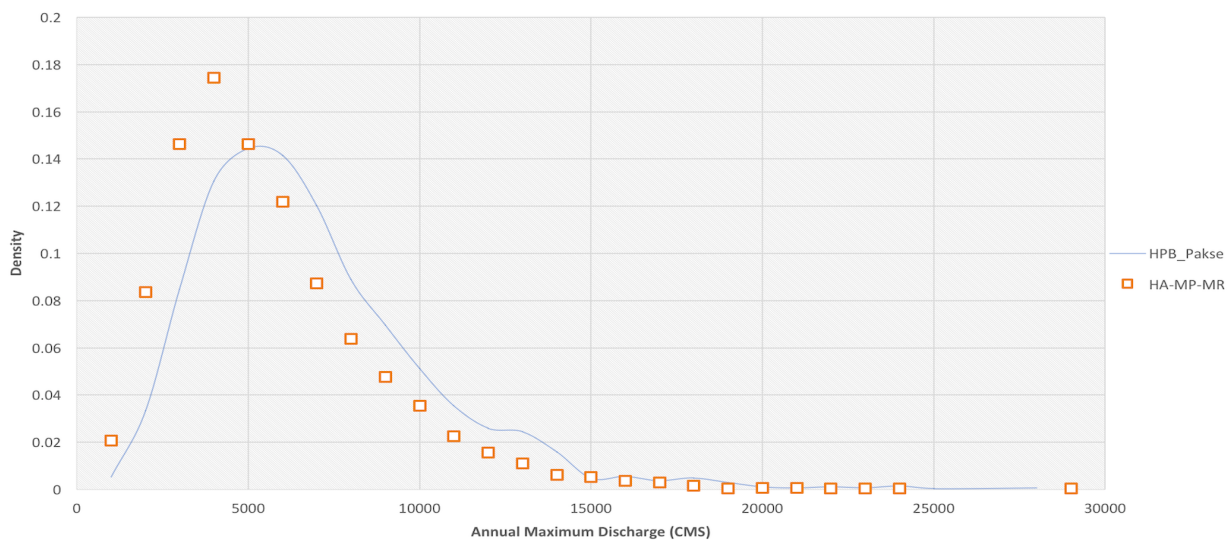


Figure 6.18 Same as Figure 6.11 but for Pakse station

Monywa station (Ayeyarwaddy River Basin)

The changes in the empirical distribution of the annual maximum daily discharge in the future climate with respect to the present climate at Monywa station (22°6'0" N, 95°7'60" E), under different number of annual maximum samples, e.g., 900 and 1,800, are shown in figure 6.19 and 6.20

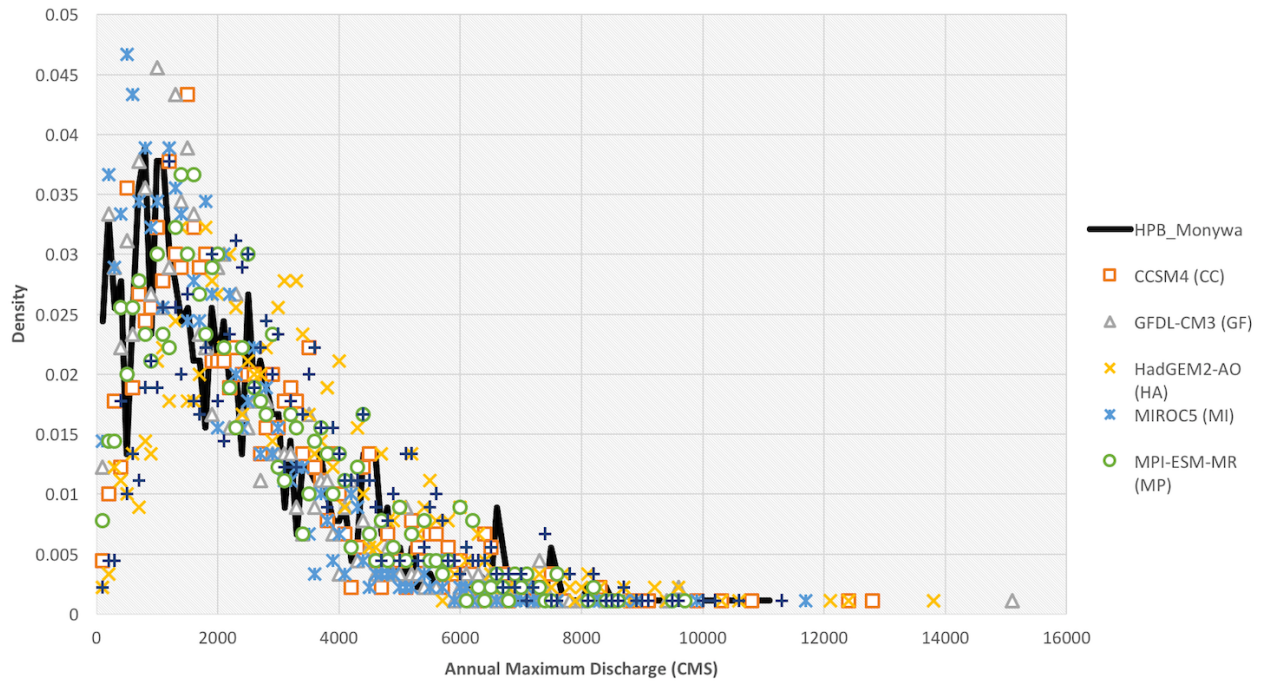


Figure 6.19 Same as Figure 6.9 but for Monywa station

The results in figure 6.19 indicate that the future distribution of the annual peak discharge is clearly shifted in the rightward direction under three SST patterns: HadGEM2-AO (HA), MPI-ESM-MR (MP), and MRI-CGCM3 (MR). These positive changes reflect the increase of the annual mean maximum flow, which is equivalent to the 2-year return period, from 40.15% (MR) to 46.83% (HA), and less so on the CCSM4 (CC) and MPI-ESM-MR (MP) with the projected increase between 7.66% - 9.97%. However, the changes of GFDL-CM3 (GF) and MIROC5 (MI) are expected to drop from 12.54% (GF) to 18.03% (MI). The Q_{95} is expected to decline by 16.18% (HadGEM2-AO) to 35.92% (GFDL-CM3). Meanwhile, the future changes in the Q_{95} relative to the present climate is somewhat more mixed, where the positive shift under the HA and MR from 6.06% to 9.67% are expected, but the negative trend was simultaneously detected between 0.15% (CC) to 11.37% (GF).

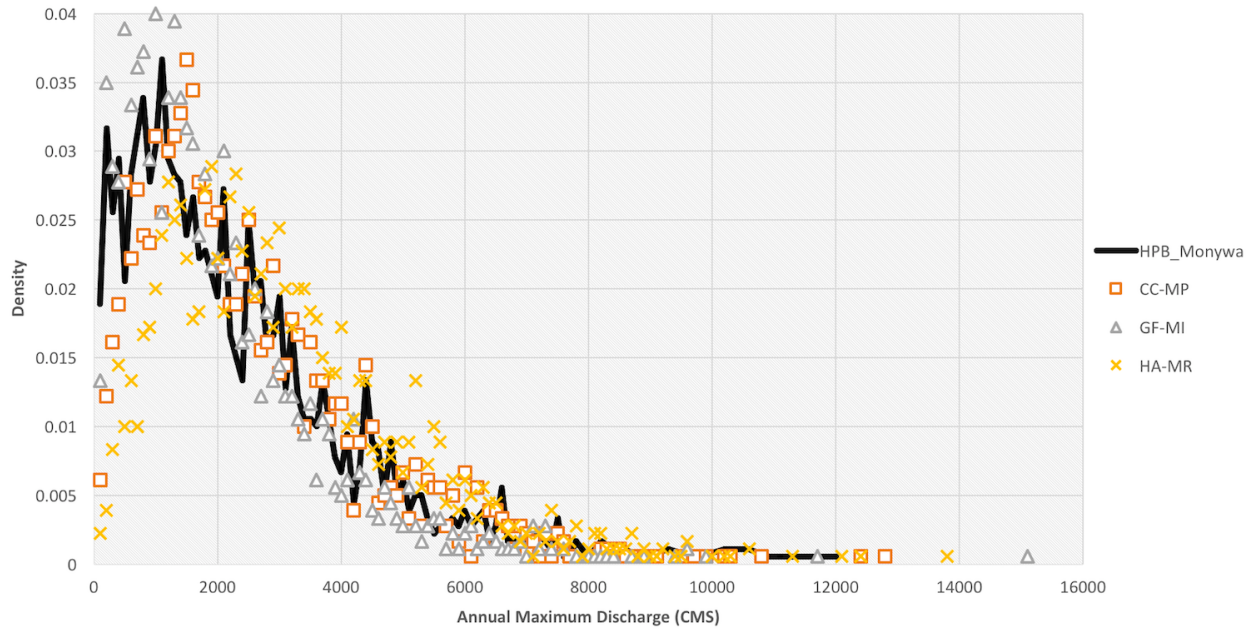


Figure 6.20 Same as Figure 6.10 but for Monywa station

The effect of larger, 1,800-member ensemble is also discussed in figure 6.20. The simulated future annual peak discharge showed that a clear rightward shift in the empirical distribution of the combined-SST CC-MP by 9.19% and HA-MR 44.36% relative to the present climate. The positive changes of were last until the 15-year return period.

Hanoi station (Red River Basin)

Finally, the changes in the empirical distribution of the annual maximum daily discharge in the future climate with respect to the present climate at the B.10 station (12°58'24" N, 99°53'10" E), under different number of annual maximum samples, e.g., 900, 1800, and 2700, are shown in figure 6.21, 6.22, and 6.23.

The results in figure 6.21 shows that the future distribution of the annual peak discharge is somewhat shifted in the right direction under the HadGEM2-AO (HA) and MRI-CGCM3 (MR), which the Q_{95} is projected to rise by 1.66% (MR) to 10.03% (HA), but the rest of the SST warming schemes expected a moderate decline from 11.24% (CC) to 26.89% (MI).

The effect of larger, 1,800 and 2,700-member ensemble was further investigated. In the first case, HA-MR SST scheme is the only one that shows a rising trend with 2.76% increase at the 2-year discharge, 3.23% for the 20-year streamflow, and 3.34% for the Q_{95} . In the latter case,

however, the future Q_{95} and 100-year river discharge at Hanoi station are projected to rise by 18.86% and 14.51%, respectively.

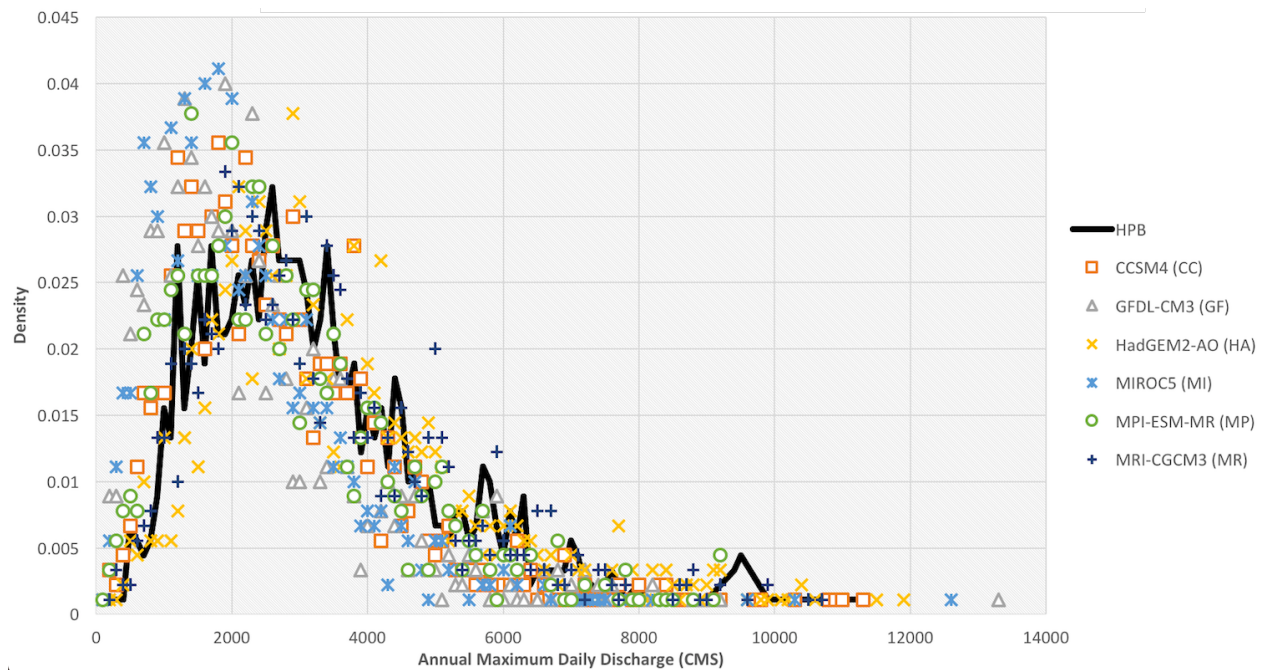


Figure 6.21 Same as Figure 6.9 but for Hanoi station

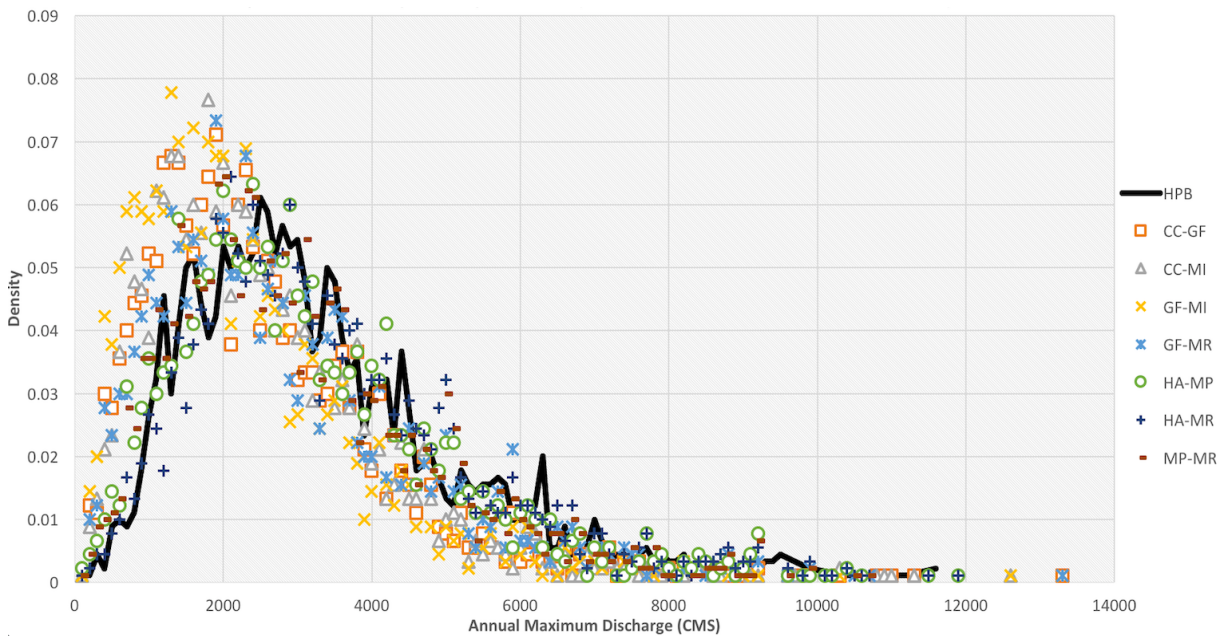


Figure 6.22 Same as Figure 6.10 but for Hanoi station

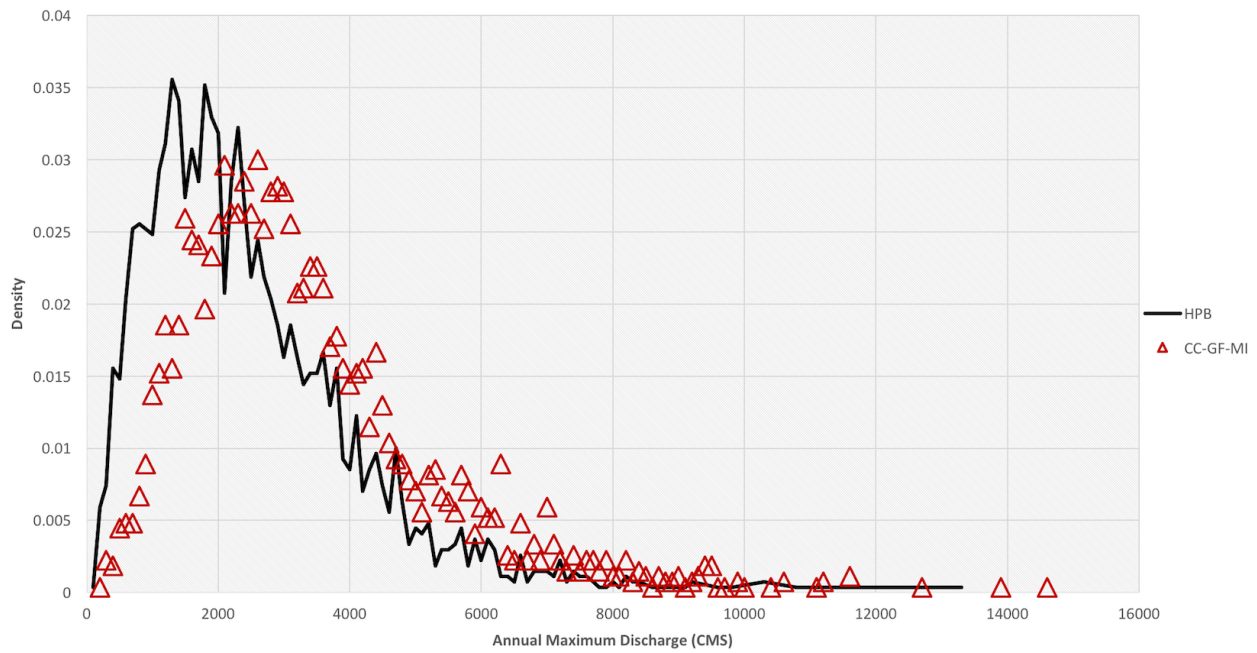


Figure 6.23 Same as Figure 6.11 but for Hanoi station

6.6 Future hydrological projections of the Indochinese Peninsula under climate change

This subsection provides the comparison of hydrological variables, e.g., 3-hourly runoff generation and hourly precipitation between the present and future climate experiments at the Indochinese Peninsula.

In general, impacts of climate change on surface water distribution cascades from the onset of changes in precipitation, total runoff, and finally to river discharge accumulated from the surface and subsurface drainage. Therefore, analysis of the shifts in these hydrological variables could be valuable with respect to the process of developing climate adaptation strategies.

Total runoff generation is the primary driver of the flow routing model, 1K-FRM, which was used for river discharge simulation in this study. It was one of the seven prognostic physical state variables simulated by an intrinsic land surface model called Simple Biosphere (SiB; Sellers et al., 1986), namely, canopy temperature, ground cover temperature, canopy and ground cover water storage, and three soil moisture stores (two of which can be reached by the vegetation root systems and one underlying recharge layer). The future changes in its spatiotemporal distribution should

provide some insight into the cause of the shifts in the annual maximum daily discharge in major river basins of the study area.

6.6.1 The changes in the future total runoff generation

In this study, the changes in the maximum total runoff generation (ROF) on a daily time scale is presented as the maximum consecutive one-day ROF (R1D), the maximum consecutive three-day ROF (R3D), the maximum consecutive five-day ROF (R5D), and the maximum consecutive seven-day ROF (R7D). The changes in the longer time scale such as June-July-August (JJA), wet season (May – October), and annual ROF are also discussed.

Maximum consecutive daily runoff (R1D)

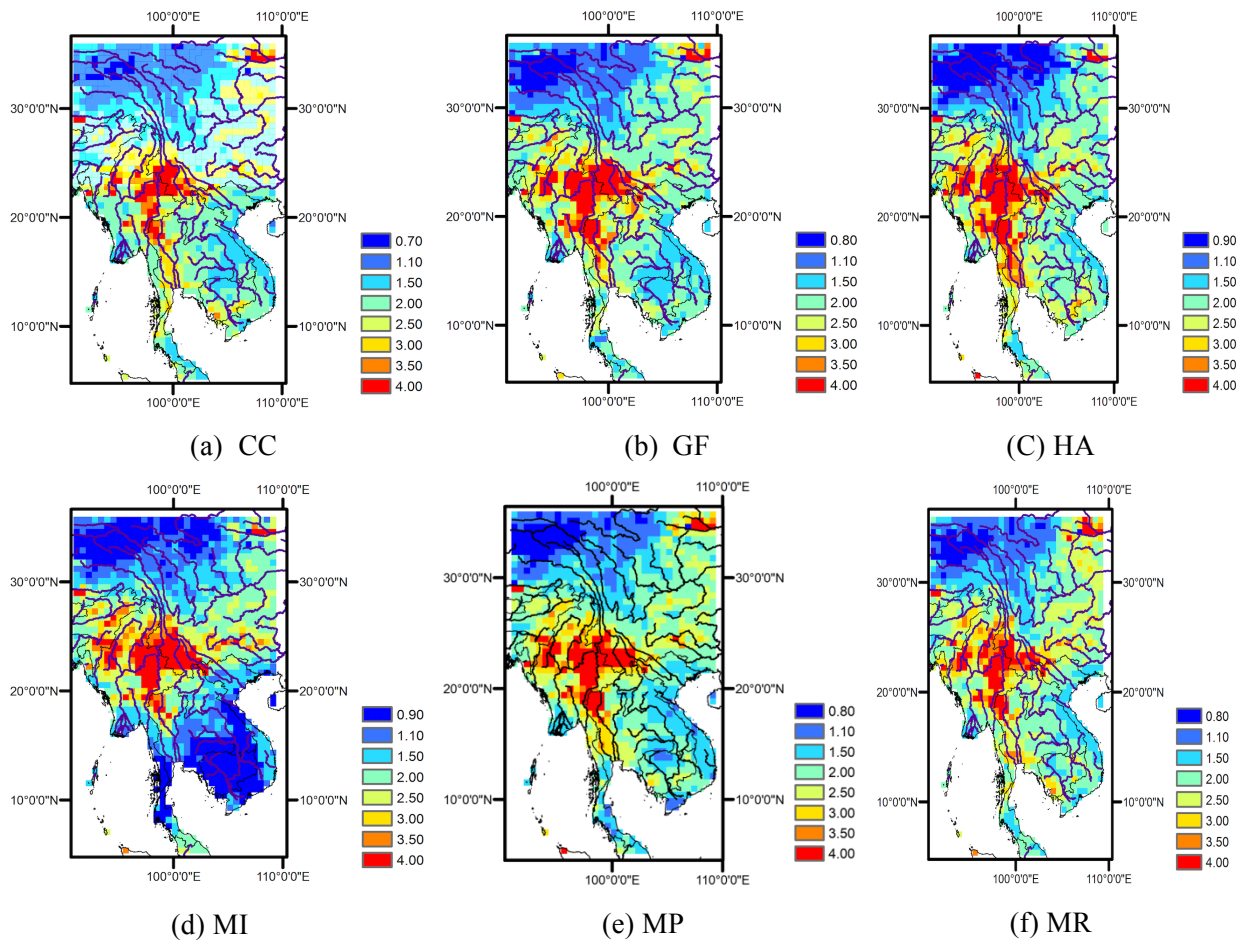


Figure 6.24 The future changes in a maximum daily ROF (R1D) across the six d4PDF SST warming patterns (a) CC, (b) GF, (c) HA, (d) MI, (e) MP and (f) MR

Figure 6.24 displays the changes ratio of the future R1D at the Indochinese Peninsula under the six d4PDF SST warming patterns (CC, GF, HA, MI, MP, MR). The overall results project an increase of the future runoff at the entire Indochina river basins underneath Mainland China by the factor of 1.10 to 4.00 in some cases. For instance, the changes in the total ROF in the Mekong, Chao Phraya, Mekong Delta, Southern Indochina, and Red River Basin are expected to shift by a factor of 1.50 – 2.00 in 5 out of 6 SST scenarios (CC, GF, HA, MP, and MR). Meanwhile, the greatest relative changes in the future runoff are found at the upstream Ayeyarwaddy and Salween River Basin, both in Myanmar, with the changes ratio of 2.50 – 4.00.

Maximum consecutive three-day daily runoff (R3D)

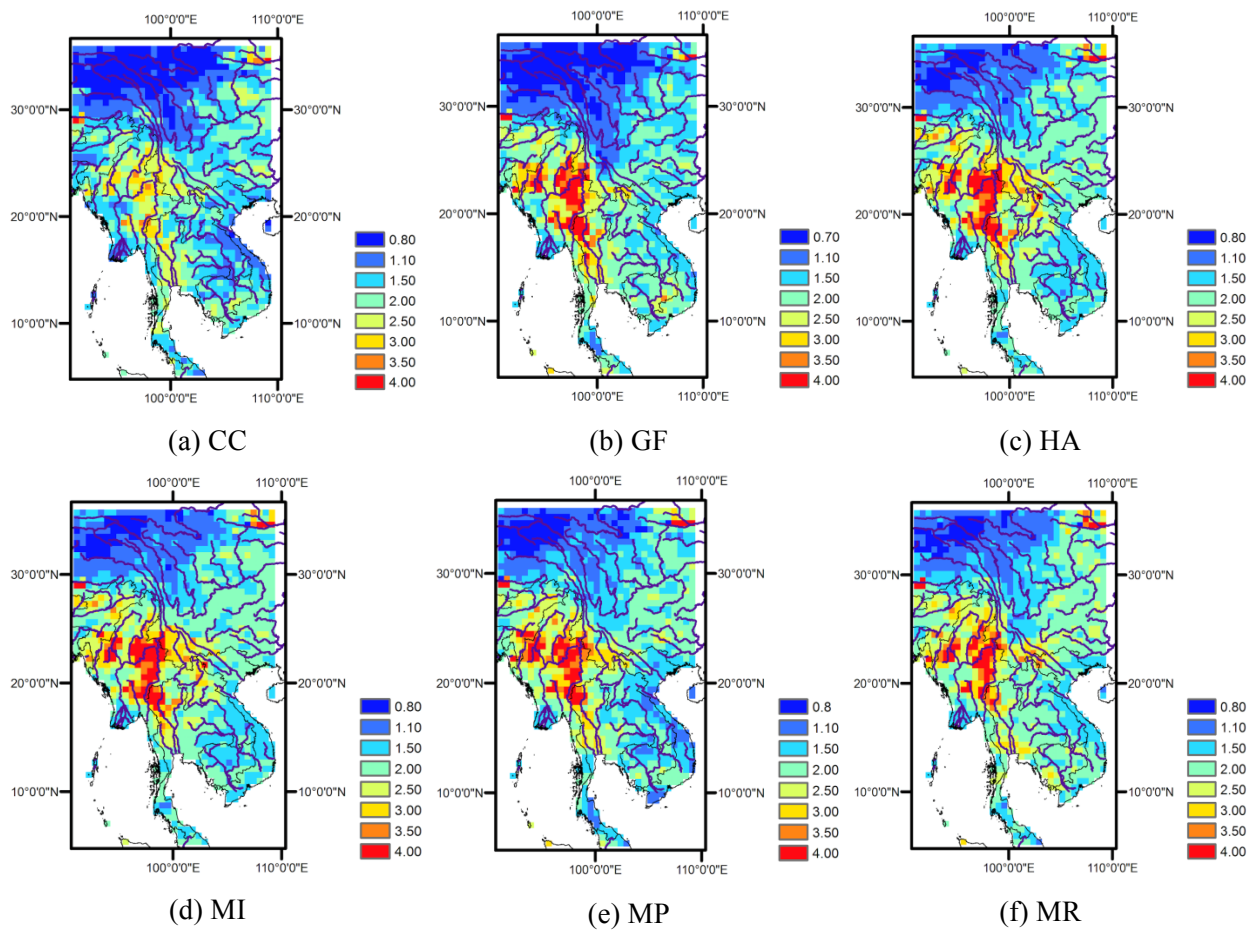


Figure 6.25 The future changes in a maximum three-day ROF (R3D) across the six d4PDF SST warming patterns (a) CC, (b) GF, (c) HA, (d) MI, (e) MP and (f) MR

Figure 6.25 displays the changes ratio of the future R3D under the six d4PDF SST warming patterns (CC, GF, HA, MI, MP, MR). The overall results project an increase of the future runoff by the factor of 1.10 to 4.00 in the future climate experiments. For instance, the growth of future ROF in the Chao Phraya Basin, Mekong Delta, southern Indochinese Peninsula, and the Red River Basin are projected by 2.00 – 2.50 for the entire SST scenarios. The projected R3D runoff at the Mekong Basin also expected to increase by 2.00 – 2.50 for the GF, HA, MI, and MR warming patterns; and 1.10 – 2.00 for the CC and MP schemes. The future R3D changes of the upper Ayeyarwaddy and Salween are projected to be largest in the upper Indochinese basin, with the relative expected changes runoff ratio of 2.50 – 4.00. Parts of the southern China is the only area showing a decrease in the R3D up to 20% compared with the present climate, while the upstream area of the Mekong and Salween are projected to increase by a factor of 1.10.

Maximum consecutive five-day daily runoff (R5D)

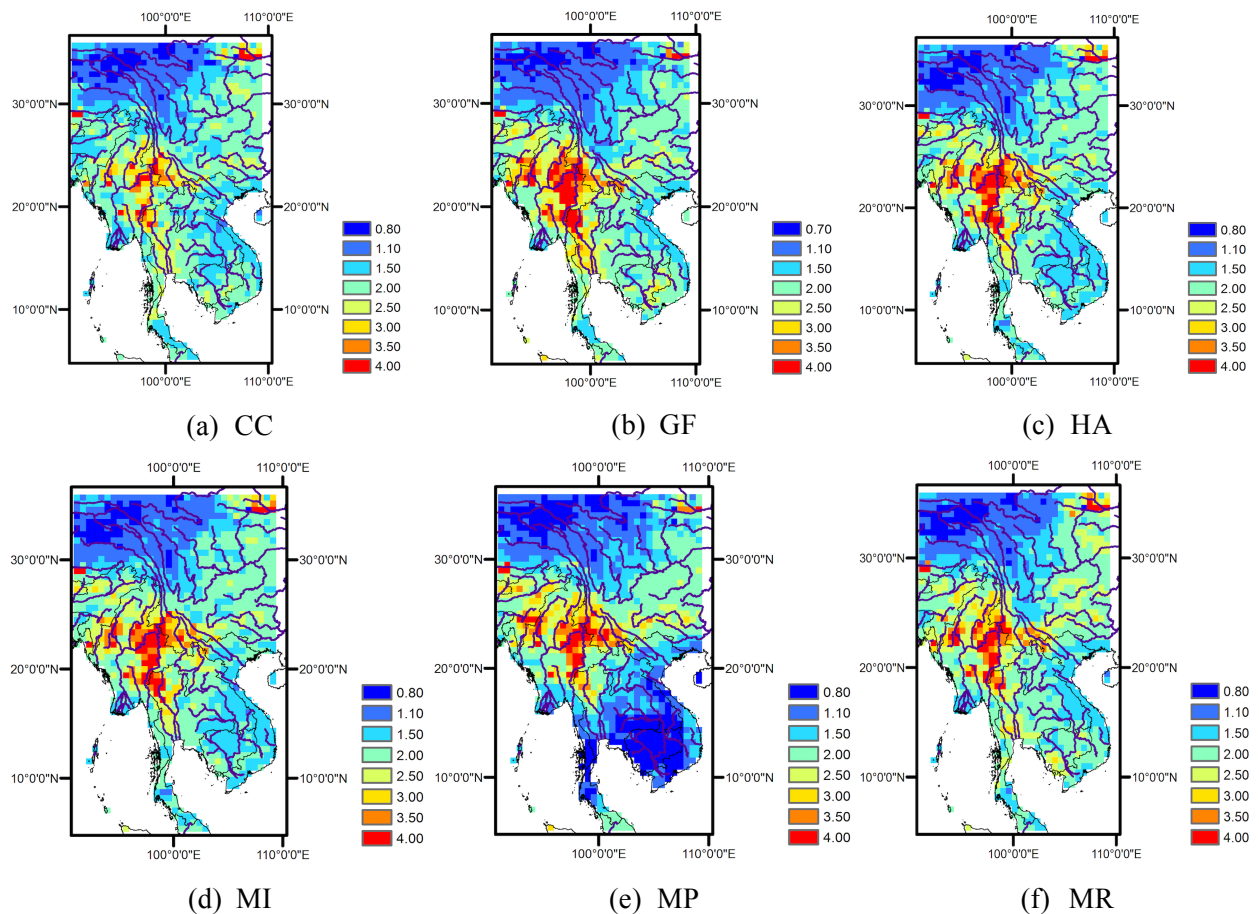


Figure 6.26 The future changes in a maximum five-day daily ROF (R5D) across the six d4PDF SST warming patterns (a) CC, (b) GF, (c) HA, (d) MI, (e) MP and (f) MR

Figure 6.26 displays the changes ratio of the future R5D under the six d4PDF SST warming patterns. The overall results project an increase of the future runoff by the factor of 1.10 to 4.00 in the future climate experiments. The growth of future ROF in the Chao Phraya Basin and the Red River Basin are expected to increase by a factor of 1.50 – 2.50 in all the SST scenarios. The future R5D runoff at the Mekong Delta and the southern Indochina region is also projected to grow by a factor of 1.50 – 2.00 for the most SST patterns (CC, GF, HA, MI and MR), except the MP scenarios where the 20% decline of R3D is expected at the end of 21st century. The central Myanmar region is again the area that probably experiences an increase of the R5D runoff by a factor of 2.00 – 2.50 at the Ayeyarwaddy and up to 4.00 at the Salween.

Maximum consecutive seven-day daily runoff (R7D)

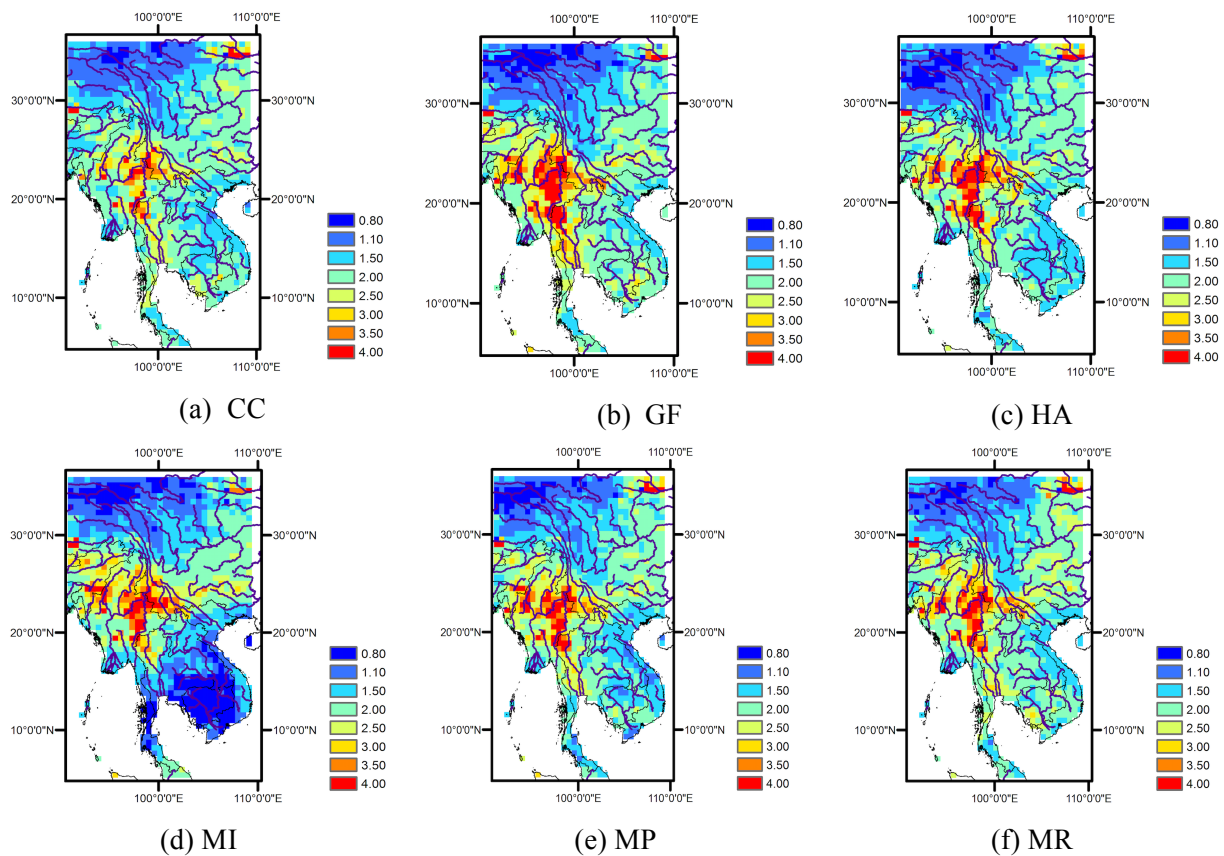


Figure 6.27 The future changes in a maximum seven-day daily ROF (R7D) across the six d4PDF SST warming patterns (a) CC, (b) GF, (c) HA, (d) MI, (e) MP and (f) MR

Figure 6.27 displays the changes ratio of the future R7D under the six warming patterns. The general results project an increase of the future runoff by the factor of 1.10 to 4.00 in the future climate at the major river basins and by 1.10 at the headwater of the Mekong and Salween. The increase of future runoff at the Chao Phraya, Mekong Delta, southern Indochina, Red River, and the lower Ayeyarwaddy Basins, are projected to rise by 2.00 – 2.50. The projected R7D runoff at the Mekong Basin also expected to increase by 2.00 to 2.50 for the CC, GF, HA, and MR but shows a mixed response under the MI and MP schemes. The projected R7D changes of the upper Ayeyarwaddy and Salween are expected to be the largest between the major Indochinese basins, with the relative changes runoff ratio of 2.50 – 4.00. The future R7D at the upstream area of the Mekong and Salween in the southern China are projected to increase by a factor of 1.10.

June-July-August (JJA) cumulative total runoff

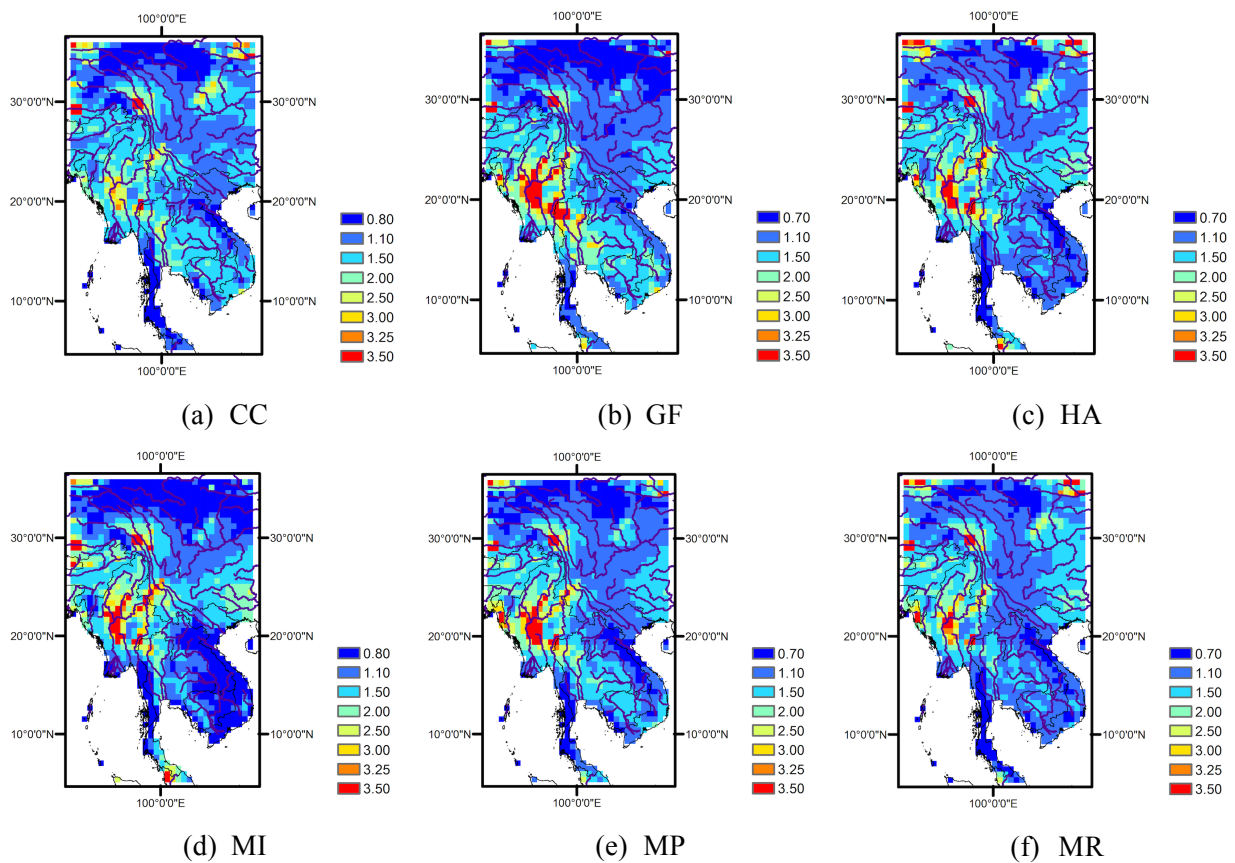


Figure 6.28 The future changes in the JJA ROF across the six d4PDF SST warming patterns (a) CC, (b) GF, (c) HA, (d) MI, (e) MP and (f) MR

Figure 6.28 presents ratios of the spatial distribution of a summer runoff for the future relative to the current climate. The results showed two principal arrangements of the ROF at the study area. The first pattern is represented by the CC, GF and MP warming scenarios, where the largest increase in JJA runoff is concentrated in the Ayeyarwaddy, Chao Phraya, and Mekong Delta, with the relative changes of ratios of 1.50 to 2.50 (CC), 1.50 to 3.50 (GF), and 1.50 to 3.50 (MP). The second pattern, which illustrated by the HA, MI, and MR scenarios, projects the largest JJA runoff increase at the Ayeyarwaddy Basin with the ratio of 1.50 to 3.50. Meanwhile, the future relative changes in the JJA runoff magnitude at the main channel of Mekong Basin, Mekong Delta, southern Indochinese Peninsula, Red River Delta, are found to more measured with changes ratio up to 1.10.

Summer monsoon (May – October) cumulative total runoff

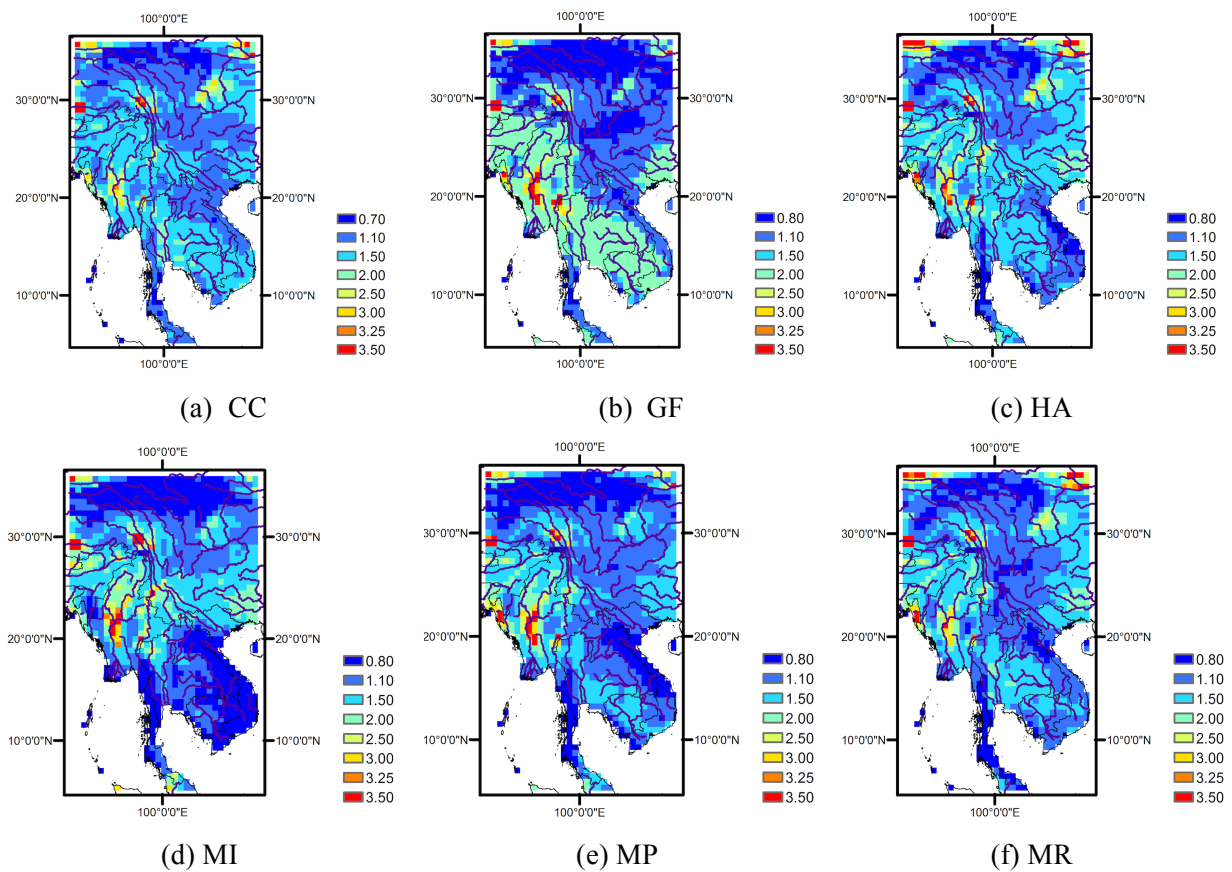


Figure 6.29 The future changes in the wet season ROF across the six d4PDF SST warming patterns (a) CC, (b) GF, (c) HA, (d) MI, (e) MP and (f) MR

Figure 6.29 presents ratios of the spatial distribution of a summer monsoon runoff for the future relative to the current climate. The results closely follow the JJA runoff with the two arrangements of the ROF of the future climate.

The first pattern is represented by the CC, GF and MP warming scenarios, where the largest increase in the ROF is concentrated in the Ayeyarwaddy, Chao Phraya, and Mekong Delta, with the relative changes of ratios of 1.50 to 2.00 (CC), 2.00 to 3.50 (GF), and 1.50 to 2.00 (MP). The second pattern, which demonstrated by the HA, MI, and MR scenarios, found the largest positive changes of summer monsoon runoff is concentrated in the Ayeyarwaddy Basin with the ratio of 1.50 to 3.50. The projected response at Mekong Delta are expected to increase by a factor of 1.10 – 1.50 in the HA and MR, but decrease slightly by a factor of 0.80-0.90 in MI scenario.

Annual total runoff

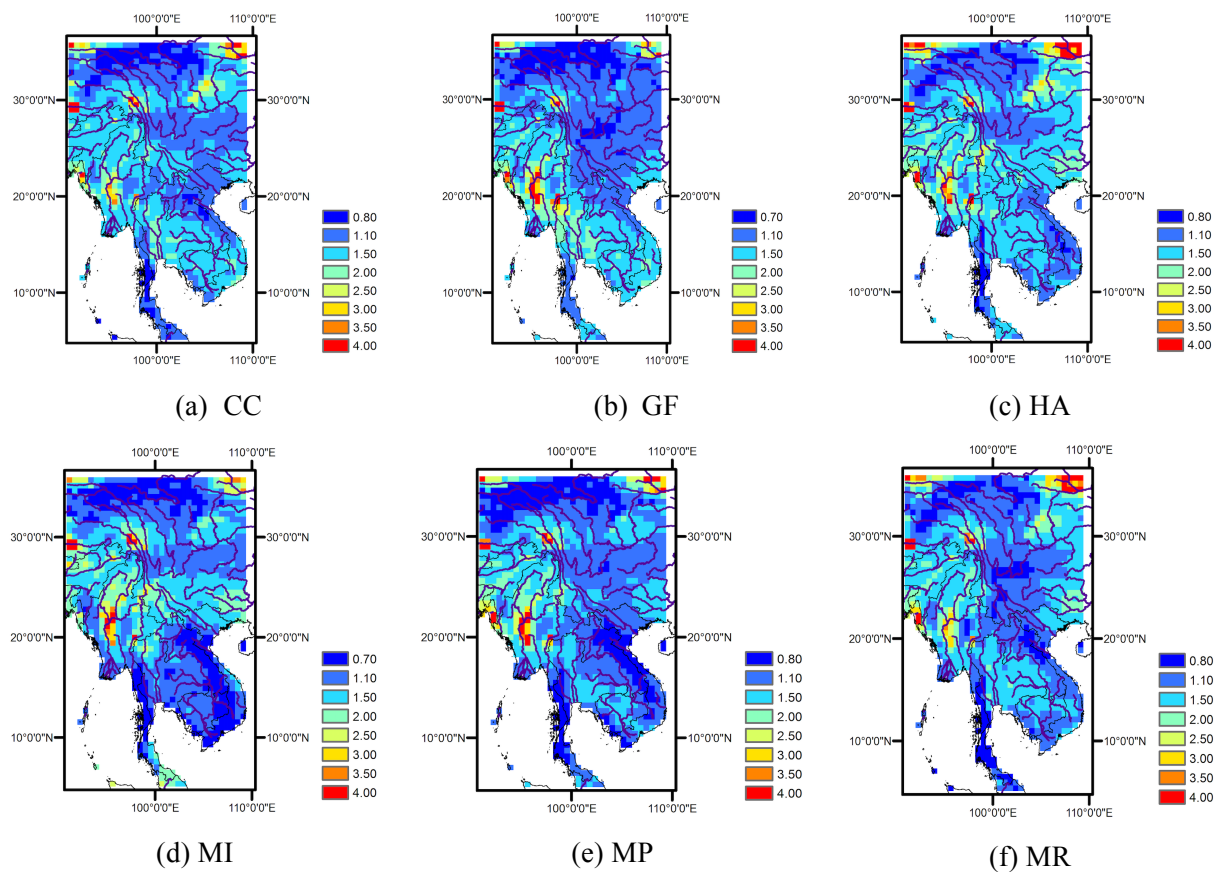


Figure 6.30 The future changes in the annual ROF across the six d4PDF SST warming patterns (a) CC, (b) GF, (c) HA, (d) MI, (e) MP and (f) MR

Figure 6.30 presents ratios of the spatial distribution of a summer monsoon runoff for the future relative to the current climate. The results are mostly similar with the JJA runoff with two arrangements of the future ROF.

The first pattern is represented by the CC, GF, and HA scenarios, where the largest increase in the ROF is concentrated in the Ayeyarwaddy, Chao Phraya, and Mekong Delta, with the relative changes of ratios of 1.50 to 2.00 (CC), 1.50 to 4.00 (GF), and from 1.50 to 2.00 (HA).

The second pattern, demonstrated by the HA, MI, MP, and MR scenarios, found that the largest positive changes of the annual ROF are concentrated in the Ayeyarwaddy Basin with the ratio of 1.50 to 3.50. In contrary, any positive changes at the Mekong Delta are subtler, with the ratio from 1.10 to 1.50 in MP and MR, and a small decline in a factor of 0.80 – 0.90 under the MI scenario. Meanwhile, the changes of annual ROF at the southern Indochinese Peninsula also found to be mixed, where the noticeable fluctuation from a small decrease (ratio 0.85 – 0.90) up to an increase of 1.10, are detected at MI and MR scenarios.

6.6.2 Results Discussion

In general, impacts of climate change on surface water distribution are most clearly represented by the state of river discharge. For instance, the occurrence of floods almost always follows a big increase in the streamflow and water level; on the contrary, significant drought event also frequently happened after prolonged period of exceptionally low flow. Unfortunately, simulated streamflow from a flow routing model partially results from the sophisticated incorporation of topological information, which made it highly complex and difficult to interpret by only relying on its effect. Therefore, in this study, the simple comparisons using the changes ratio between the future and present ROF in a different temporal scale were made to support the results of future projection of river discharge and significance of changes in physical phenomena.

Ayeyarwaddy Basin

The outcomes of future variations in the annual maximum daily discharge in terms of mean, standard deviation, and the 95th percentile are all indicated the upward trend, with a higher ratio than 1.10 in nearly all the SST scenarios. Meanwhile, the projected 60-km ROF from d4PDF datasets showed the larger increase in the daily extreme ROF indices (R1D, R3D, R5D, and R7D)

relative to the changes in river discharge. Seasonal (JJA and summer monsoon) and annual ROF are projected to increase by a factor of 1.5 – 2.0. Therefore, the increase in river discharge at Monywa station was caused by the rise in the extreme, seasonal, and annual ROF in the Ayeyarwaddy Basin.

Mekong Basin and Mekong Delta

The future changes in river discharge at Pakse station was not robust because there is a clear consensus in changes direction but lacking the statistical significance, which most of SST showed a small decrease of mean, standard deviation, and Q_{95} by a factor of 1.10. These changes were probably caused by 10 – 20% decrease in the JJA ROF under all six SST warming patterns at the upstream area of Mekong Basin. The further comparison also found that the summer and annual ROF are also following the similar trend showed by the JJA, but with less robustness.

The Mekong Delta is designated as the “hotspot area” in this study due to significance increase in mean, standard deviation, and the 95th percentile of the annual maximum daily discharge by a factor of 1.50 – 2.00. These findings were strongly supported by a multiplicity of an increase of ROF indices, with 1.50 – 2.50 for R1D to R7D, 1.10 – 1.50 for JJA and summer season runoff.

Southern Indochinese Peninsula

Southern Indochinese Peninsula region also projected to be a future hotspot area due to the significance changes in the annual maximum discharge and its variability, with the changes ratio from 2.00 up to 3.00. The increasing tendency of river discharge projection in this area may be due to an increase of the extreme ROF indices such as R1D, R3D, R5D, and R7D from a southwest monsoon by a factor of 1.50 – 3.00 throughout the region. On the contrary, the future amount of seasonal and annual ROF is expected to fluctuate between the decline of 10 – 20% to an increase of 10% compared with the present climate in 5 out of 6 SST scenarios.

Red River Basin

The mouth of Red River Basin at Hanoi station is one of the area that expected a large increase of mean and the variability of annual peak discharge by a factor of 1.50 – 2.50. These finding is made possible by the matching increase of R1D, R3D, R5D, and R7D, by a similar magnitude. The cumulative ROF during JJA and the entire summer season were also projected to rise by 10-

15% from the present climate. Therefore, the main contribution of the future increase of river discharge in the area should come the rise of extreme daily ROF indices.

Chao Phraya River Basin

Future projection of mean of the annual maximum discharge at the central Chao Phraya Basin are mostly pointed to a slightly declining trend of 5 – 10% in all the d4PDF SST scenarios. In addition, several projections of backward shift in the empirical probability distribution of the annual maximum discharge at C.2 station of plausible ensembles. An increase by a factor of 2.00 – 2.50 from extreme daily ROF indices were projected throughout the SST scenarios, which make it unlikely to be a reason of a decline of the future river discharge in this area.

The possible cause of river discharge reduction might have emanated from a slight fluctuation between decrease and increase of 5-10% of a cumulative runoff at the upstream Chao Phraya Basin during JJA or the summer season in some SST scenarios, e.g., HA, MI, and MR. Further evidences could be found in the annual ROF, which shows the similar reduction of 5-10% in the accumulated runoff compared with the present climate.

6.7 Conclusions

This chapter investigated the change in river discharge at the Indochinese Peninsula under climate change by utilizing the d4PDF datasets. The hydrologic simulation is carried out using distributed flow routing model 1K-FRM under 100-member present climate ensemble and 15-member from six SST warming patterns of the future period. Statistical analysis techniques were performed to examine the statistical significance of river discharge changes in terms of mean, standard deviation, and the extreme 95th percentile (Q_{95}) in the region. Finally, the selected river gauging stations at the hydrological hotspot area were picked up and analyzed changes in the empirical probability distribution of the annual maximum discharge. As a result, two major river gauging stations were chosen as a representative of the hydrological hotspot regions due to the significant of changes in future annual peak flows and the potential number of sample to be analyzed which are the Kanpong Chhnang station (Mekong Delta) and B.10 station (Southern Indochinese Peninsula).

Using different SST ensembles projection in the future climate experiments demonstrated a

strong agreement between the SST warming ensembles on the large increase of mean, standard deviation, the Q_{95} , and the empirical distribution of the annual maximum discharge at the Mekong Delta, Southern Indochinese Peninsula and Red River Basin. In addition, a large majority of future projection results show a tangible increase in mean of variability of annual maximum discharge at the central part of Ayeyarwaddy Basin, but a slight decline in those quantities throughout the Chao Phraya River Basin.

In terms of the runoff generation climatology, there was a clear indication that the projected increasing in river discharge in the relatively large river basin such as Mekong Delta and Ayeyarwaddy are strongly connected to the positive development of variation in seasonal indices such as JJA and summer season ROF. At the same time, the river discharge in smaller basins such as the Red River Basin and the southern Indochinese Peninsula tend to be more responsive on the changes in an extreme ROF indices, e.g., R1D, R3D, R5D, and R7D.

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Chapter 7

Concluding Remarks

7.1 Overall summary

The primary objectives of this dissertation are as follows:

- To evaluate the source and quantify the hydrologic projection uncertainties from a range of parameters by examining statistical differences of mean in precipitation, total runoff, and daily river discharge projections; provided by GCMs outputs with different cloud convection parameterization schemes and SST warming pattern.
- To examine the prior distribution difference of the annual maximum daily discharge in the future climate from various SST warming pattern with large output ensembles.
- To project changes of daily river discharge at the Indochinese Peninsula region using a distributed flow routing model and outputs from general circulation models with large output ensembles.
- To analyze the statistical significance of the detected changes in daily river discharge changes at the Indochinese Peninsula to locate possible hotspot areas where significant changes in related to the peak discharge event could occur.
- To compare the empirical probability distribution function of the annual maximum daily discharge of the present and future climate at the hotspot regions.

All of the above objectives are involved with the analysis of the changes in river discharge and quantification of the uncertainty in the future projections. Therefore, the content is consisting of 7 chapters.

Chapter 1 discuss the sources of hydrologic projection uncertainties, statistical difference of prior distribution of the annual maximum daily discharge from SST patterns, prediction of changes ratio of mean, standard deviation, and the 95th percentile of the annual maximum river

discharge, statistical significance of future changes in daily river discharge, and comparison of the empirical probability distribution of the daily peak discharge at the hotspot regions of the Indochinese Peninsula.

Chapter 2 describes basic information of the study area – Indochinese Peninsula. A short introduction on general circulation model's configurations, which drives the changes of a hydrological cycle, were discussed. Finally, physically-based, distributed flow routing model (1K-FRM), mathematical construction and its assumption were also elaborated.

In Chapter 3, river discharge at the Indochinese Peninsula was calibrated and ready for further usage on future projections. Subsequently, the primary sources of streamflow projection and its contribution to the total uncertainty were successfully attributed using two-way ANOVA *without replication*. The results indicated that the use of different convection parameterization schemes to drive the flow routing model is the principal cause of the projection uncertainty at the majority of the Indochinese Peninsula. The simulated river discharges were calculated from the distributed flow routing model called 1K-FRM with the total runoff (ROF) as an input forcing from two climate experiments: present climate (1979 – 2010) and future climate (2075 – 2099).

Chapter 4 expands the scope of the prior chapter by evaluating the source of hydrologic projection uncertainties at the Asia Pacific Region. This chapter performs uncertainty quantification method that generally similar with those in chapter 3, but incorporate an effect of interactions between the use of different cumulus convection schemes (AS, KF, and YS) and SST warming patterns (C1, C2, and C3). Two-way ANOVA *with replication* was conducted for the projected precipitation and total runoff (ROF) data retrieved from the MRI – AGCM 3.2H with nine multi-physics experiments. The results showed that the dominant sources of hydrologic projection uncertainty at the Indochinese Peninsula are mainly derived from the use of different cloud convection schemes. Thus, there is a high possibility that the combination of hydrological datasets retrieved from various cloud convection systems into a much larger sample could results in a significant projection uncertainty due to the different constitution of mother population. The further conclusion could be made that the utilization of hydrological datasets originated from the various SST patterns could potentially be combined into a much larger sample in most of the northern region of the Indochinese Peninsula, e.g., Ayeyarwaddy, Salween, the middle part of Mekong Basin within Cambodia and Laos, and the Red River Basin. Nevertheless, notable exceptions can be found in the Chao Phraya Basin and the Mekong Delta, regions with relatively close proximity to the gulf of Thailand, equatorial regions such as the Southern Indochinese Peninsula, and maritime archipelagoes of Indonesia.

Chapter 5 addressed the questions left after chapter 4 that relates to the difference between prior distribution between two independent datasets, by conducting the non-parametric, two-sample Kolmogorov-Smirnov and Anderson-Darling tests to examine the statistical difference on a shape and tail of the empirical distribution of the projected annual maximum daily discharge at the Indochinese Peninsula. Application of the two-sample K-S and the AD tests to the studied area showed that there is a significant difference between the empirical probability in most of the SST combination (12 out of 15 cases) at the Ayeyarwaddy, Chao Phraya, the middle part of Mekong River Basin, and 8 out of 15 combinations at the Salween River Basin. The finding also showed that the difference of the probability distribution at the Mekong Delta and the southern Indochinese Peninsula are not statistically significant in most of the SST warming patterns combinations. These findings also help to clarify that it is possible to increase a total number of sample in the future annual maximum discharge datasets up to multi-thousands, which in theory, should lead to a better derivation of the empirical probability distributions and could be useful for the hydrological frequency analysis of extreme floods.

Finally, chapter 6 utilize the investigated information from chapter 3,4 and 5 to determine the impact of climate change on daily extreme river discharge and locating possible hotspot areas in the Indochinese Peninsula by conducting the statistical analysis on the changes in mean, standard deviation, and the 95th percentile of the annual maximum daily discharge for the entire study area. The primary purpose of this analysis is to evaluate whether the changes in river discharge are statistically significant or just occur by chance. Furthermore, this chapter also presents the future projections of the hydrologic variables such as total runoff (ROF), to provide physical reasons to support the finding related to the river discharge. The results pointed to a significant shift in the mean, standard deviation, and the 95th percentile of the annual maximum discharge at Mekong Delta and Southern Indochinese Peninsula, which makes them a nice candidate to be hotspot areas. Moreover, the total number of samples at each catchment is calculated from the SST pattern couples that did not reject the null hypothesis of the two-sample KS and AD tests. the Mekong Delta and Southern Indochinese Peninsula are expected to generate various possible future ensemble combinations of the annual maximum discharge datasets with at least 1,800 and up to 2,700 samples.

Detail comparison of the empirical probability density exhibit a clear shift rightward in terms of mean and extreme 95th percentile river discharge at both hotspot stations, namely, Kampong Chnnang and B.10 stations.

Using different SST ensembles projection in the future climate experiments demonstrated a strong agreement between the SST warming ensembles on the large increase of mean, standard

deviation, the Q_{95} , and the empirical distribution of the annual maximum discharge at the Mekong Delta, Southern Indochinese Peninsula and Red River Basin. In addition, a large majority of future projection results showed a tangible increase in mean of variability of annual maximum discharge at the central part of Ayeyarwaddy Basin, but a slight decline in those quantities throughout the Chao Phraya River Basin.

The future projections of the annual maximum river discharge are generally correlates well with the onset of the ROF indices, where the changes in future floods at the large-scale river basins such as Mekong, Ayeyarwaddy, and Mekong Delta were found having a strong relationship with the trend of seasonal extreme indices such as JJA, summer season, and annual ROF. Likewise, the future changes of the annual peak discharge at the coastal regions or smaller river basins such as southern Indochinese Peninsula and Red River Basin are mainly follows an increase of short-term, multi-day ROF indices, e.g., R1D, R3D, R5D, and R7D.

7.2 Study limitations and suggested future works

Despite the advantage of having an unprecedentedly large ensemble database – d4PDF, the projection of the annual maximum daily discharge under climate change still subjected to the systematic bias, which fundamentally belonged to the spatiotemporal resolution of the datasets and the limitation of physical parameterization of sub-grid scale atmospheric processes such as cumulus convection, cumulonimbus convection, microscale turbulence etc. These are the structural limitations that requires solutions. In general practice, several bias correction methods such as quantile mapping (Ines and Hansen, 2006; Sharma et al., 2007), hybrid bias correction (Kiem et al., 2008; Inomata et al., 2011), should be implemented to correct the bias in terms of monthly mean, average intensity, or frequency of any given input forcing data before conducting hydrological simulations.

In future research, the statistical analysis on the significant of changes should also expand to others hydrological variable such as precipitation, total runoff, evapotranspiration, to strongly reaffirms the future trend of river discharge at the Indochinese Peninsula.

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APPENDIX A:

KS-test distance (D_n)

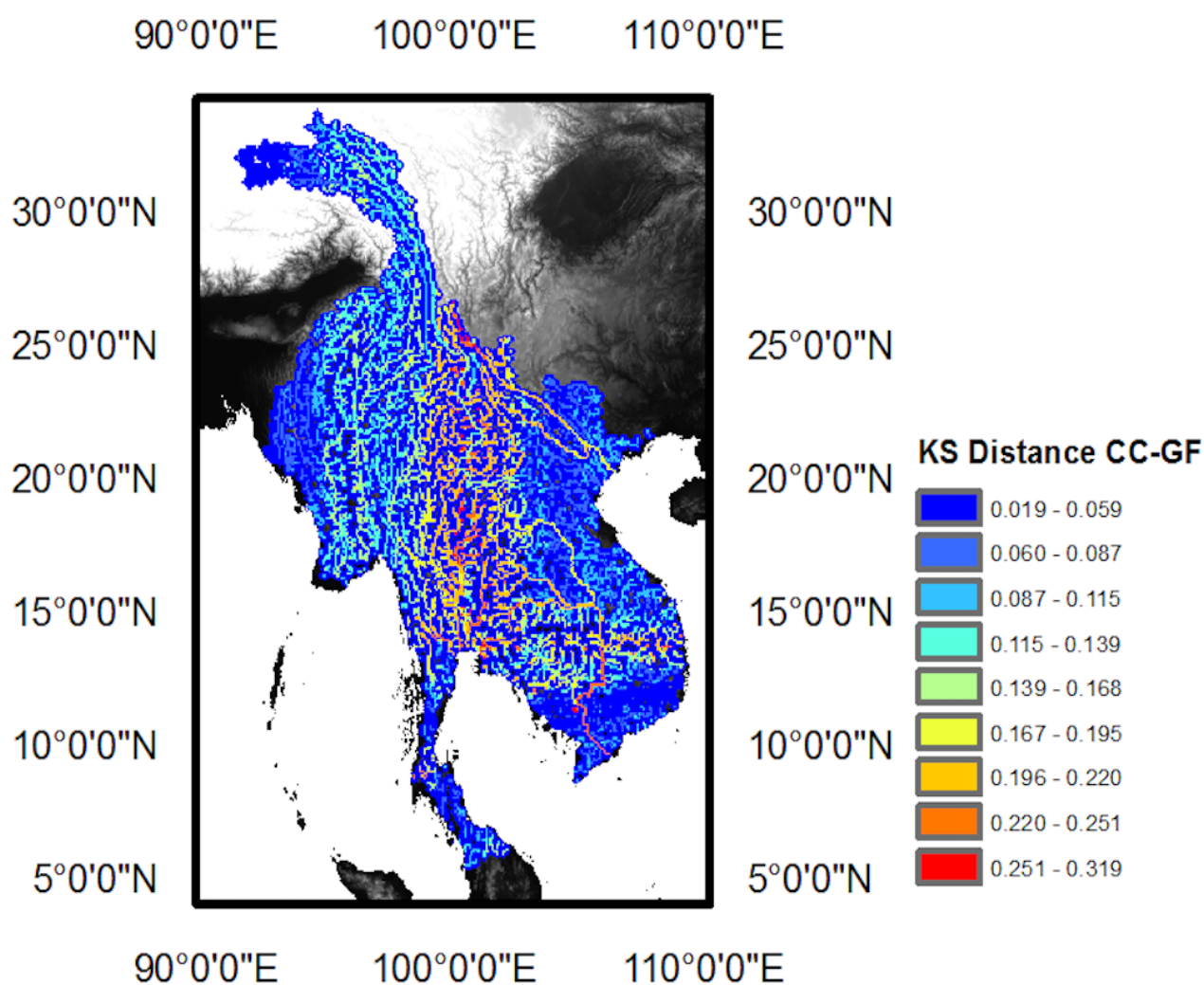


Figure A-1 Two-sample KS-test distance (D_n) for CC-GF combination

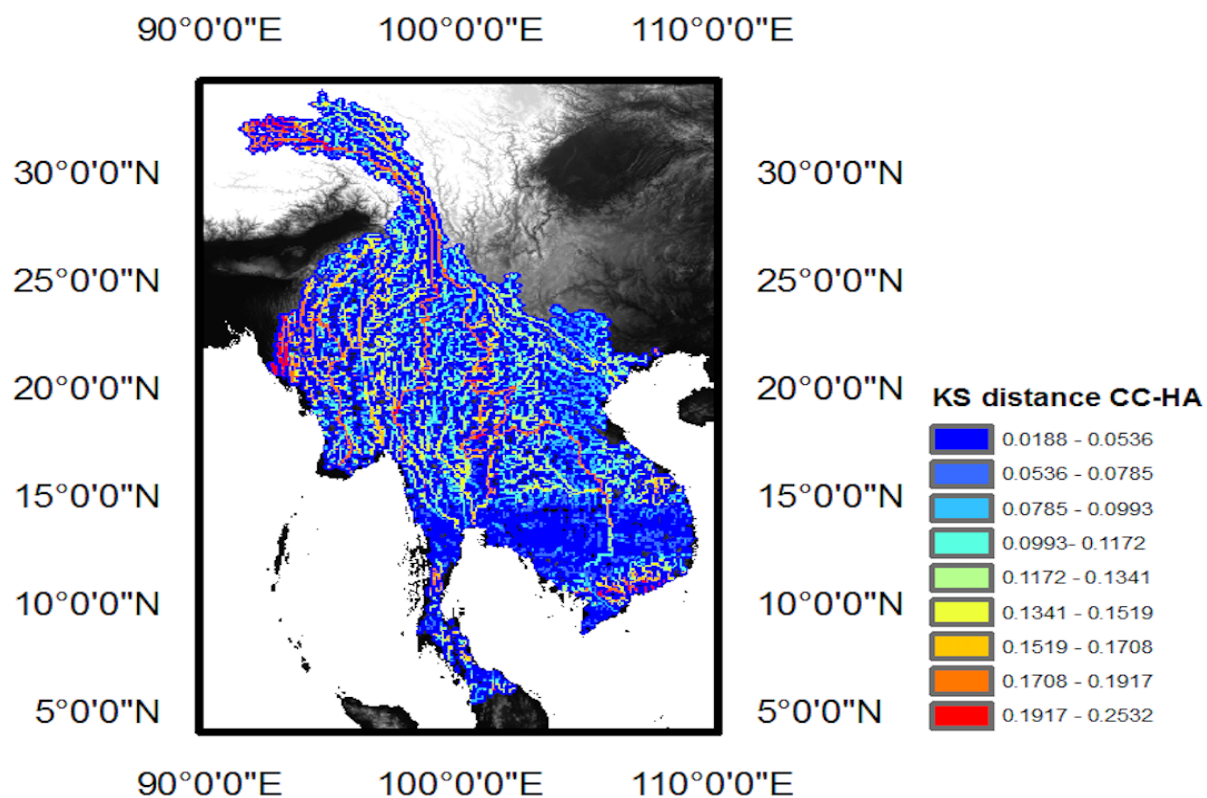


Figure A-2 Two-sample KS-test distance (D_n) for CC-HA combination

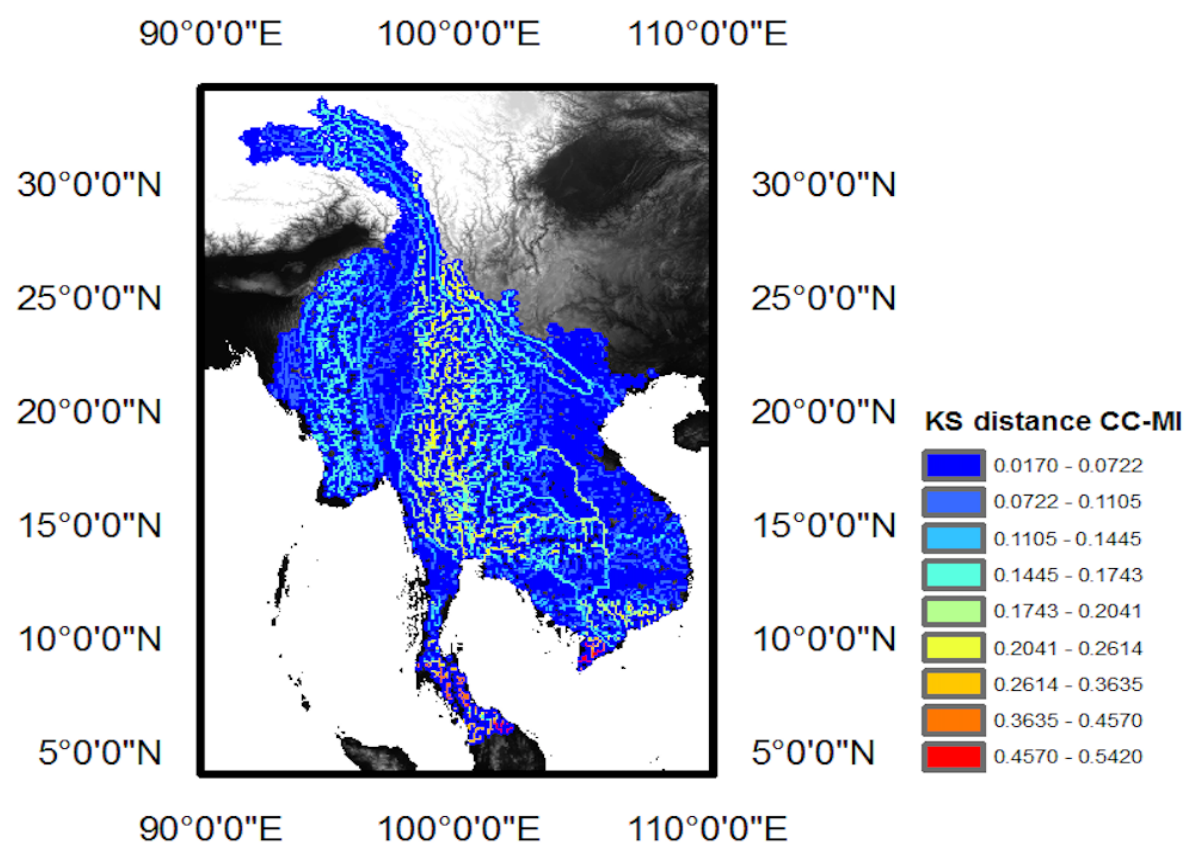


Figure A-3 Two-sample KS-test distance (D_n) for CC-MI combination

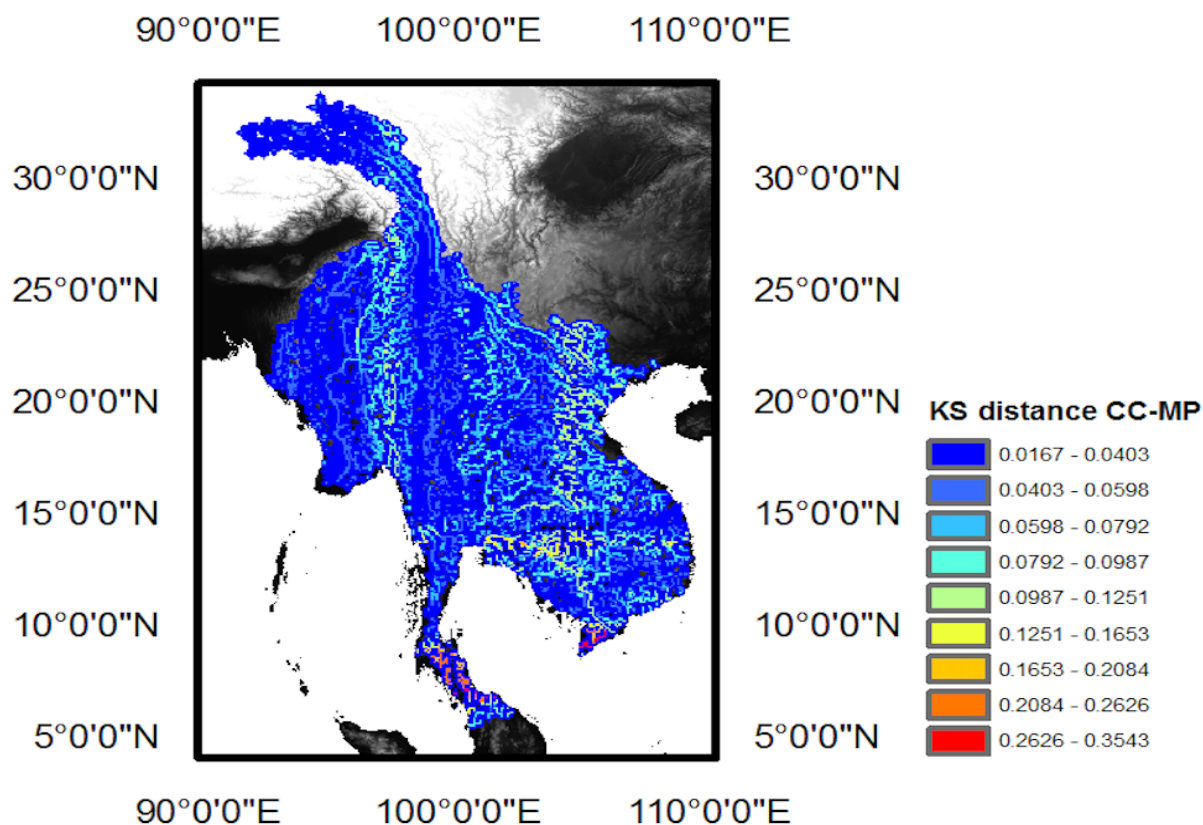


Figure A-4 Two-sample KS-test distance (D_n) for CC-MP combination

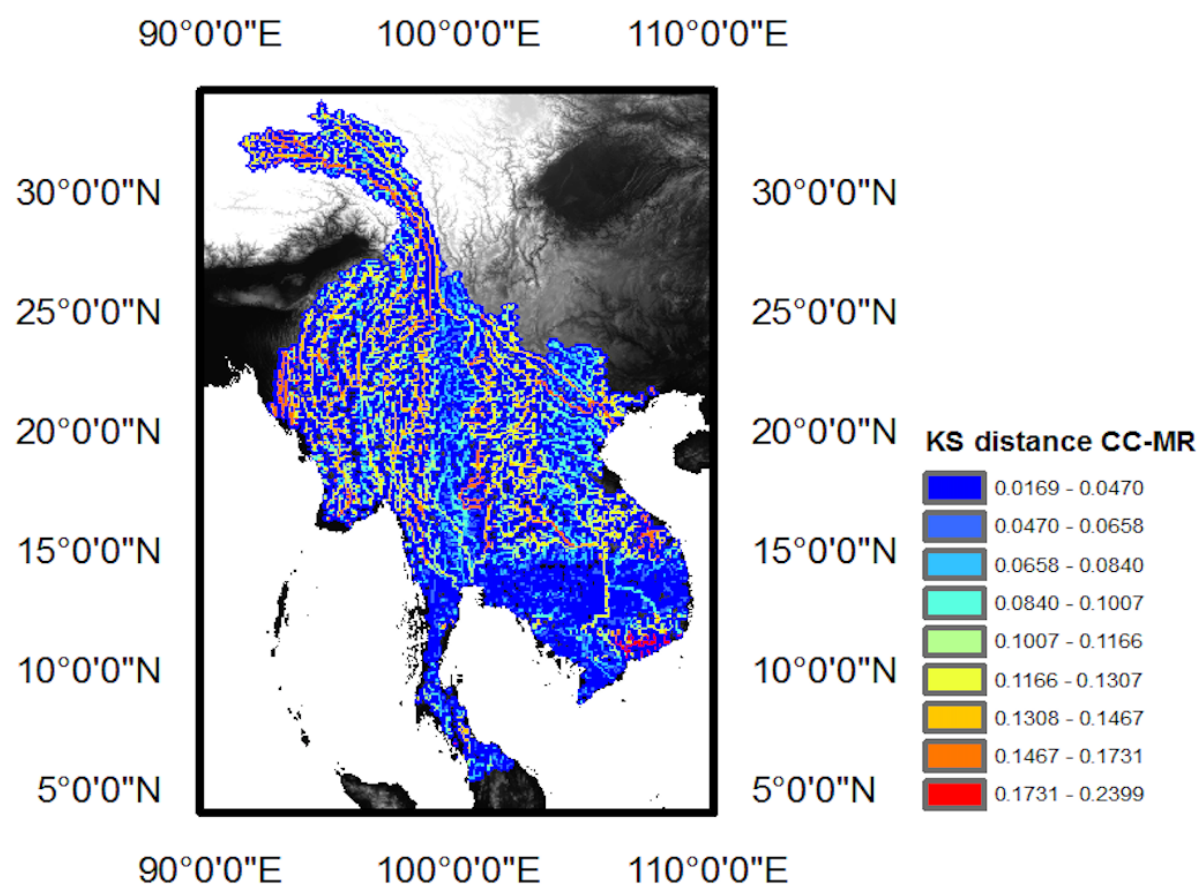


Figure A-5 Two-sample KS-test distance (D_n) for CC-MR combination

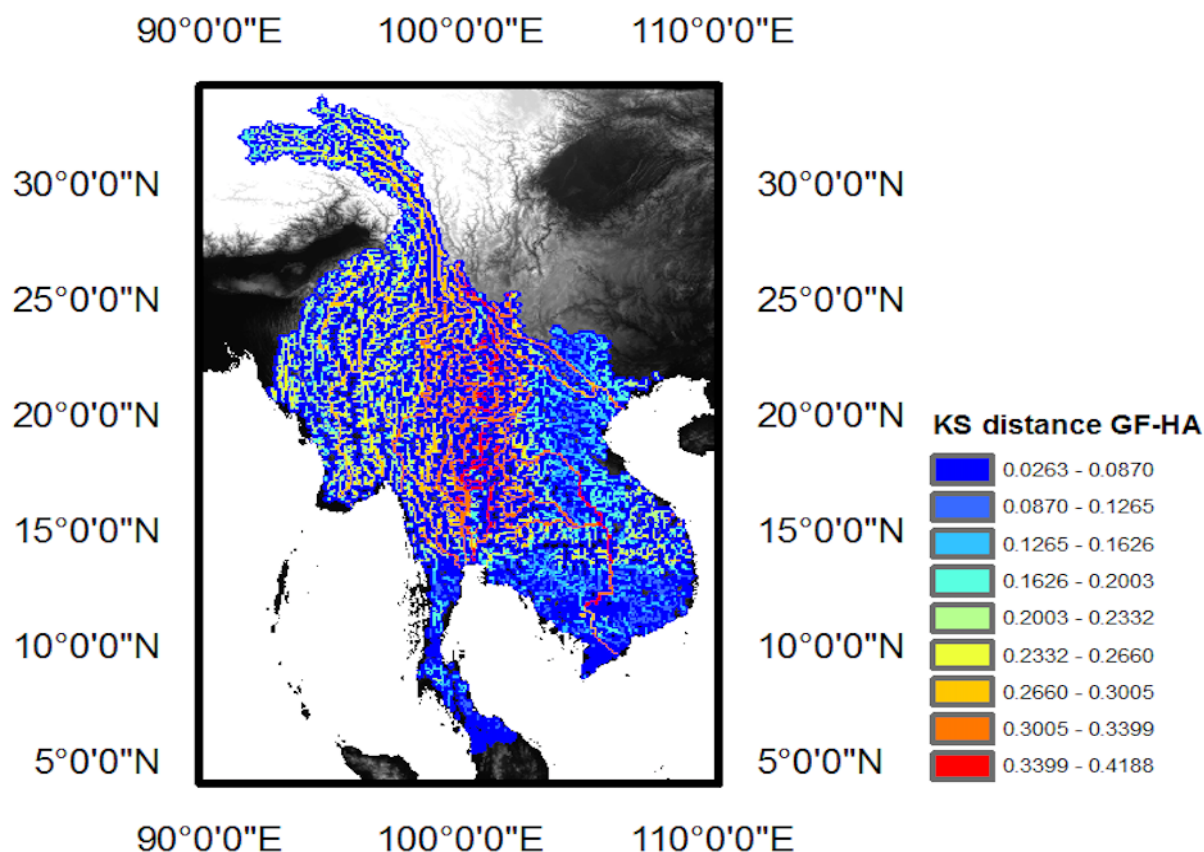


Figure A-6 Two-sample KS-test distance (D_n) for GF-HA combination

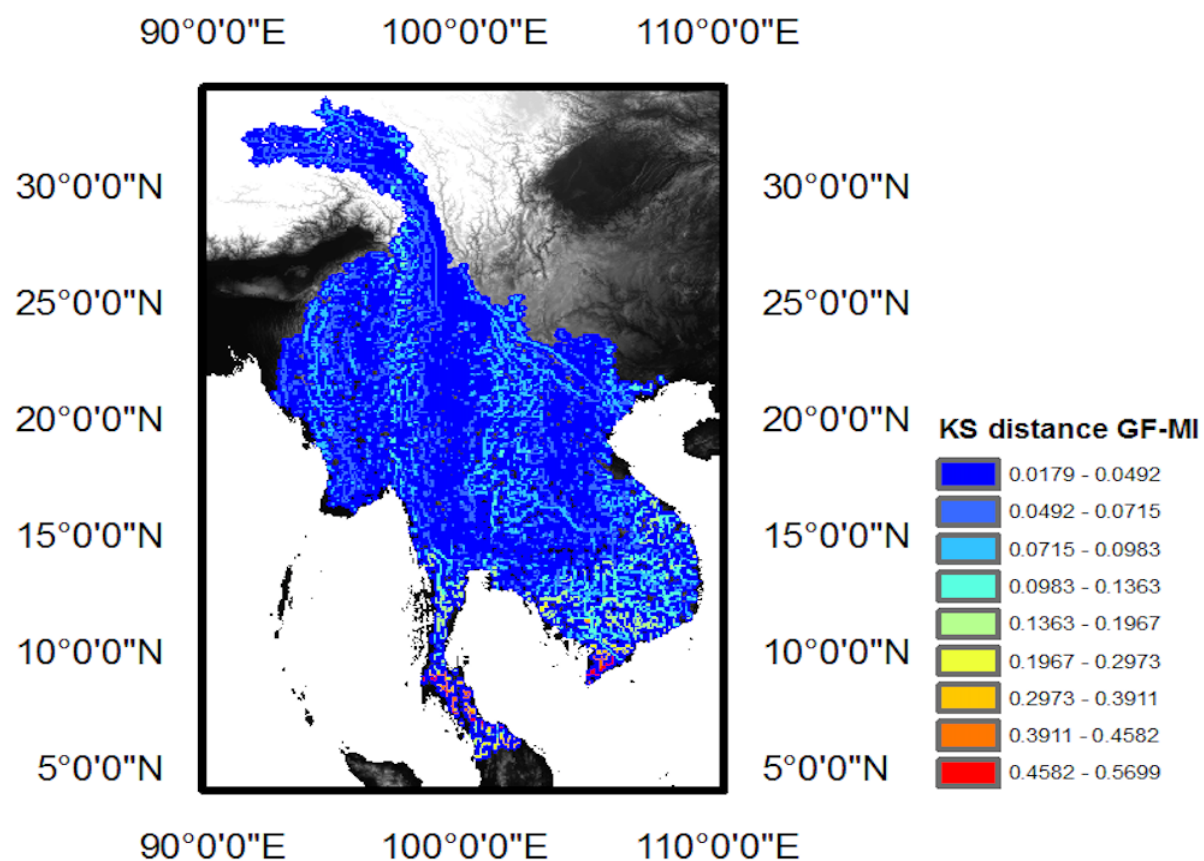


Figure A-7 Two-sample KS-test distance (D_n) for GF-MI combination

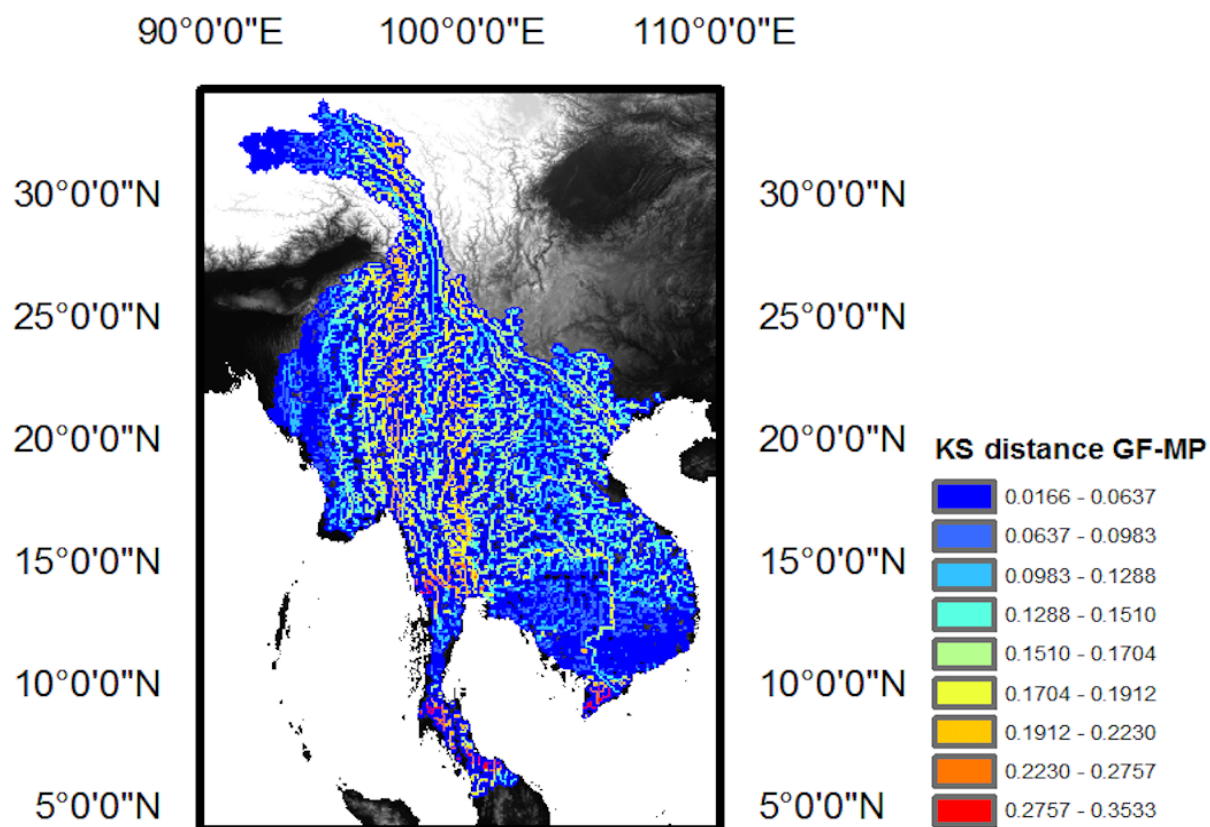


Figure A-8 Two-sample KS-test distance (D_n) for GF-MP combination

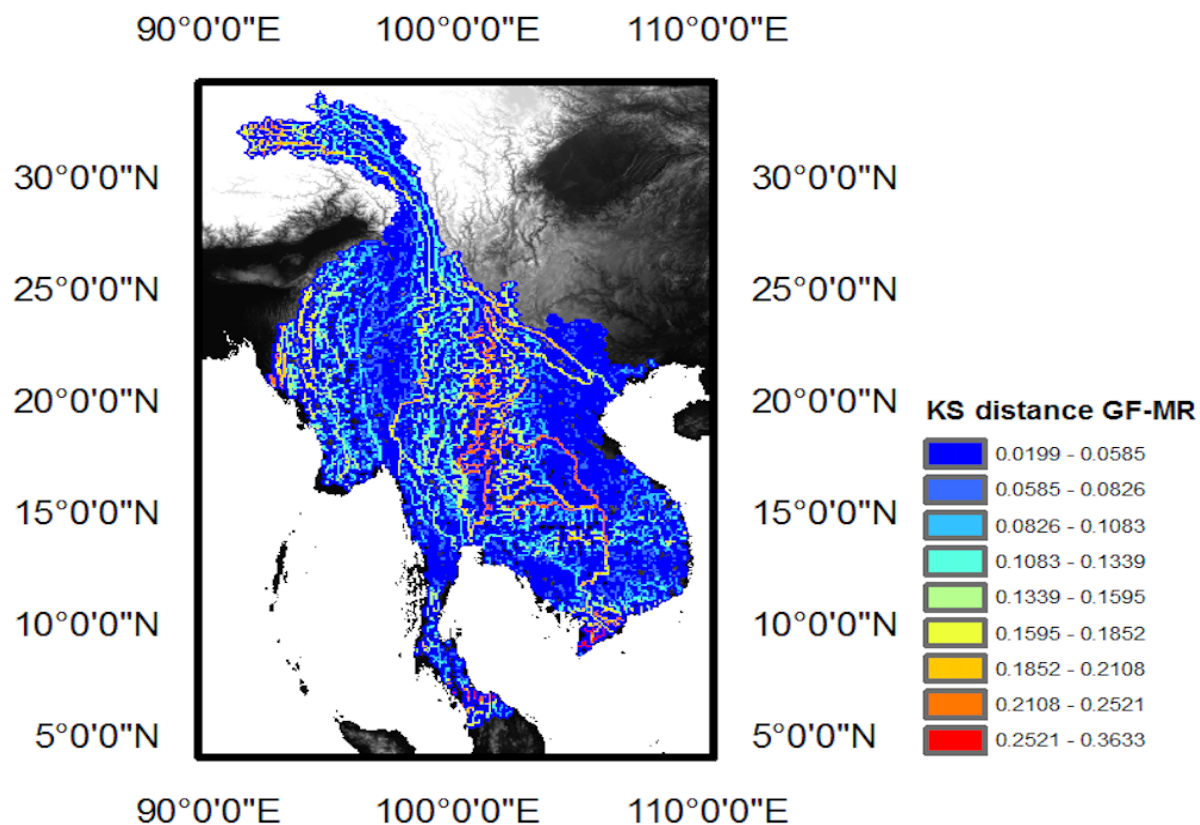


Figure A-9 Two-sample KS-test distance (D_n) for GF-MR combination

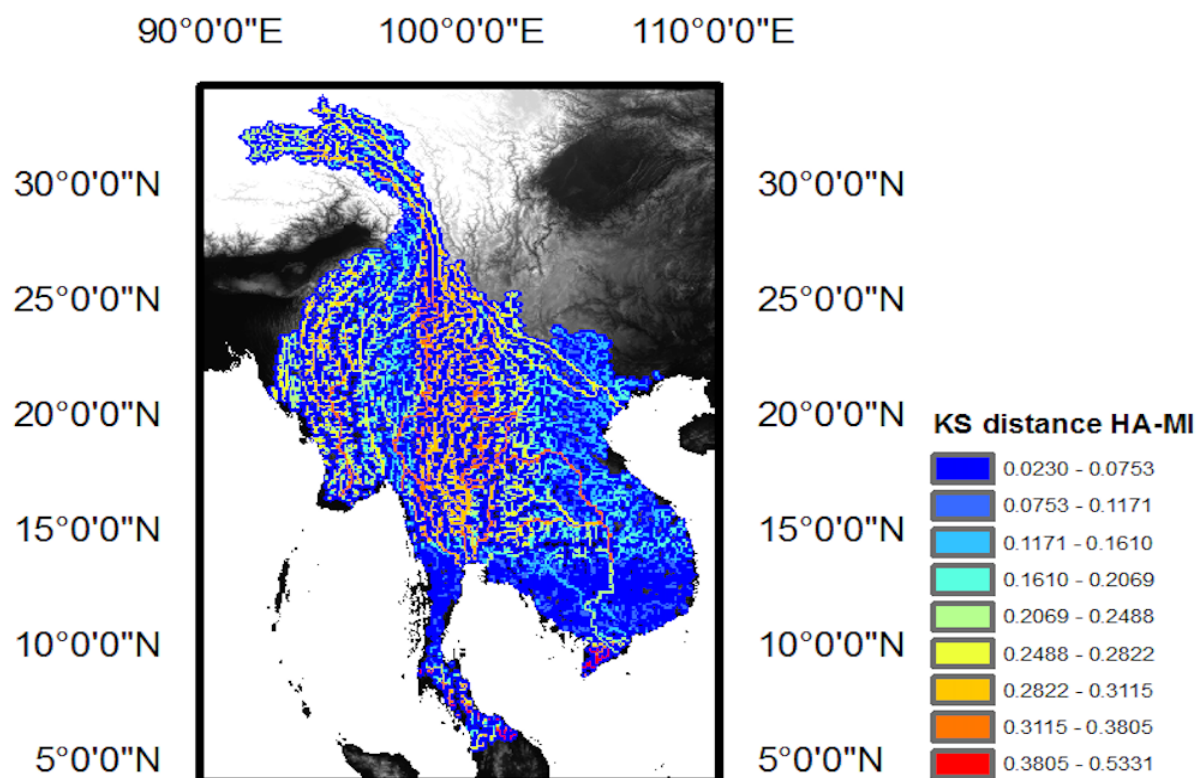


Figure A-10 Two-sample KS-test distance (D_n) for HA-MI combination

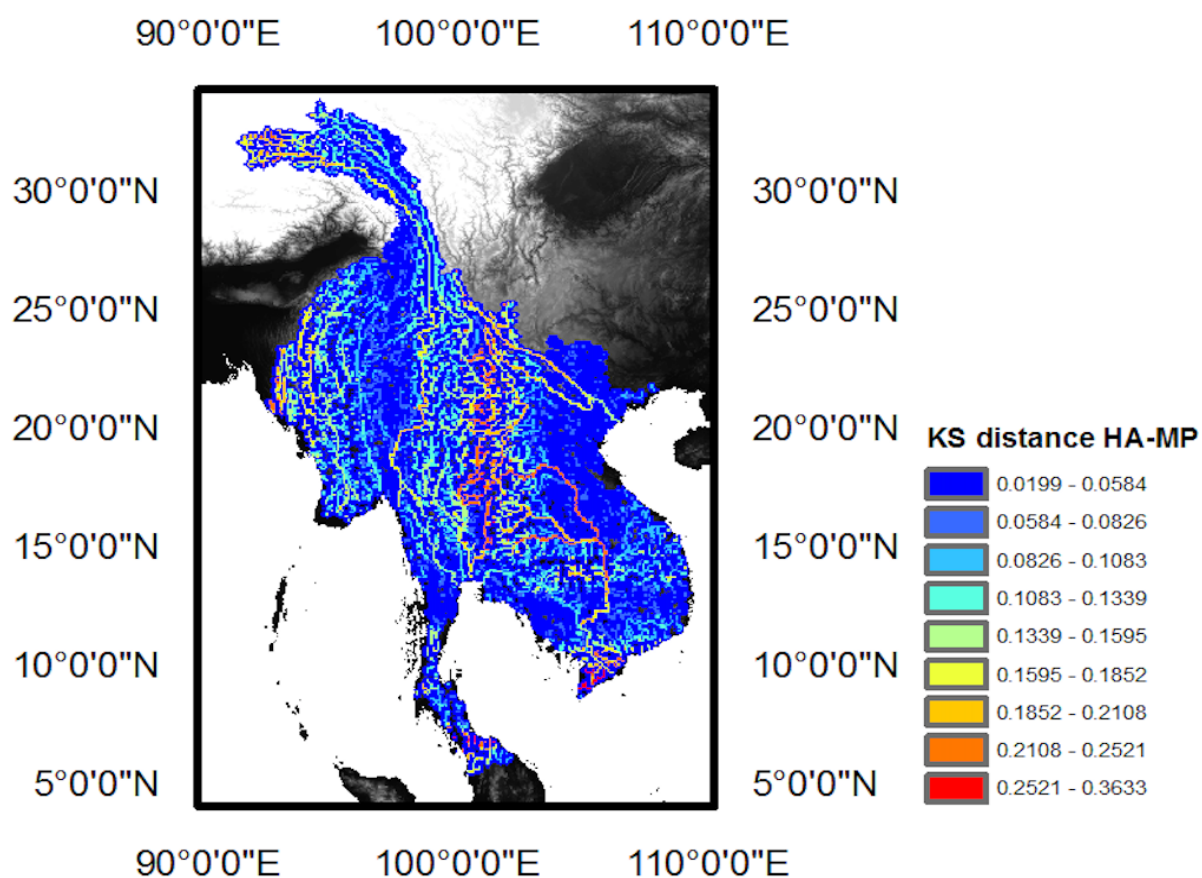


Figure A-11 Two-sample KS-test distance (D_n) for HA-MP combination

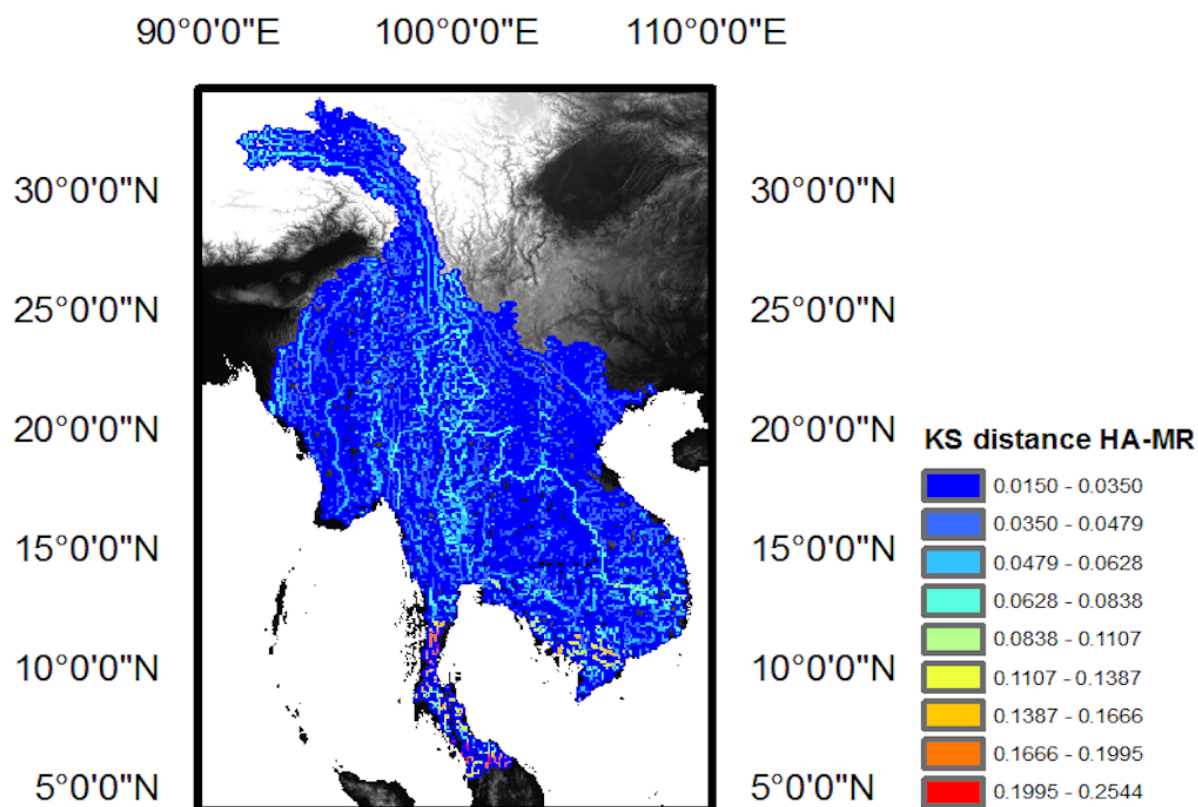


Figure A-12 Two-sample KS-test distance (D_n) for HA-MR combination

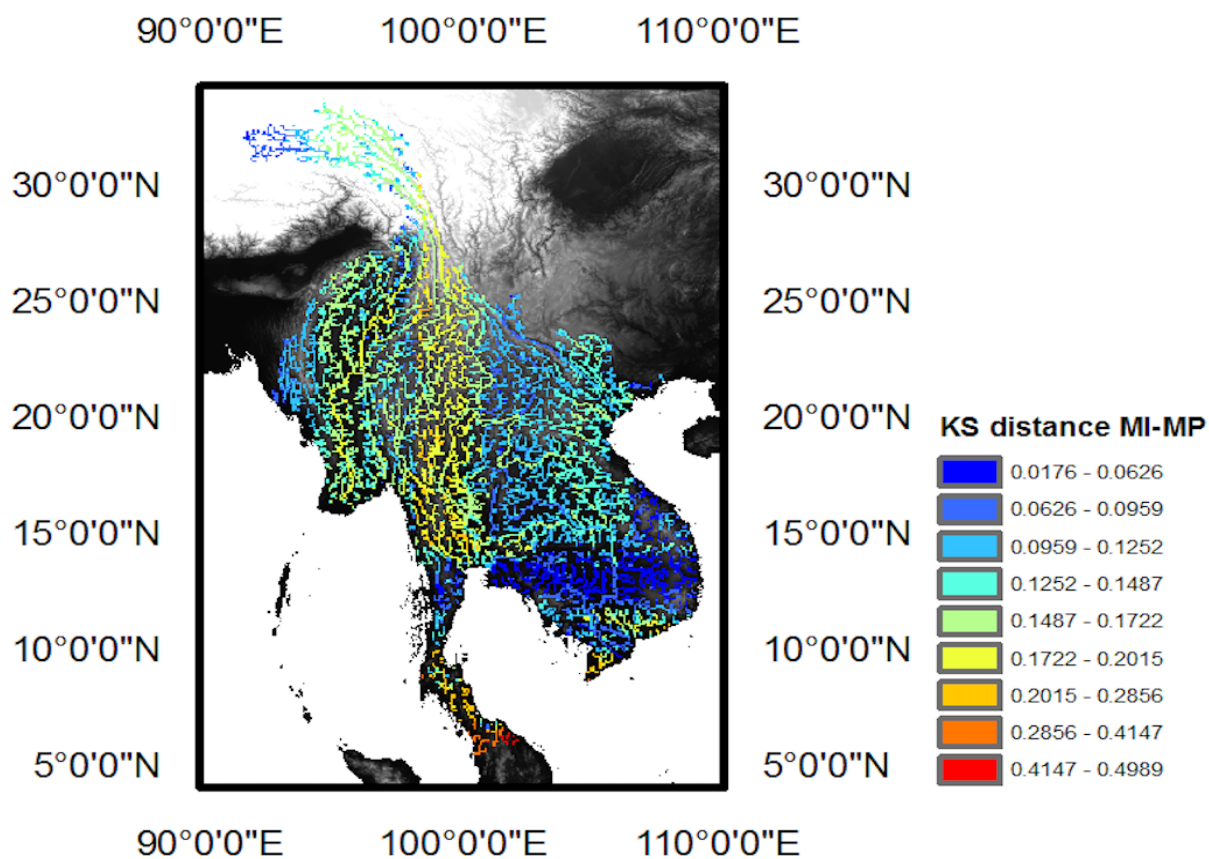
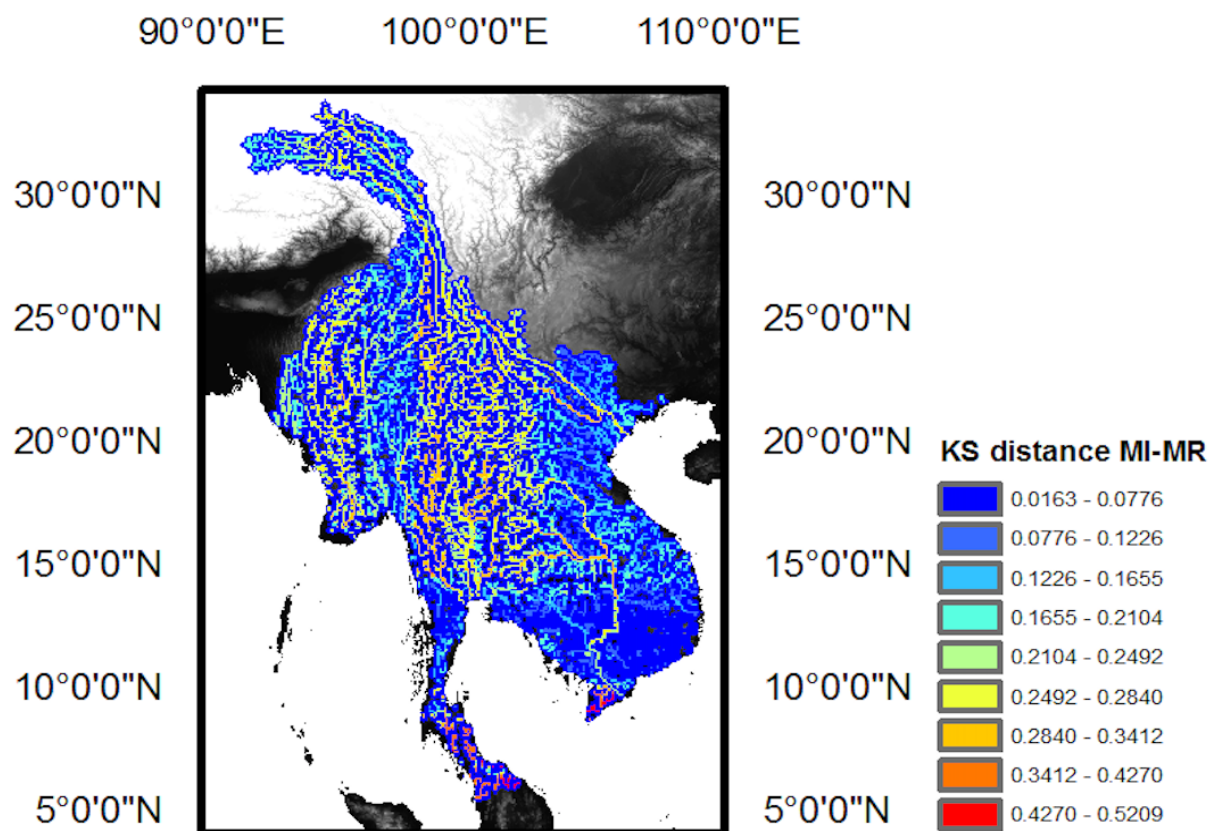
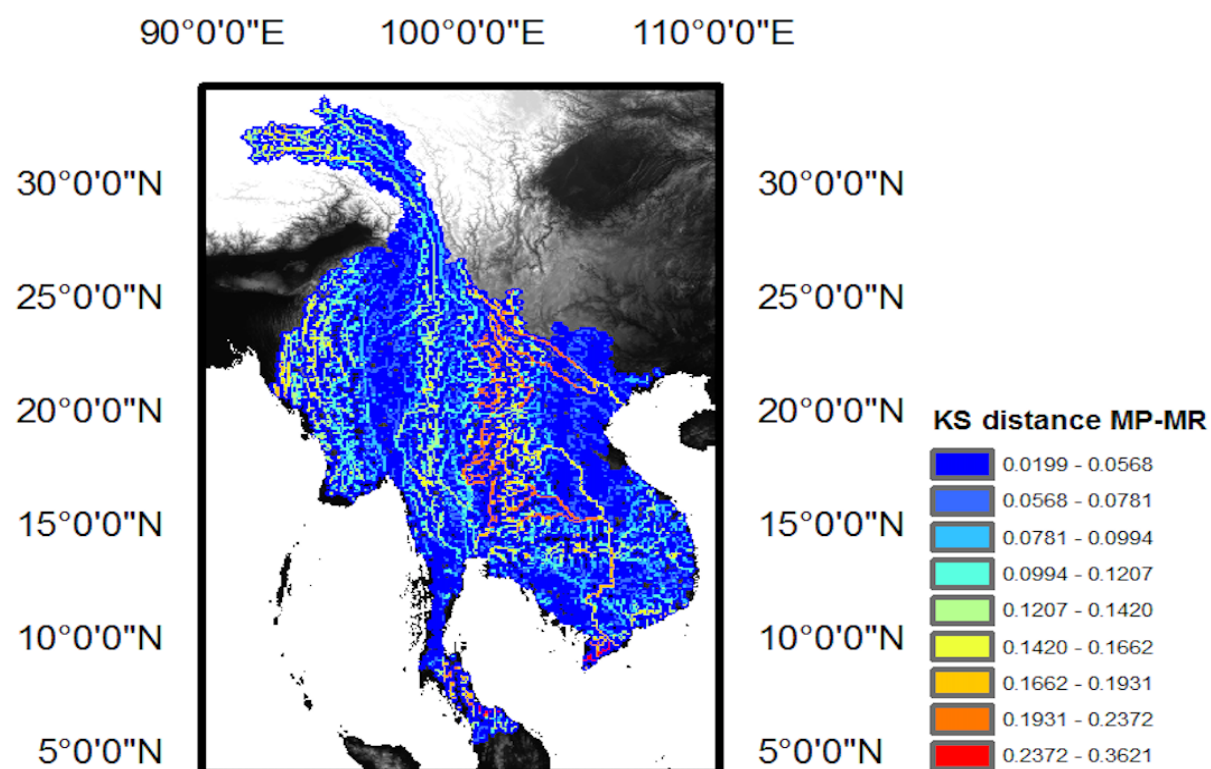


Figure A-13 Two-sample KS-test distance (D_n) for MI-MR combination



90°0'0"E 100°0'0"E 110°0'0"E

Figure A-14 Two-sample KS-test distance (D_n) for MI-MR combination



90°0'0"E 100°0'0"E 110°0'0"E

Figure A-15 Two-sample KS-test distance (D_n) for MP-MR combination

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APPENDIX B:

Annual maximum discharge and return period relationships for future SST warming patterns

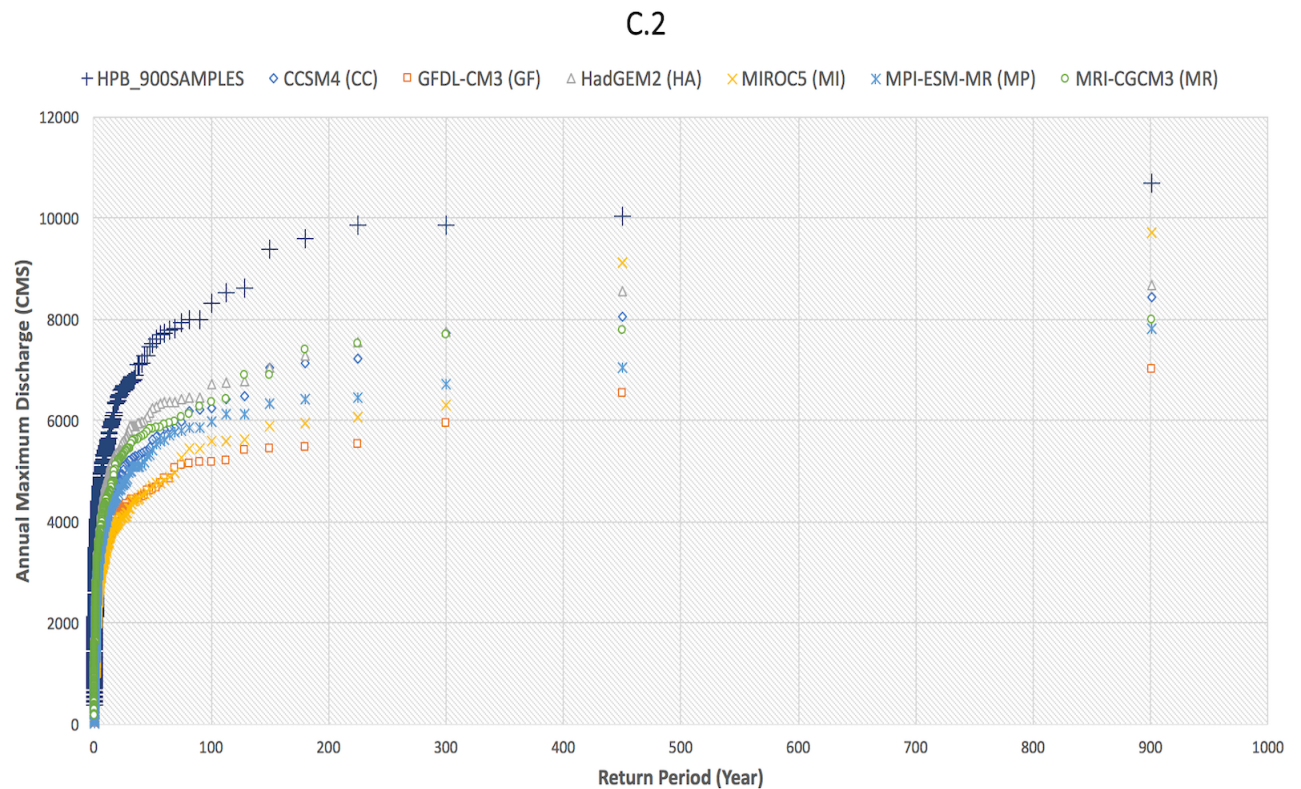


Figure B-1 Annual maximum river discharge and return period relationship of six SST warming patterns (CC, GF, HA, MI, MP, and MR) at C.2 station

C.2

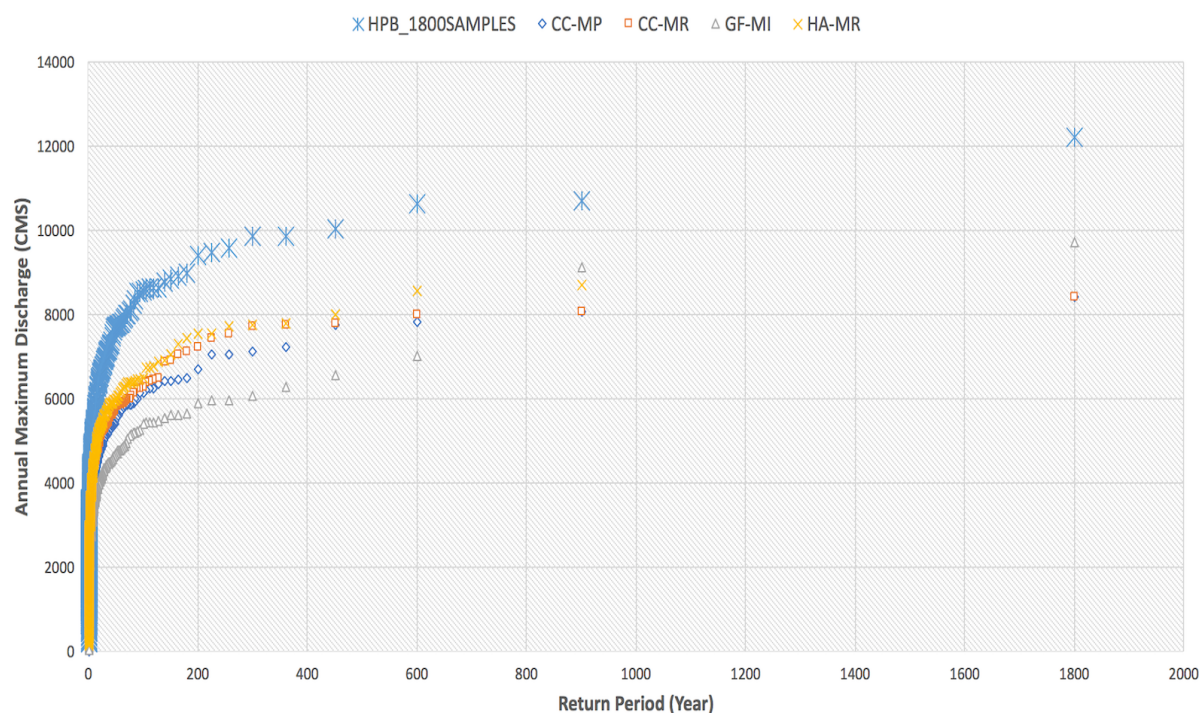


Figure B-2 Annual maximum river discharge and return period relationship of four combined SST ensembles with sample size of 1,800 at C.2 station

Monywa station

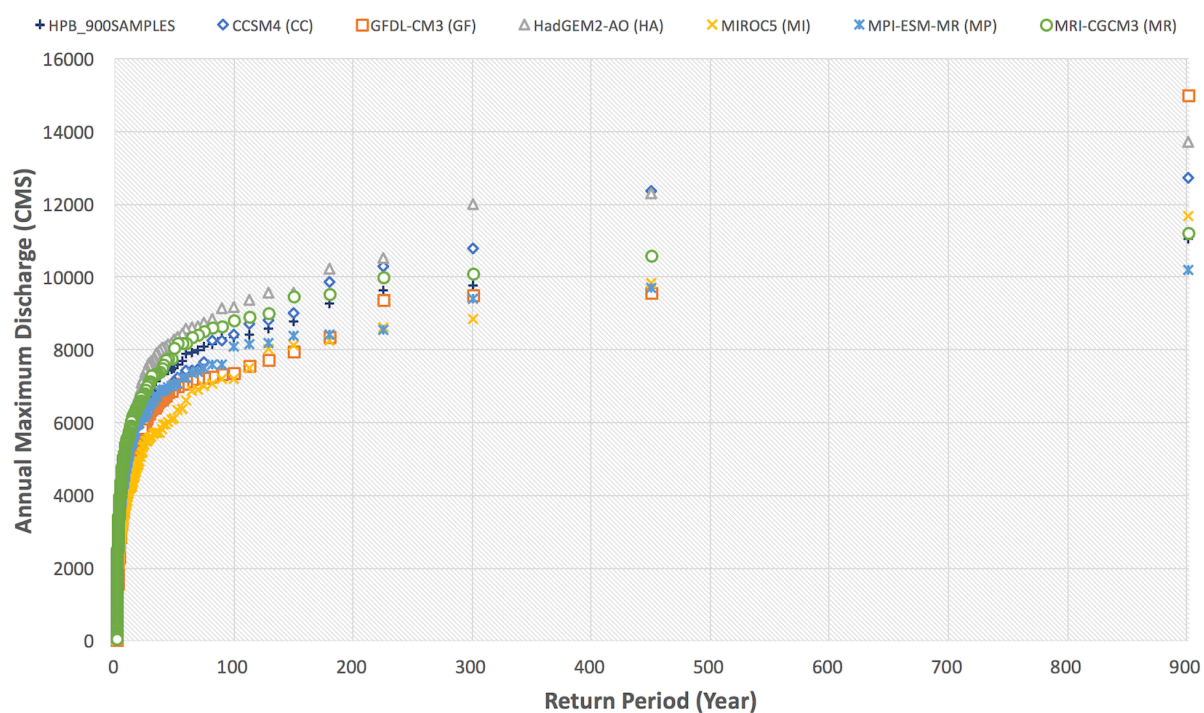


Figure B-3 Annual maximum river discharge and return period relationship of six SST warming patterns (CC, GF, HA, MI, MP, and MR) at Monywa station

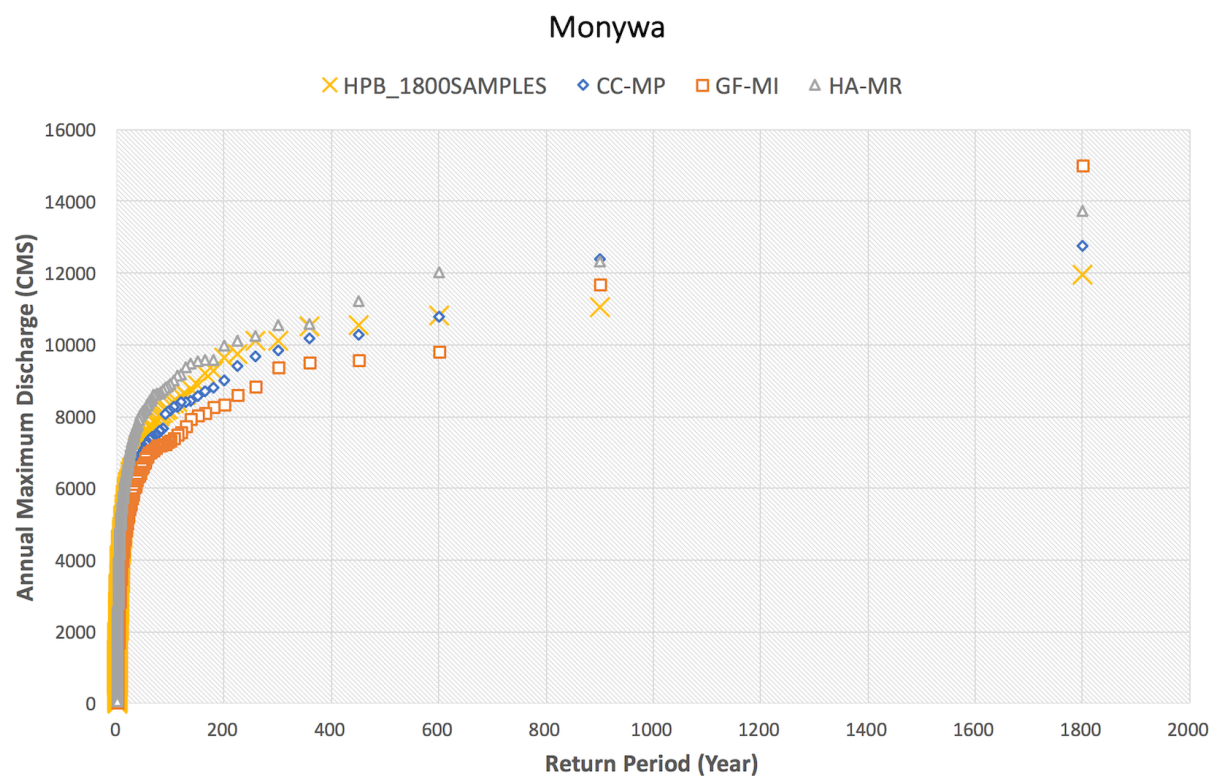


Figure B-4 Annual maximum river discharge and return period relationship of three combined SST ensembles with sample size of 1,800 at Monywa station

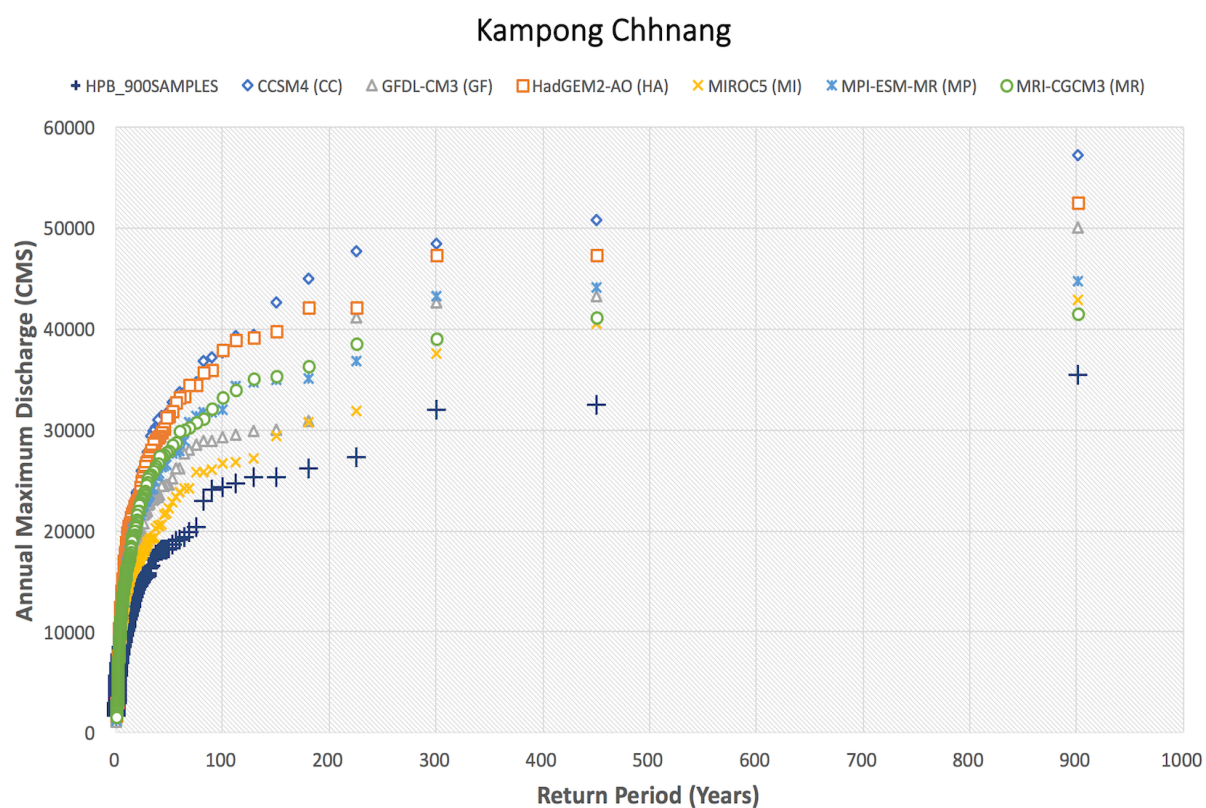


Figure B-5 Annual maximum river discharge and return period relationship of six SST warming patterns (CC, GF, HA, MI, MP, and MR) at Kampong Chhnang station

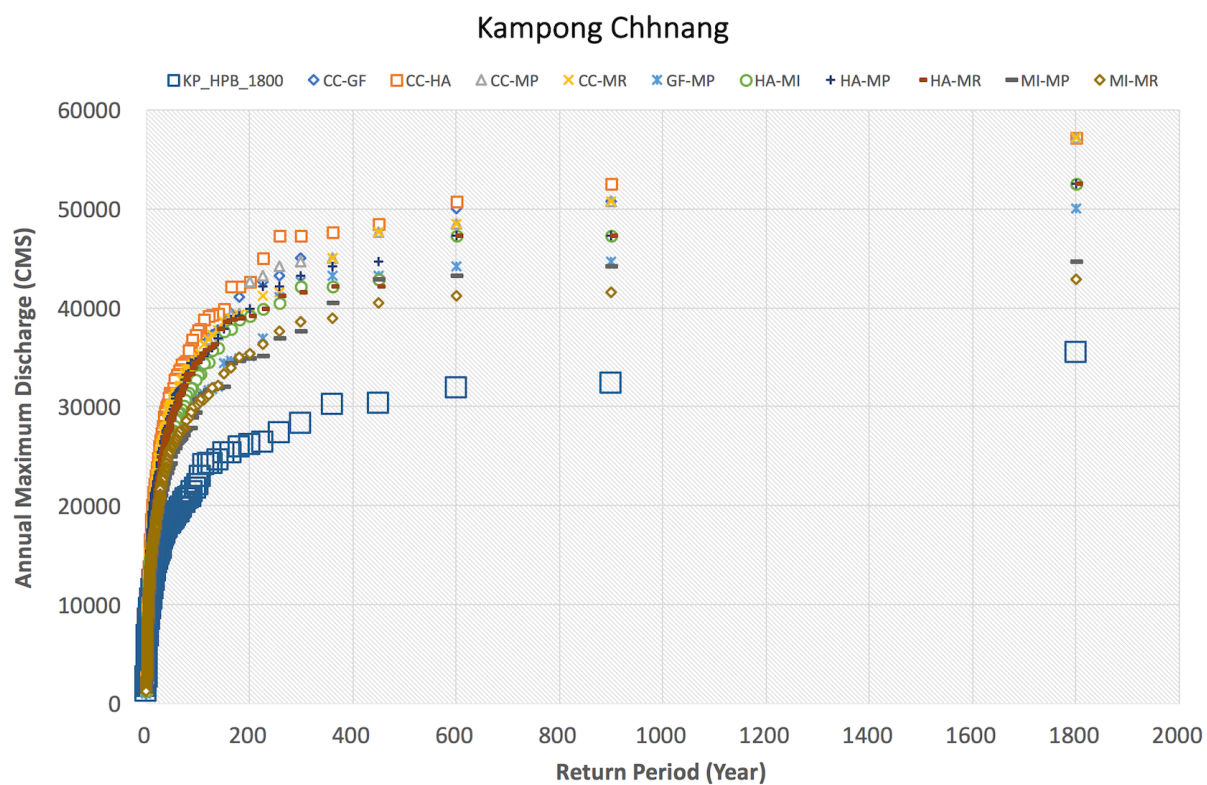


Figure B-6 Annual maximum river discharge and return period relationship of three combined SST ensembles with sample size of 1,800 at Kampong Chhnang station

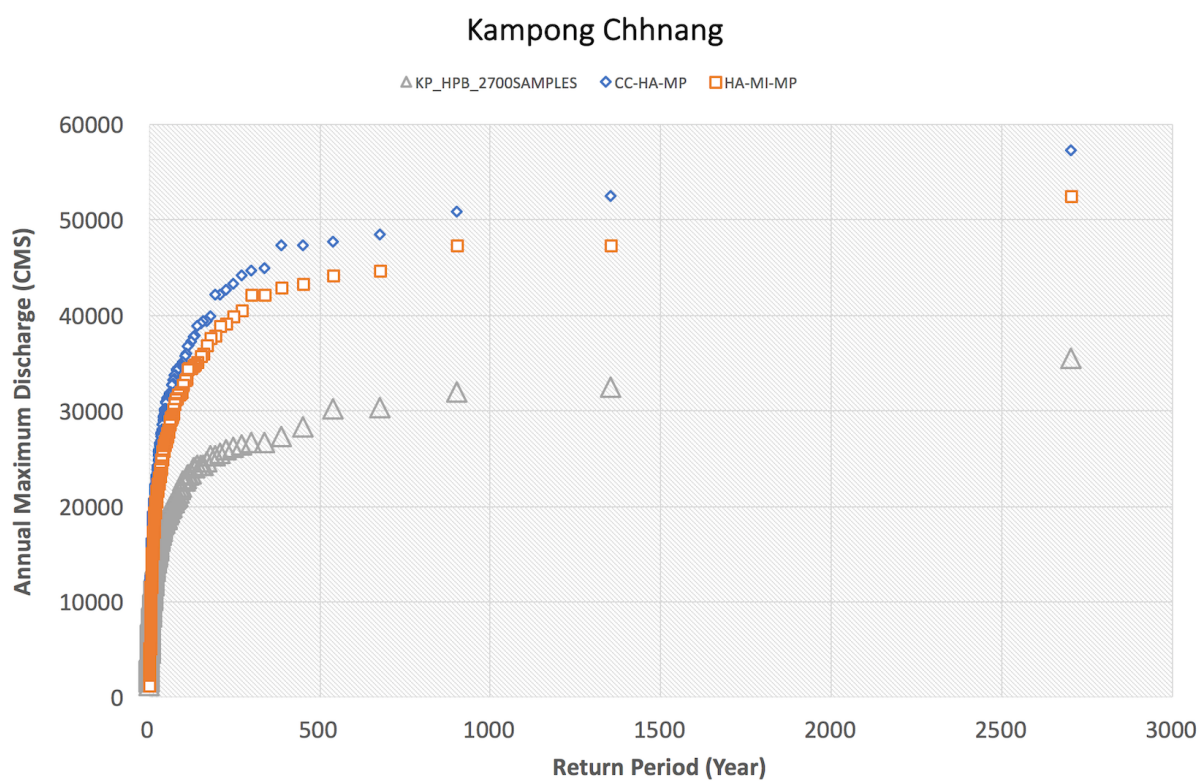


Figure B-7 Annual maximum river discharge and return period relationship of three combined SST ensembles with sample size of 2,700 at Kampong Chhnang station

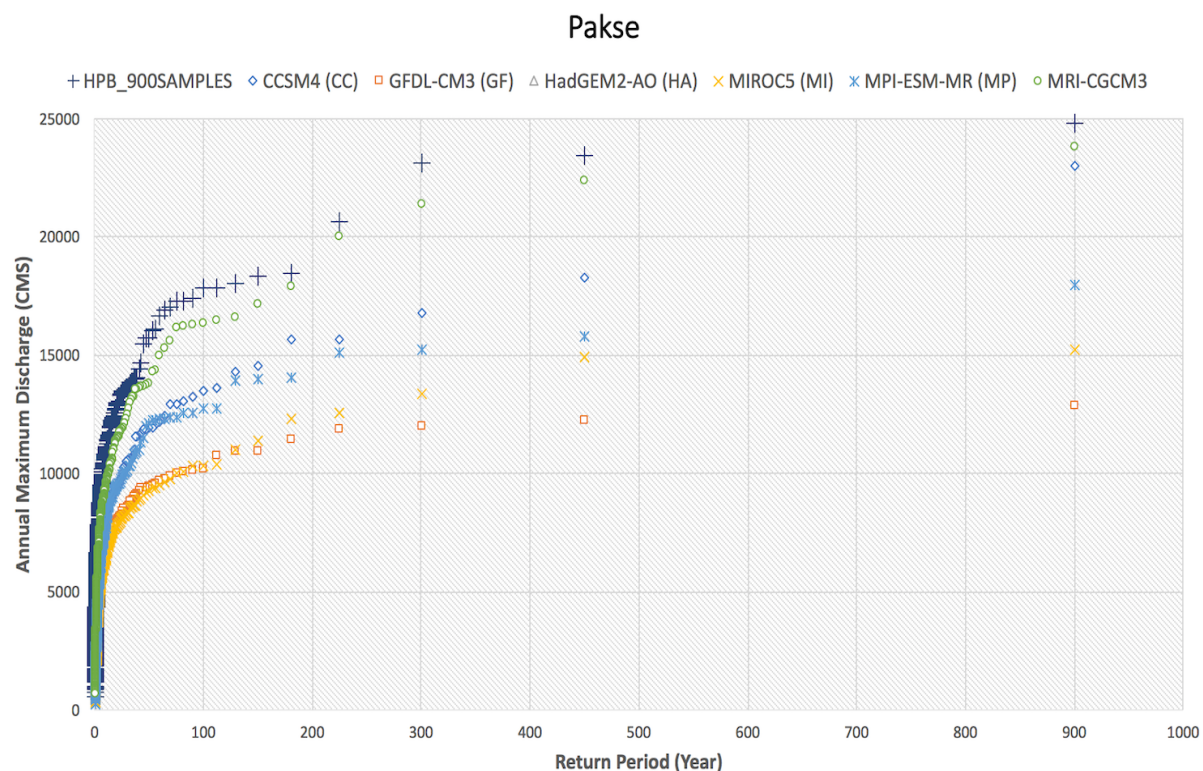


Figure B-8 Annual maximum river discharge and return period relationship of six SST warming patterns (CC, GF, HA, MI, MP, and MR) at Pakse station

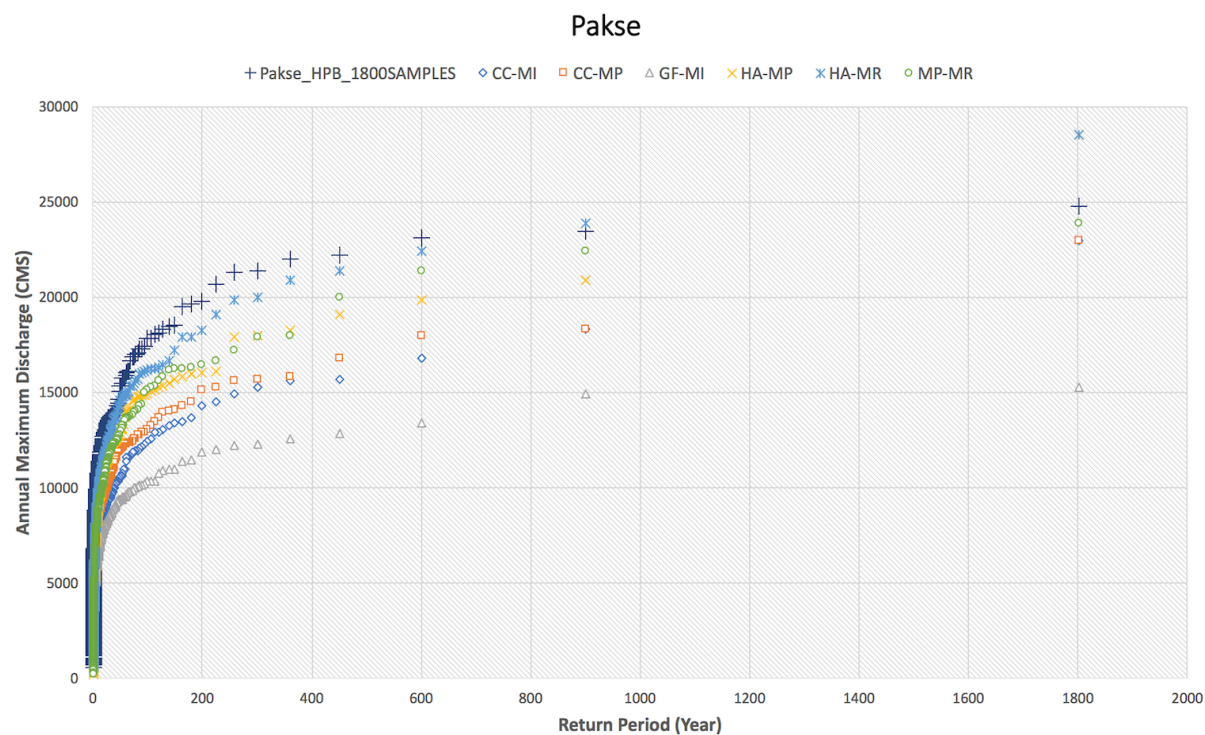


Figure B-9 Annual maximum river discharge and return period relationship of six combined SST ensembles with sample size of 1,800 at Pakse station

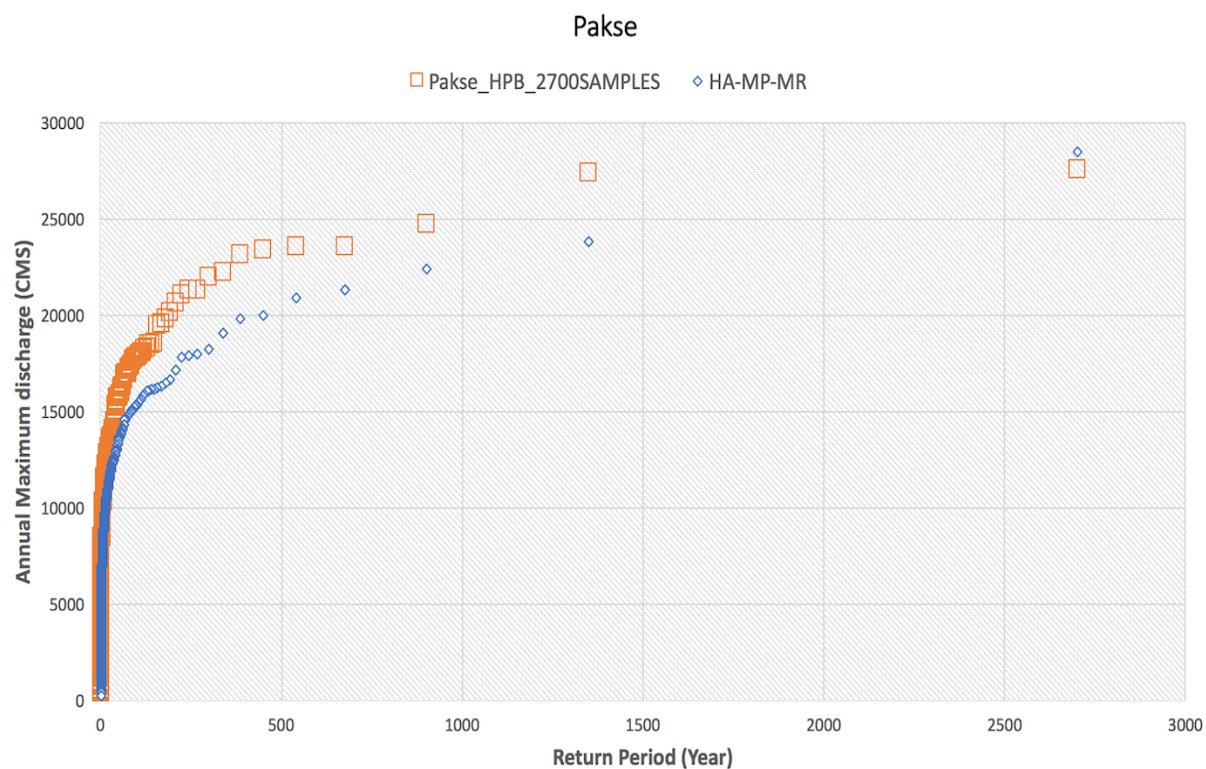


Figure B-10 Annual maximum river discharge and return period relationship of single combined SST ensemble with sample size of 2,700 at Pakse station

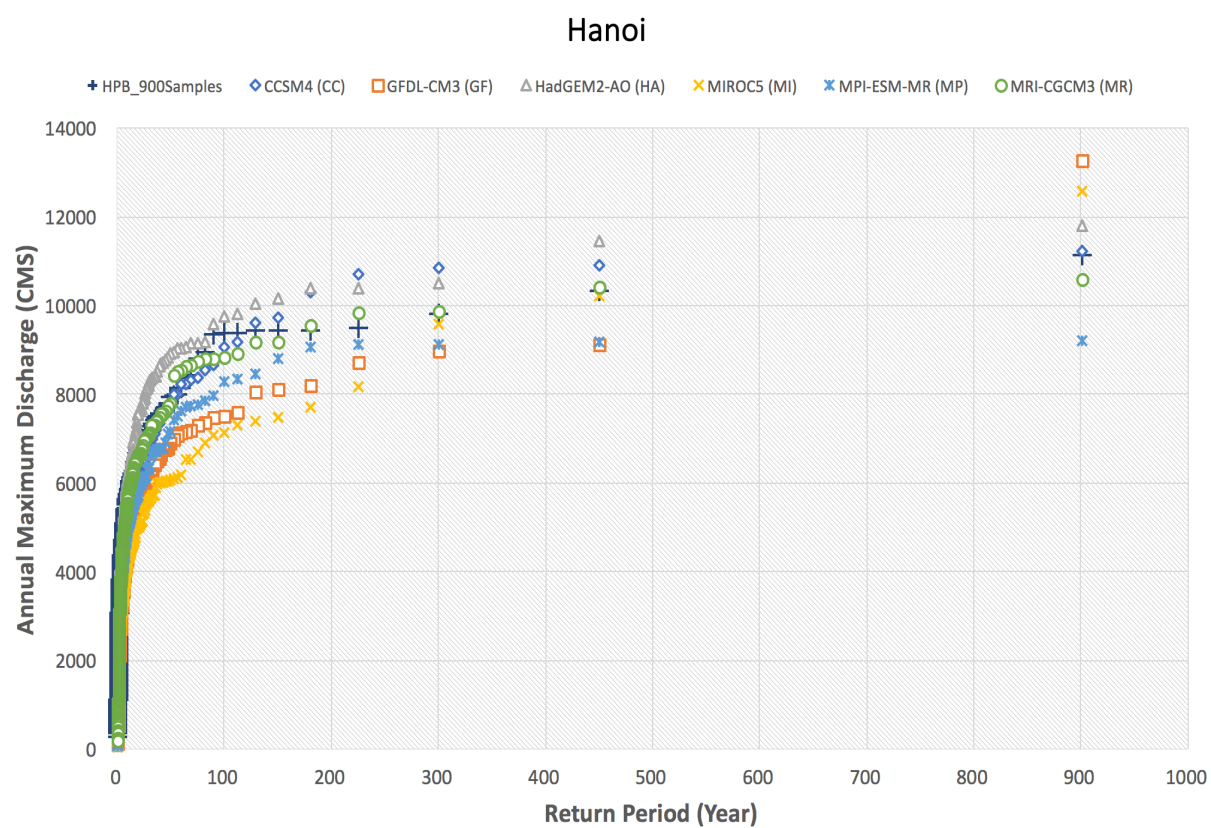


Figure B-11 Annual maximum river discharge and return period relationship of six SST warming patterns (CC, GF, HA, MI, MP, and MR) at Hanoi station

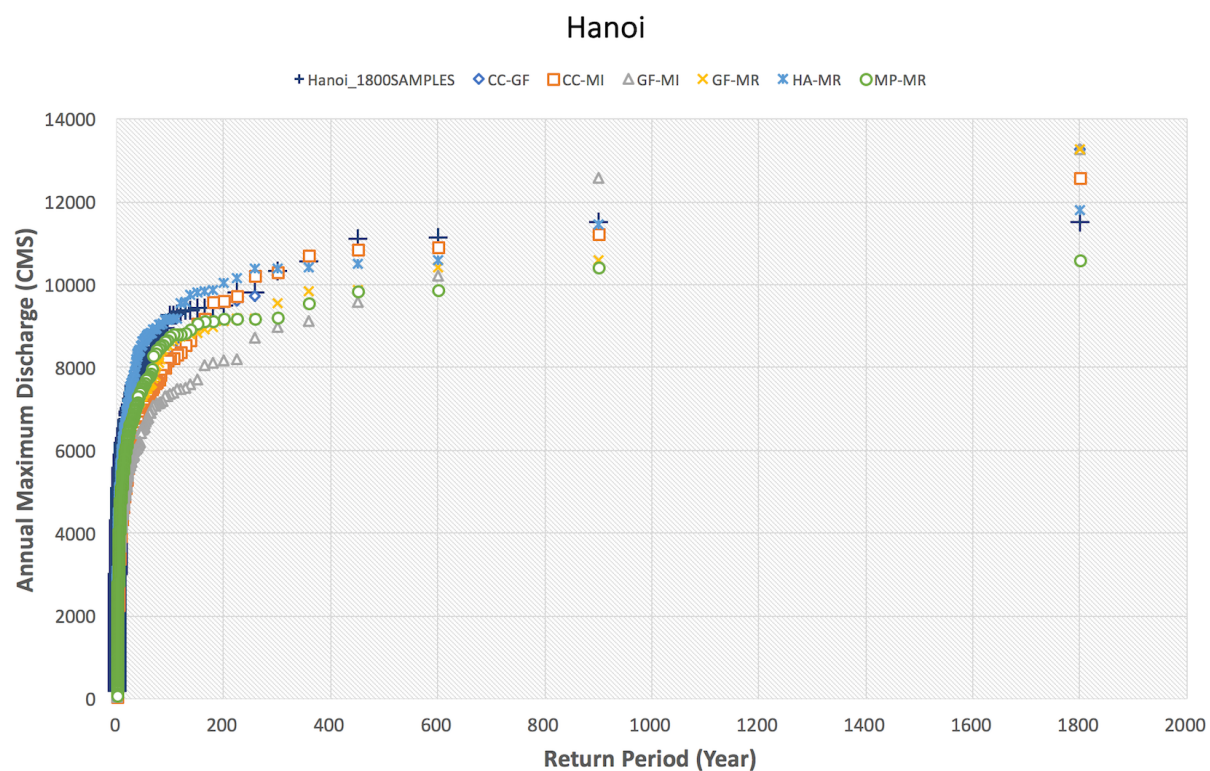


Figure B-12 Annual maximum river discharge and return period relationship of six combined SST ensembles with sample size of 1,800 at Hanoi station

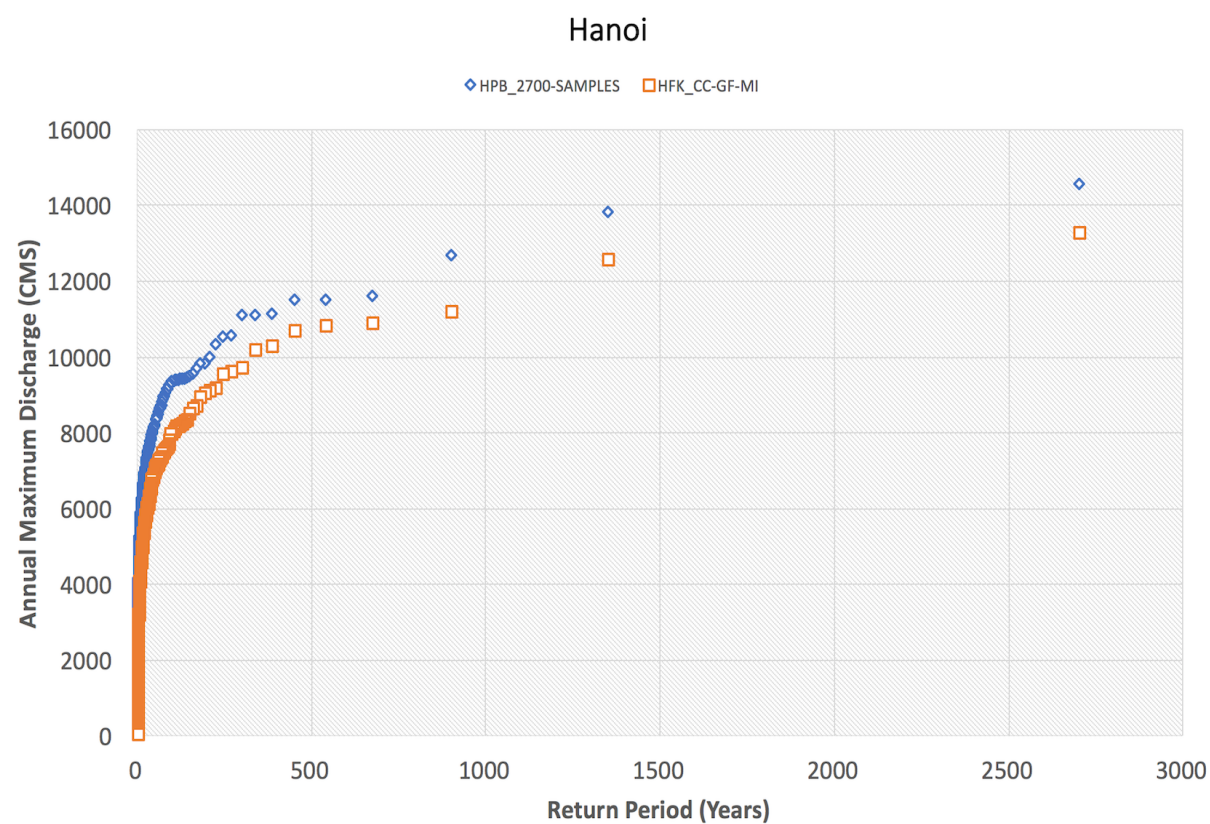


Figure B-13 Annual maximum river discharge and return period relationship of single combined SST ensemble with sample size of 2,700 at Hanoi station

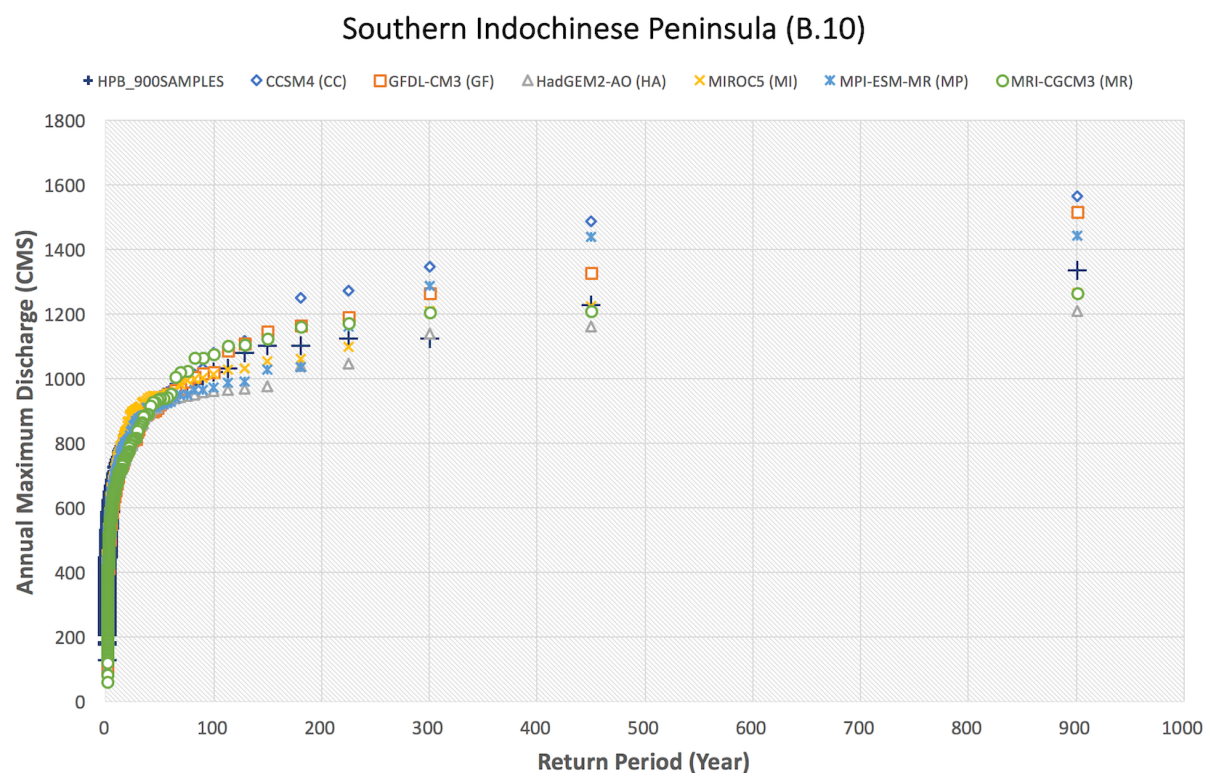


Figure B-14 Annual maximum river discharge and return period relationship of six SST warming patterns (CC, GF, HA, MI, MP, and MR) at B.10 station

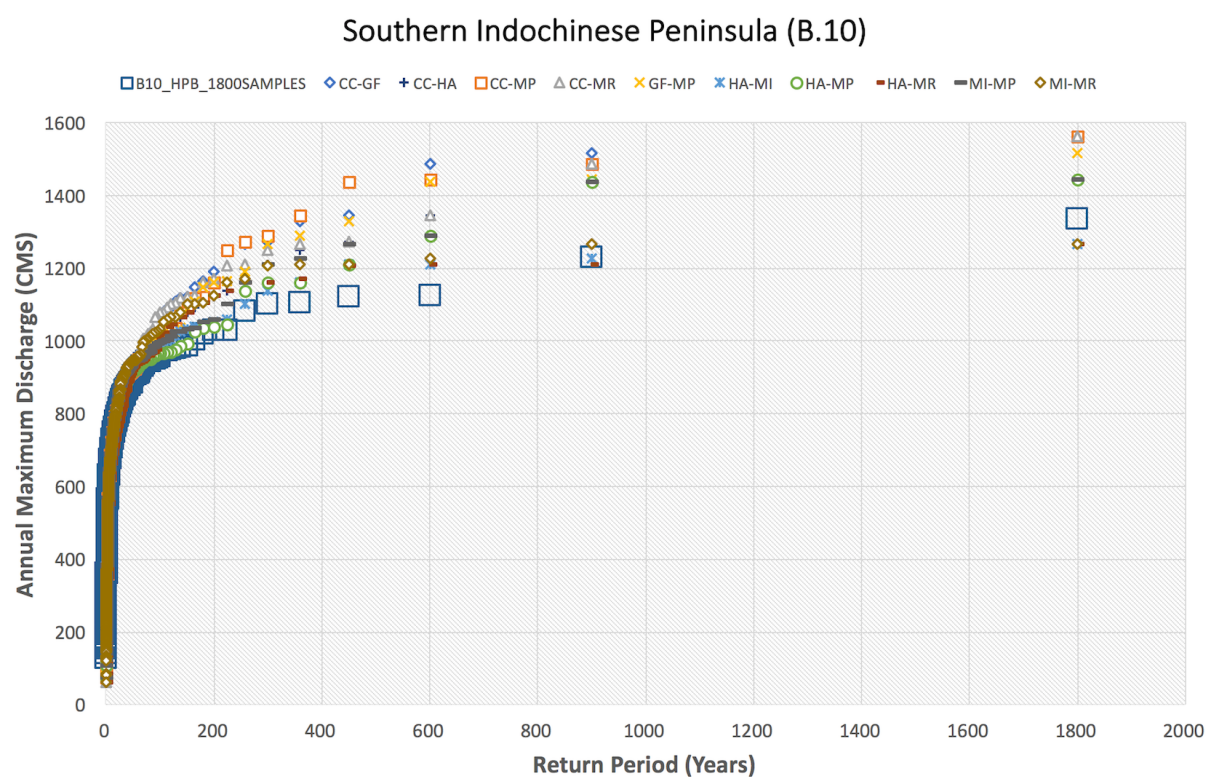


Figure B-15 Annual maximum river discharge and return period relationship of ten combined SST ensembles with sample size of 1,800 at B.10 station

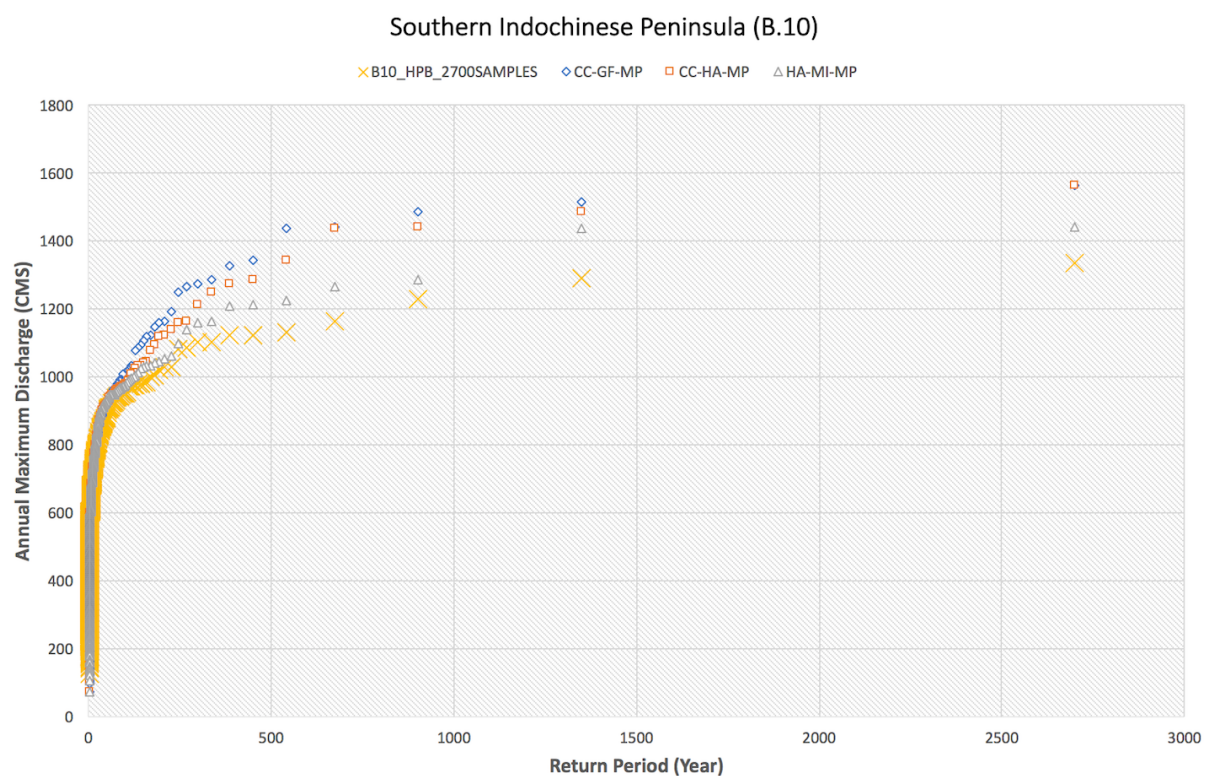


Figure B-16 Annual maximum river discharge and return period relationship of three combined SST ensemble with sample size of 2,700 at B.10 station

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APPENDIX C: Runoff Generation data

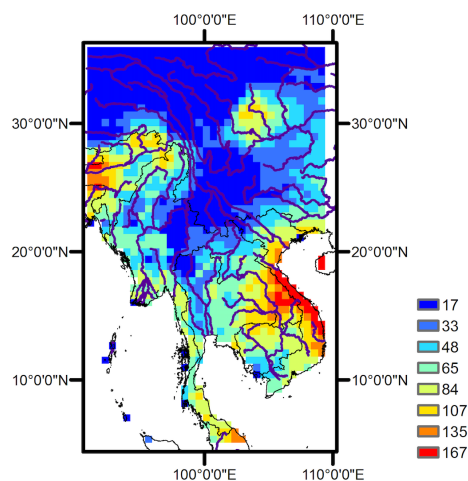


Figure C-1 Average Annual R1D for the present climate (HPB) in mm

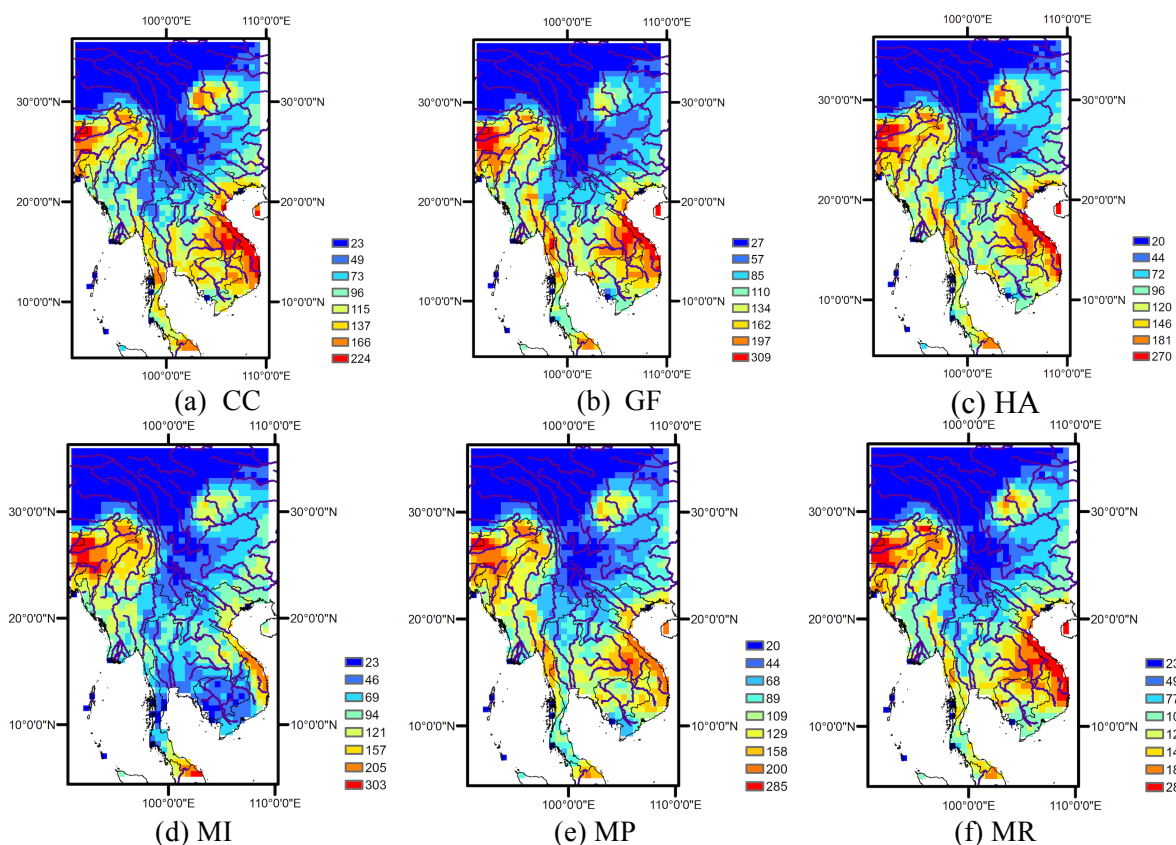


Figure C-2 The future Average Annual R1D in mm, under six SST warming patterns: (a) CC, (b) GF, (c) HA, (d) MI, (e) MP and (f) MR

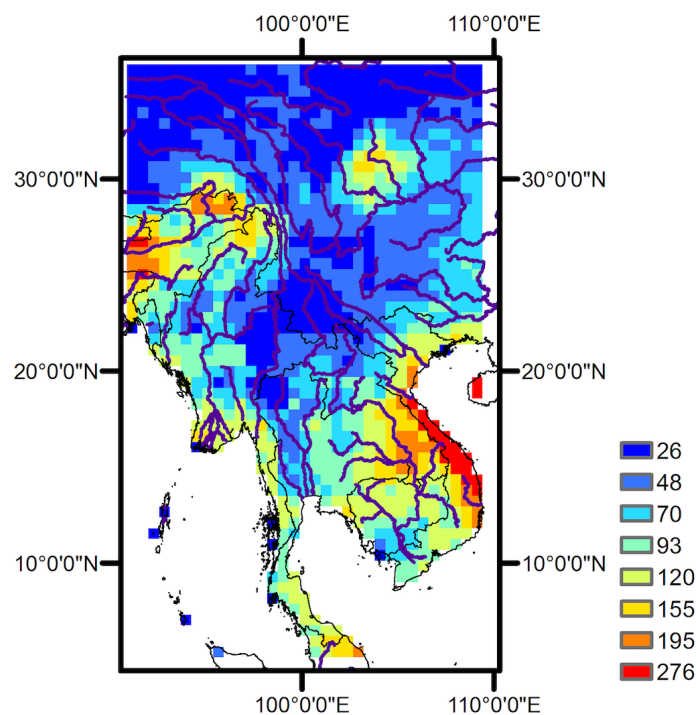


Figure C-3 Average Annual R3D for the present climate (HPB) in mm

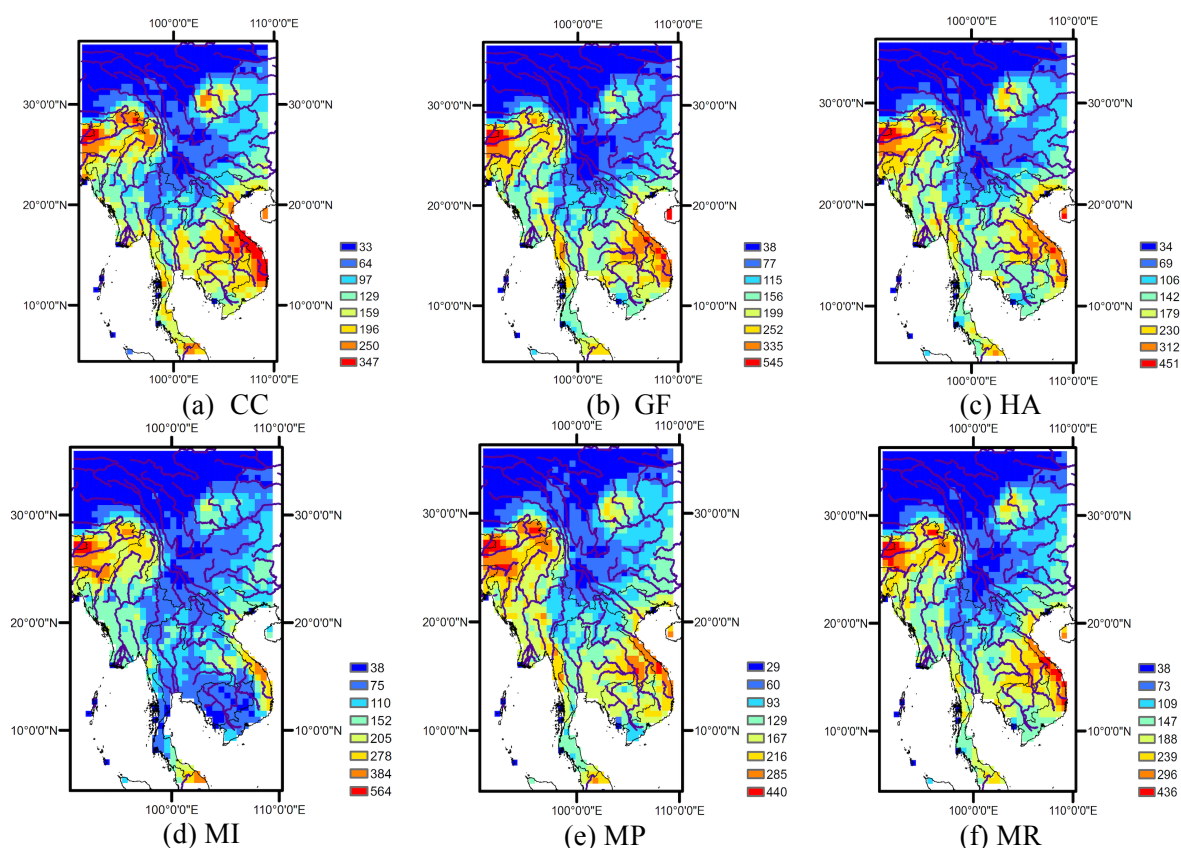


Figure C-4 The future Average Annual R3D in mm, under six SST warming patterns: (a) CC, (b) GF, (c) HA, (d) MI, (e) MP and (f) MR

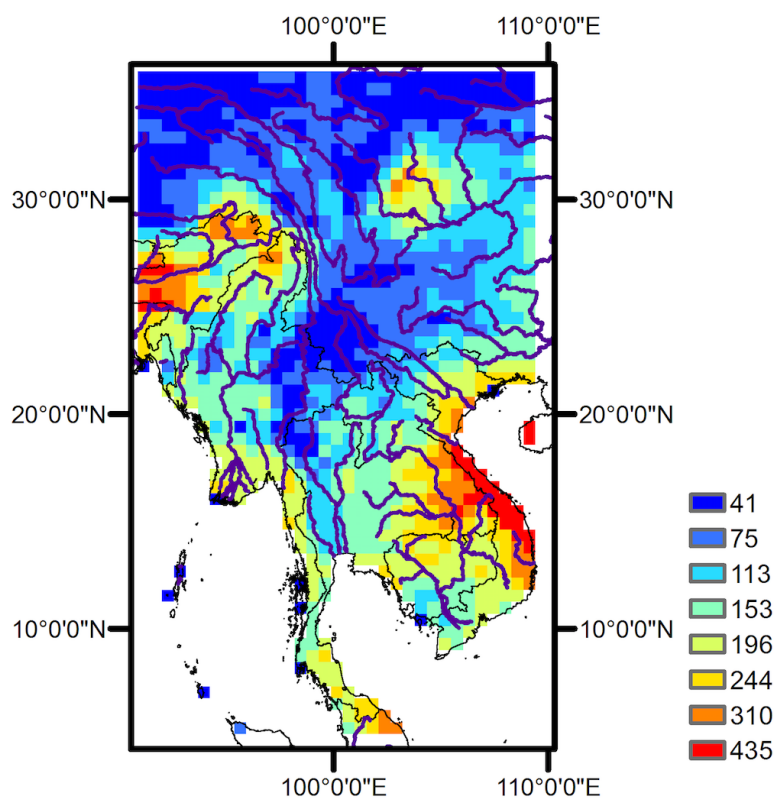


Figure C-5 Average Annual R7D for the present climate (HPB) in mm

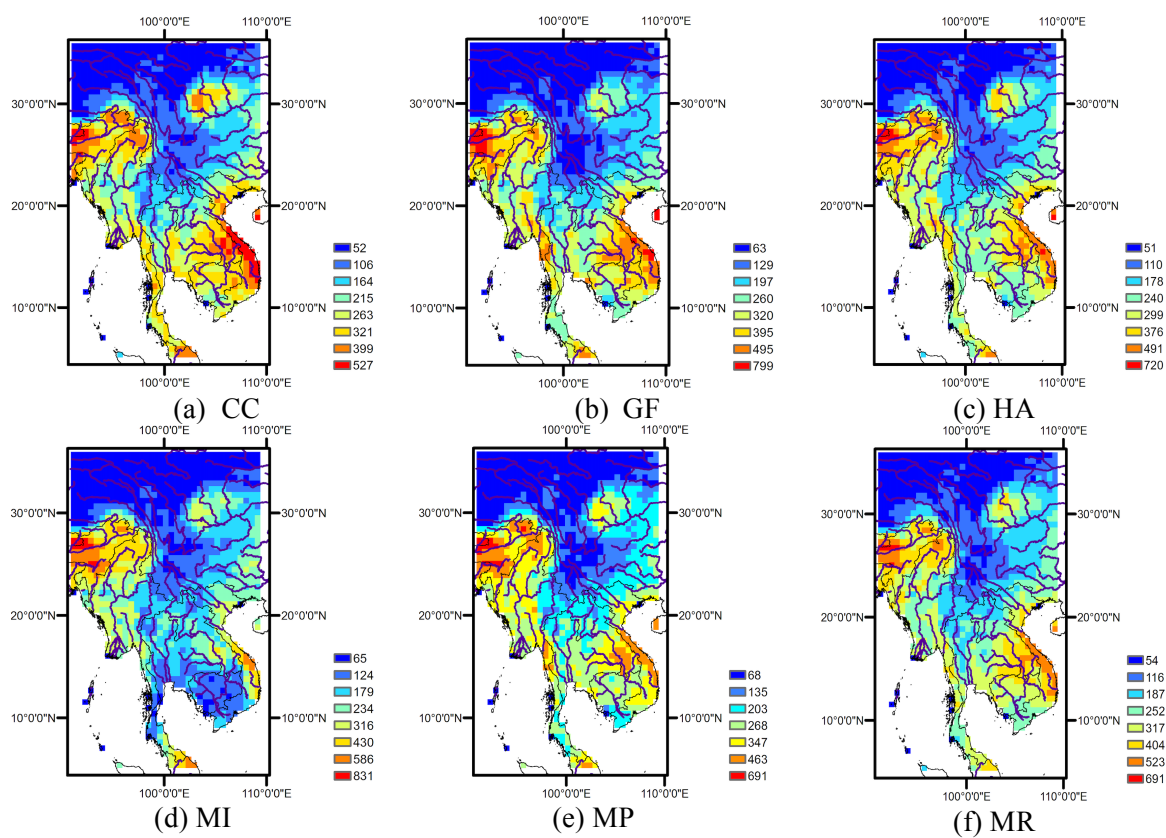


Figure C-6 The future Average Annual R7D in mm, under six SST warming patterns: (a) CC, (b) GF, (c) HA, (d) MI, (e) MP and (f) MR

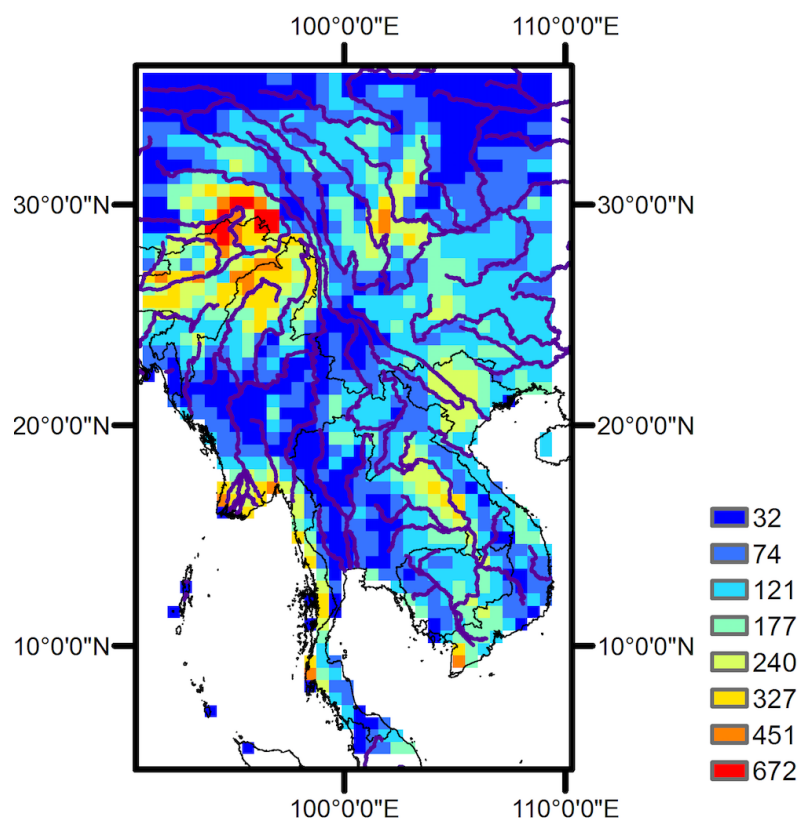


Figure C-7 Average ROF during JJA for the present climate (HPB) in mm

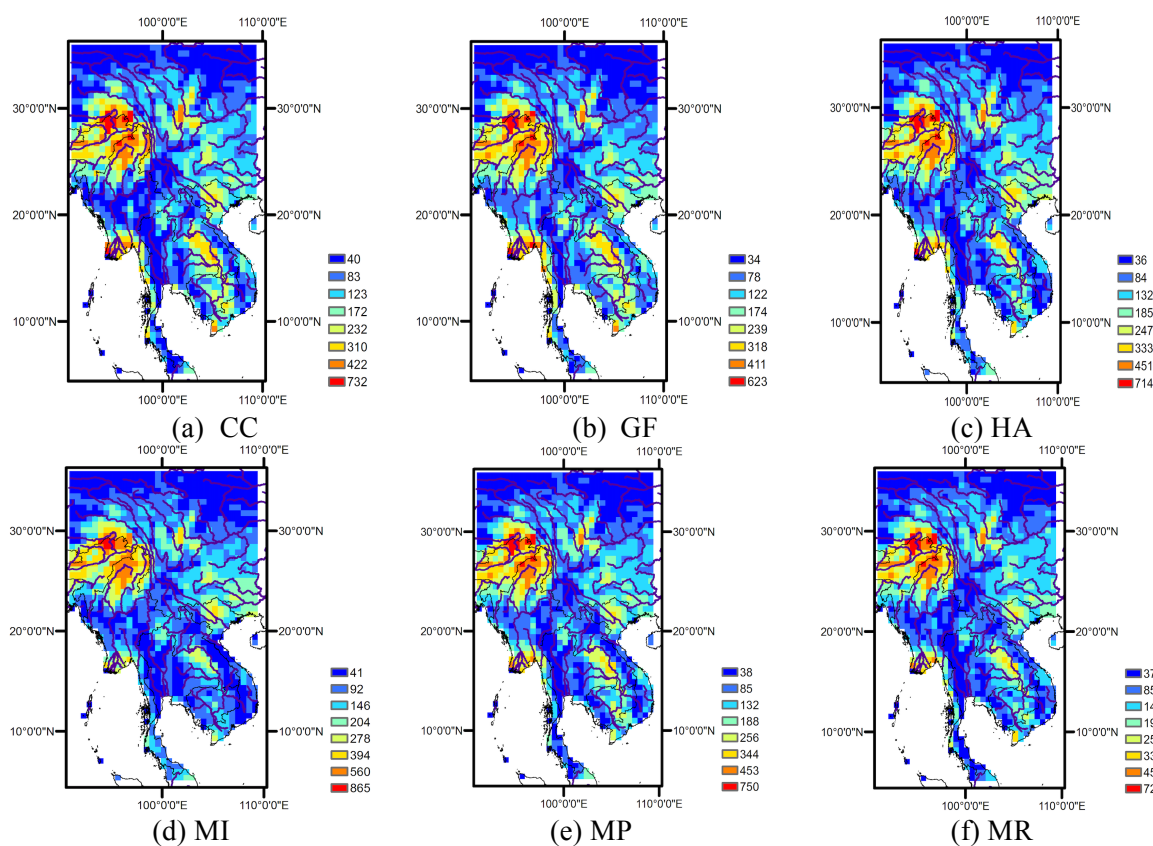


Figure C-8 The future Average ROF during JJA in mm, under six SST warming patterns: (a) CC, (b) GF, (c) HA, (d) MI, (e) MP and (f) MR

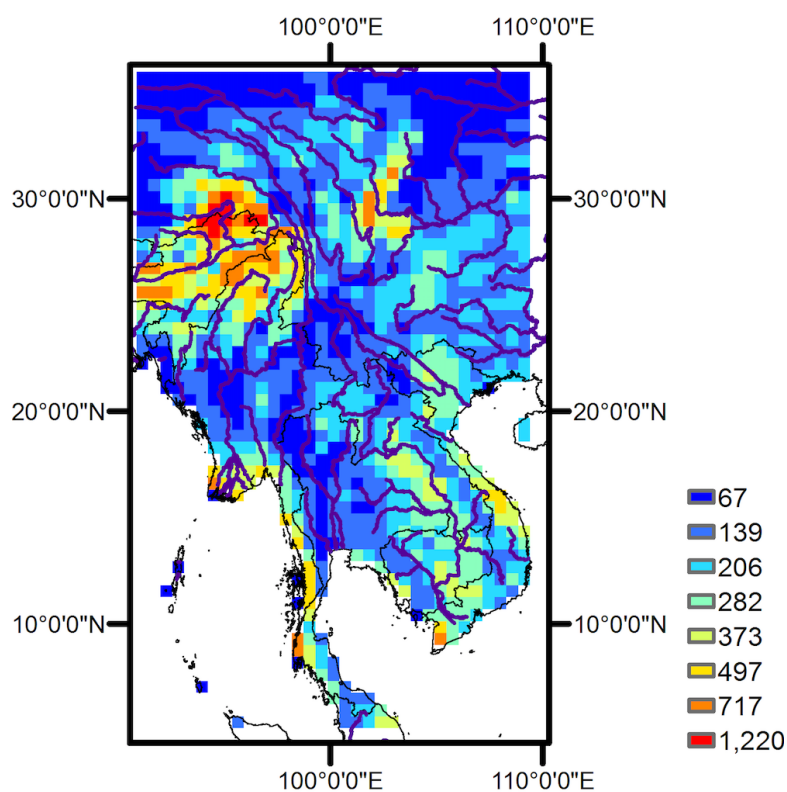


Figure C-9 Average ROF during wet season for the present climate (HPB) in mm

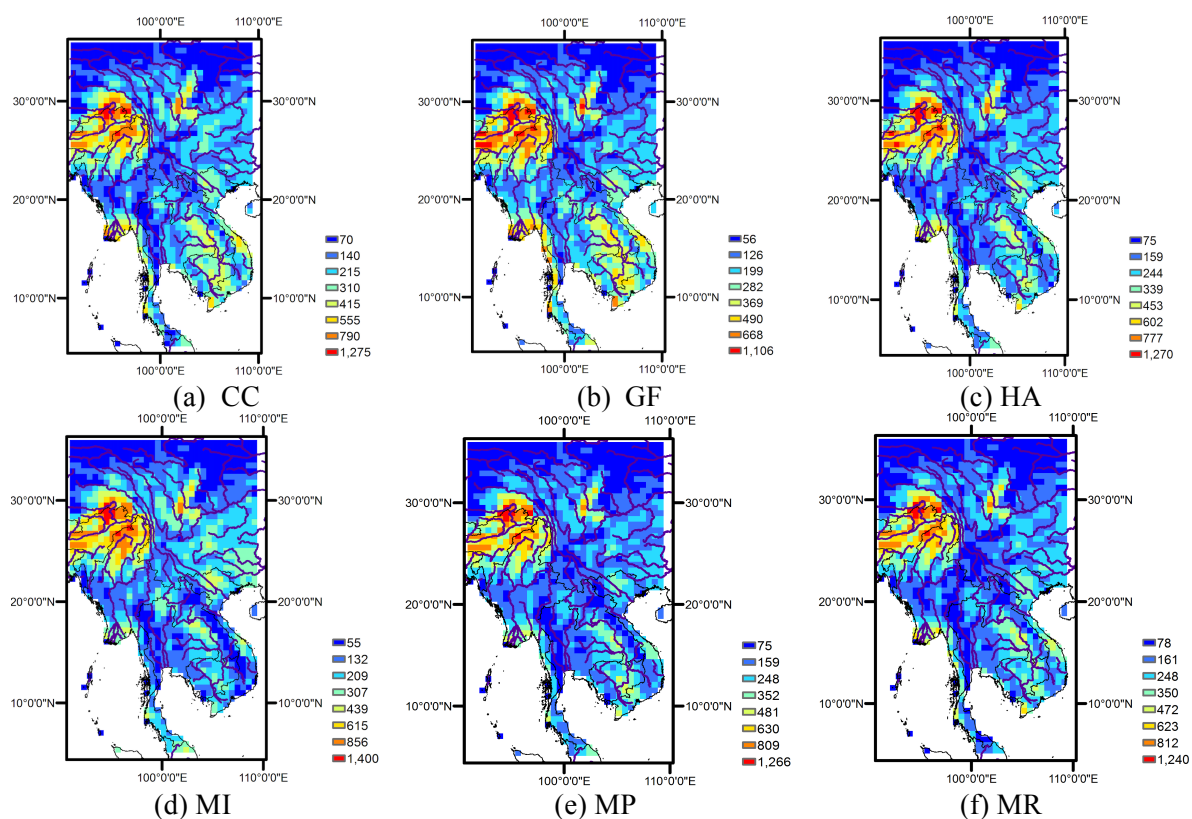


Figure C-10 The future Average ROF during wet season in mm, under six SST warming patterns: (a) CC, (b) GF, (c) HA, (d) MI, (e) MP and (f) MR

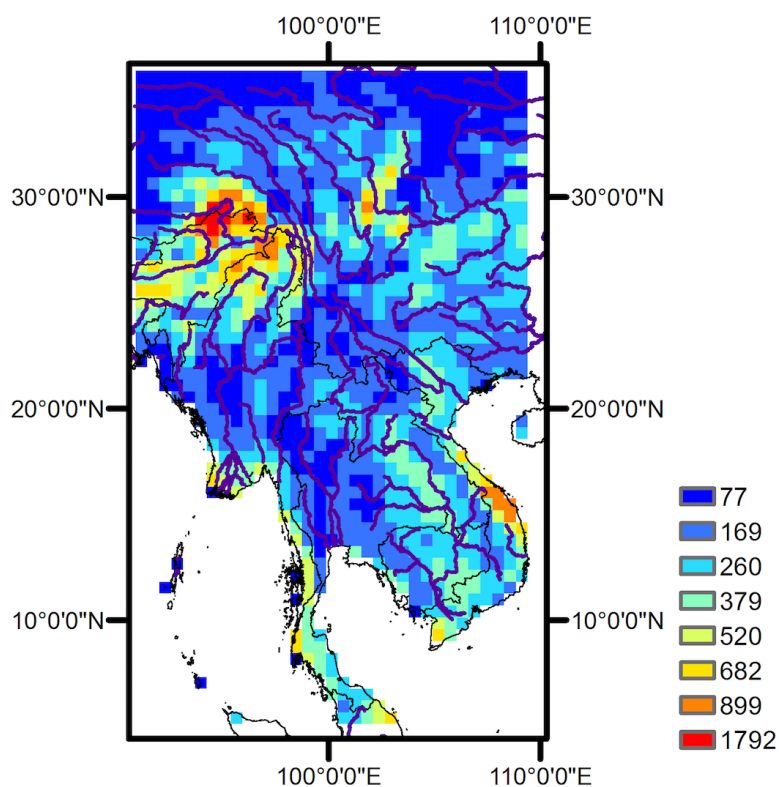


Figure C-11 Average Annual ROF for the present climate (HPB) in mm

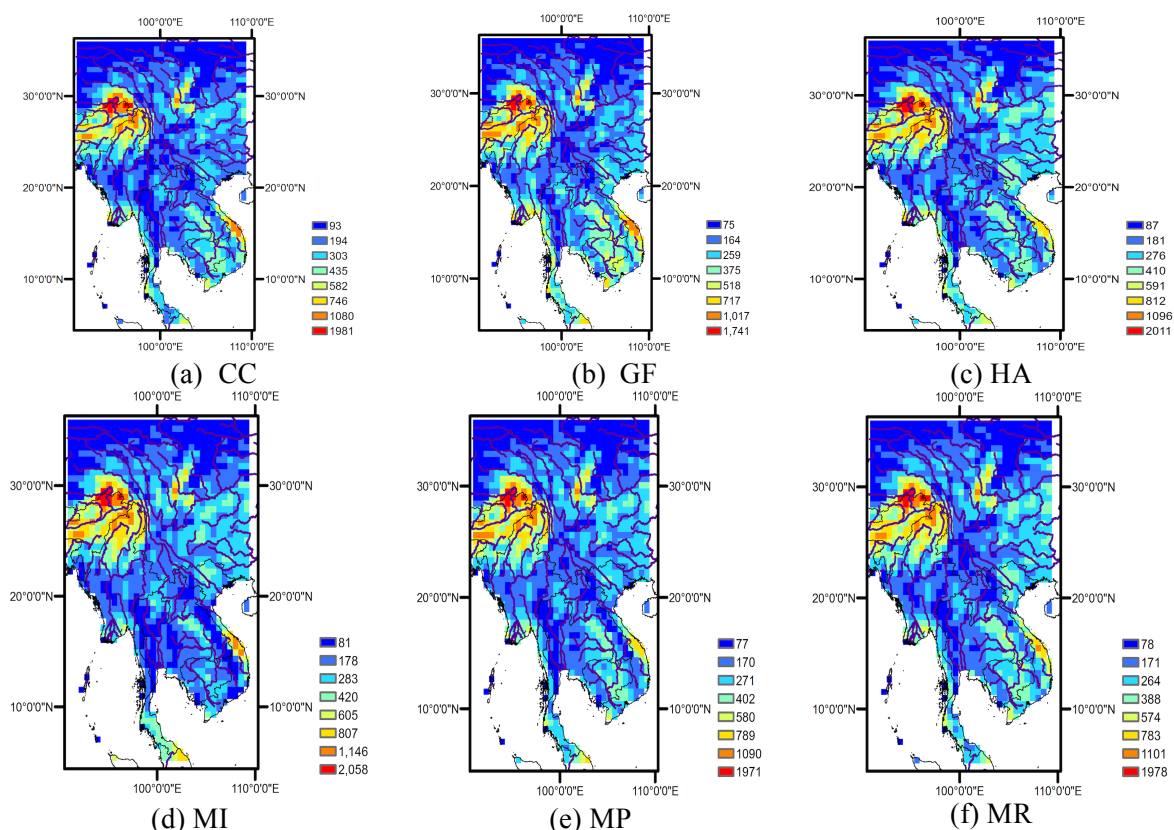


Figure C-12 The future Average Annual ROF in mm, under six SST warming patterns: (a) CC, (b) GF, (c) HA, (d) MI, (e) MP and (f) MR

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APPENDIX D: sample program for GCMs data handling

D-1 d4PDF data extraction: Present climate experiment (HPB)

```
#!/bin/sh

startYear=1951
endYear=2010
startMonth=1
endMonth=12
XDEF=640
YDEF=320
xxtar=152.8906 # yytar is longitude of target area for extracting the area
yytar=-25.0 # xxtar is latitude of target area for extracting the area
xxerror=100000000
yyerror=100000000

lon=()
for (( xlon=0 ; xlon<XDEF ; xlon++))
do
    test=`echo "scale=5; (($xlon * 0.56250))" | bc`
    lon=("${lon[@]}" $test)
done

lat=()
iii=0
while read line
do
    for ((ii=1 ; ii<=5 ; ii++))
    do
        cutlat=`echo $line | cut -d ' ' -f $ii`
        lat=("${lat[@]}" "$cutlat"+90.0)
        iii=$((iii+1))
    done
done < d4PDF_global_lat.txt # this file is written the latitude in d4PDF global.

yytarnew=`echo "scale=5; ($yytar"+90.0)" | bc`

#for (( nx=0 ; nx<XDEF ; nx++))
#do
#    xxtest=`echo "scale=5; ((${lon[$nx]} - "$xxtar"))" | bc`
#    xxtestint=`echo "$xxtest"*100000/1 | bc`
#    absxx=`echo "sqrt("$xxtestint"^2)" | bc`
#    xxerror=$(echo "$xxerror" | bc)
#    if [ "$xxerror" -gt "$absxx" ]
#    then
#        nxtar=$nx
#        xxerror=$absxx
#    fi
#done
#echo $nxtar

#for (( ny=0 ; ny<YDEF ; ny++))
#do
#    yytest=`echo "scale=5; ((${lat[$ny]} - "$yytarnew"))" | bc`
#    yytestint=`echo "$yytest"*100000/1 | bc`
#    absyy=`echo "sqrt("$yytestint"^2)" | bc`
#    yyerror=$(echo "$yyerror" | bc)
#    if [ "$yyerror" -gt "$absyy" ]
```

```

#      then
#          nytar=$ny
#          yyerror=$absyy
#      fi
#done
#echo $nytar

# set cutting area using sell number. In this case the xl, xr, yb, and yt are for the Indochina Peninsula. Please change the number
# accordingly to each targeted area.
xl=162 # xl is number of left (west) side for cutting area. (the number of left (west) longitude, however this is not degree)
xr=194 # xr is number of right (east) side for cutting area. (the number of right (east) longitude, however this is not degree)
yb=169 # xb is number of bottom (south) side for cutting area. (the number of bottom (south) latitude, however this is not
# degree)
yt=223 # yt is number of top (north) side for cutting area. (the number of top (north) latitude, however this is not degree)

if [ -e CutAreaLongitude.dat ]
then
    echo warning!! this file exists!!
else
    touch CutAreaLongitude.dat
    for (( nx=$xl; nx<=$xr; nx++))
    do
        echo "${lon[$nx]}" >> CutAreaLongitude.dat
    done
fi

if [ -e CutAreaLatitude.dat ]
then
    echo warning!! this file exists!!
else
    touch CutAreaLatitude.dat
    for (( ny=$yb; ny<=$yt; ny++))
    do
        latnew=`echo "scale=5; ((${lat[$ny]}"-90.0))" | bc`
        echo "$latnew" >> CutAreaLatitude.dat
    done
fi

# "grib"data starts from (1,1), not (0,0). so, the number of grid point should need to do "+1" for "nxstar" and "nytar".
# therefore, xl, xr, yb and yt are done "+1".

# In this case xl, xr, yb, and yt are for the Indochina Peninsula. Please change these numbers accordingly to each targeted area.
xl=163 # xl is number of left (west) side for cutting area. (the number of left (west) longitude, however this is not degree)
xr=195 # xr is number of right (east) side for cutting area. (the number of right (east) longitude, however this is not degree)
yb=170 # xb is number of bottom (south) side for cutting area. (the number of bottom (south) latitude, however this is not
# degree)
yt=224 # yt is number of top (north) side for cutting area. (the number of top (north) latitude, however this is not degree)

for (( en=1 ; en<=100 ; en++)) # Future d4PDF ensemble analysis ranging from ensemble number = 101 to ensemble
# number = 115
do
    if [ "$en" -lt 10 ]
    then
        nam=00${en}
    elif [ "$en" -lt 100 ]
    then
        nam=0${en}
    else
        nam=${en}
    fi

    for (( year=startYear ; year<=endYear ; year++))
    do
        for (( mon=startMonth ; mon<=endMonth ; mon++))
        #
        #      then
        if [ "$mon" == 1 ] || [ "$mon" == 3 ] || [ "$mon" == 5 ]

```



```

#           tday = 31
#       elif [ "$mon" == 7 ] || [ "$mon" == 8 ] || [ "$mon" == 10 ] || [ "$mon" == 12 ]
#           then
#               tday = 31
#           elif [ "$mon" == 4 ] || [ "$mon" == 6 ] || [ "$mon" == 9 ] || [ "$mon" == 11 ]
#               then
#                   tday = 30
#       elif [ `echo "$year%4" | bc -eq 0` ] && [ "$mon" == 2 ]
#           then
#               tday = 29
#           else
#               tday = 28
#       fi
#   done
#       fname="I:/gluster2/data/d4PDF/global/original/HFB_4K_CC_m"${nam}"/" # Set the
directory that folder of d4PDF in SOUSEI server is mounted
#       fname="I:/gluster2/data/d4PDF/global/original/HFB_4K_"${sst}"_m"${nam}"/" # Set the directory that folder of
d4PDF in SOUSEI server is mounted
#       fname="I:/gluster2/data/d4PDF/global/original/HPB_m"${nam}"/" # Set the directory that folder of d4PDF in
SOUSEI server is mounted
#       fname="/d4PDF_output_test/test2/HPB/" # Set the directory that some data is written

#       if [ "$mon" -lt 10 ]
#           then
#               month=0${mon}
#           else
#               month=${mon}
#           fi
#       fname=$fname${year}${month}
#       echo $fname

#       cdo sifon $fname"/sfc_avr_mon_HFB_4K_CC_m101_"${year}${month}.grib # you may need to
carry out this line to make sure variable name (the variable name which is included in the grib data on terminal as "parameter
name") that you use and can make sure corresponding variable by checking variable number on control file.

#       cdo -f nc4 selindexbox,$xl,$xr,$yb,$yt
$fname"/precipi_avr_1hr_HPBB_m"${nam}"_"${year}${month}.grib
$fname"/netcdf/precipi_avr_1hr_"${year}${month}"_m"${nam}.nc # convert from grib to netcdf
#       cdo selname,var255 $fname"/netcdf/precipi_avr_1hr_"${year}${month}"_m"${nam}.nc
$fname"/netcdf/precip/precipi_avr_1hr_"${year}${month}"_m"${nam}"_pr".nc # select variable (e.g. "var255" is TA
(temperature) on "sfc_avr_mon...")
#       cdo output,
$fname"/netcdf/precip/precipi_avr_1hr_"${year}${month}"_m"${nam}"_pr".nc >
$fname"/dat/precip/precipi_avr_1hr_"${year}${month}"_m"${nam}"_pr".dat # convert from netcdf to ascii, ascii file will
be written on a directory same as netcdf file in this setting, however you can change it
#       done
done
done
done

```

D-2 d4PDF data extraction: Future climate experiment (HFK)

```
#!/bin/sh

startYear=2051
endYear=2110
startMonth=1
endMonth=12
XDEF=640
YDEF=320
xxtar=152.8906 # yytar is longitude of target area for extracting the area
yytar=-25.0 # xxtar is latitude of target area for extracting the area
xxerror=100000000
yyerror=100000000

lon=()
for (( xlon=0 ; xlon<XDEF ; xlon++))
do
    test=`echo "scale=5; (($xlon * 0.56250))" | bc`
    lon=("${lon[@]}" $test)
done

lat=()
iii=0
while read line
do
    for ((ii=1 ; ii<=5 ; ii++))
    do
        cutlat=`echo $line | cut -d ' ' -f $ii`
        lat=("${lat[@]}" "$cutlat"+90.0)
        iii=$((iii+1))
    done
done < d4PDF_global_lat.txt # this file is written the latitude in d4PDF global.

yytarnew=`echo "scale=5; ($yytar+90.0)" | bc`

#for (( nx=0 ; nx<XDEF ; nx++))
#do
#    xxtest=`echo "scale=5; (($lon[nx]]-"$xxtar))" | bc`
#    xxtestint=`echo "$xxtest"*100000/1 | bc`
#    absxx=`echo "sqrt("$xxtestint"^2)" | bc`
#    xxerror=$(echo "$xxerror" | bc)
#    if [ "$xxerror" -gt "$absxx" ]
#    then
#        nxtar=$nx
#        xxerror=$absxx
#    fi
#done
#echo $nxtar

#for (( ny=0 ; ny<YDEF ; ny++))
#do
#    yytest=`echo "scale=5; (($lat[ny]]-"$yytarnew))" | bc`
#    yytestint=`echo "$yytest"*100000/1 | bc`
#    absyy=`echo "sqrt("$yytestint"^2)" | bc`
#    yyerror=$(echo "$yyerror" | bc)
#    if [ "$yyerror" -gt "$absyy" ]
#    then
#        nytar=$ny
#        yyerror=$absyy
#    fi
#done
#echo $nytar
```

set cutting area using sell number. In this case the xl, xr, yb, and yt are for the Indochina Peninsula. Please change the number accordingly to each targeted area.

xl=162 # xl is number of left (west) side for cutting area. (the number of left (west) longitude, however this is not degree)
 xr=194 # xr is number of right (east) side for cutting area. (the number of right (east) longitude, however this is not degree)
 yb=169 # xb is number of bottom (south) side for cutting area. (the number of bottom (south) latitude, however this is not degree)
 yt=223 # yt is number of top (north) side for cutting area. (the number of top (north) latitude, however this is not degree)

```
if [ -e CutAreaLongitude.dat ]
then
    echo warning!! this file exists!!
else
    touch CutAreaLongitude.dat
    for (( nx=$xl; nx<=$xr; nx++))
    do
        echo "${lon[$nx]}" >> CutAreaLongitude.dat
    done
fi

if [ -e CutAreaLatitude.dat ]
then
    echo warning!! this file exists!!
else
    touch CutAreaLatitude.dat
    for (( ny=$yb; ny<=$yt; ny++))
    do
        latnew=`echo "scale=5; ((${lat[$ny]}"-90.0)" | bc`
        echo "$latnew" >> CutAreaLatitude.dat
    done
fi
```

"grib" data starts from (1,1), not (0,0). so, the number of grid point should need to do "+1" for "nxstar" and "nytar".
 # therefore, xl, xr, yb and yt are done "+1".

In this case xl, xr, yb, and yt are for the Indochina Peninsula. Please change these numbers accordingly to each targeted area.
 xl=163 # xl is number of left (west) side for cutting area. (the number of left (west) longitude, however this is not degree)
 xr=195 # xr is number of right (east) side for cutting area. (the number of right (east) longitude, however this is not degree)
 yb=170 # xb is number of bottom (south) side for cutting area. (the number of bottom (south) latitude, however this is not degree)
 yt=224 # yt is number of top (north) side for cutting area. (the number of top (north) latitude, however this is not degree)

```
for (( case=3 ; case <=3 ; case++)) # type of Sea Surface Temperature Patterns in d4PDF MRI-AGCM 3.2H
do
    if [ "$case" = 1 ]
    then
        sst="CC"
    elif [ "$case" = 2 ]
    then
        sst="GF"
    elif [ "$case" = 3 ]
    then
        sst="HA"
    elif [ "$case" = 4 ]
    then
        sst="MI"
    elif [ "$case" = 5 ]
    then
        sst="MP"
    elif [ "$case" = 6 ]
    then
        sst="MR"
    else
        echo Your SST pattern is not available. Please change it to the d4PDF format!!
    fi
done
```

```

for ((en=111 ; en<=115 ; en++)) # Future d4PDF ensemble analysis ranging from ensemble number = 101 to ensemble
number = 115
do
    if [ "$en" -lt 10 ]
    then
        nam=00${en}
    elif [ "$en" -lt 100 ]
    then
        nam=0${en}
    else
        nam=${en}
    fi

    for (( year=startYear ; year<=endYear ; year++))
    do
        for (( mon=startMonth ; mon<=endMonth ; mon++))
        if [ "$mon" == 1 ] || [ "$mon" == 3 ] || [ "$mon" == 5 ]
        then
            tday = 31
        elif [ "$mon" == 7 ] || [ "$mon" == 8 ] || [ "$mon" == 10 ] || [ "$mon" == 12 ]
        then
            tday = 31
        elif [ "$mon" == 4 ] || [ "$mon" == 6 ] || [ "$mon" == 9 ] || [ "$mon" == 11 ]
        then
            tday = 30
        elif [ `echo "$year%4" | bc -eq 0` ] && [ "$mon" == 2 ]
        then
            tday = 29
        else
            tday = 28
        fi
        do
            # filename="/gluster2/data/d4PDF/global/original/HFB_4K_CC_m"${nam}"/" # Set the
            directory that folder of d4PDF in SOUSEI server is mounted
            filename="/gluster2/data/d4PDF/global/original/HFB_4K_"${sst}"_m"${nam}"/" # Set the directory that folder of
            d4PDF in SOUSEI server is mounted
            # filename="/gluster2/data/d4PDF/global/original/HPB_m"${nam}"/" # Set the directory that folder of d4PDF in
            SOUSEI server is mounted
            filename="/d4PDF_output_test/test2/" # Set the directory that some data is written

            if [ "$mon" -lt 10 ]
            then
                month=0${mon}
            else
                month=${mon}
            fi
            filename=$filename${year}${month}
            echo $filename

            # cdo sinfon $filename"/sfc_avr_mon_HFB_4K_CC_m101_"${year}${month}.grib # you may need to
            carry out this line to make sure variable name (the variable name which is included in the grib data on terminal as "parameter
            name") that you use and can make sure corresponding variable by checking variable number on control file.

            cdo -f nc4 selindexbox,$x1,$xr,$yb,$yt
            $filename"/precipi_avr_1hr_HFB_4K_"${sst}"_m"${nam}"_"${year}${month}.grib
            $filename"/netcdf/precipi_avr_1hr_"${sst}"_"${year}${month}"_m"${nam}.nc # convert from grib to netcdf
            cdo selname,var255
            $filename"/netcdf/precipi_avr_1hr_"${sst}"_"${year}${month}"_m"${nam}.nc
            $filename"/netcdf/precip/precipi_avr_1hr_"${sst}"_"${year}${month}"_m"${nam}"_pr".nc # select variable (e.g. "var255" is
            TA (temperature) on "sfc_avr_mon..."
            cdo output,
            $filename"/netcdf/precip/precipi_avr_1hr_"${sst}"_"${year}${month}"_m"${nam}"_pr".nc >
            $filename"/dat/precip/precipi_avr_1hr_"${sst}"_"${year}${month}"_m"${nam}"_pr".dat # convert from netcdf to ascii,
            ascii file will be written on a directory same as netcdf file in this setting, however you can change it

        done
    done
done

```

done

D-3 d4PDF data arrangement from text into 4-byte Binary format

```

#include <iostream>
#include <iomanip>
#include <fstream>
#include <math.h>
#include <stdio.h>
#include <stdlib.h>
#include <string>

using namespace std;

//definition of the function
int main()
{
    //      int startEnsemble_future = 101 ;
    //      int endEnsemble_future  = 115 ;
    //      int startYear      = 2051 ;
    //      int endYear        = 2100 ;
    //      int startMonth     = 1   ;
    //      int endMonth       = 12  ;
    //      int Col            = 33  ;
    //      int Row            = 55  ;
    // const int startFolNum   = 4    ;
    //      const int endFolNum           = 15    ;
    //      const int startEnsemble_future = 3    ;
    //      const int endEnsemble_future  = 15    ;
    //      const int startYear      = 1951 ;
    //      const int endYear        = 2010 ;
    //      const int startMonth     = 1   ;
    //      const int endMonth       = 12  ;
    //      const int Col            = 33  ;
    //      const int Row            = 55  ;
    //  int dayMonth[] = {31, 28, 31, 30, 31, 30, 31, 31, 30, 31, 30, 31};
    //      float data ;
    //      char IOFfilename[256] ;
    //      char IWOFFilename[256] ; // For writing Ascii file
    //      char IWBOFFilename[256] ; // For writing Binary file
    //      ifstream inFile;
    //      ofstream outFile;
    //      float lat[Row] ; // latitude coordinates matrices (Y).
    //      float lon[Col] ; // longitude coordinates matrices (X).

    // to check whether we get the right domain for climate data. (Patinya)
    ifstream finlat("./CutAreaLatitude.dat") ; // Latitude file
    ifstream finlon("./CutAreaLongitude.dat") ; // Longitude file
    if(!finlat){
        cout << "latitude file cannot be opened."; // if the program can not find the latitude file.
        exit(1);
    }
    if(!finlon){
        cout << "longitude file cannot be opened."; // if the program cannot find the longitude file.
        exit(1);
    }

    for(int nx = 0; nx < Col; nx++){
        finlon >> lon[nx] ;
    }

    for(int ny = 0; ny < Row; ny++){
        finlat >> lat[ny] ;
    }
}

```

```

for(int ensemble = startEnsemble_future; ensemble <= endEnsemble_future; ensemble++){
    for(int year = startYear; year <= endYear; year++){
        int dayMonth[] = {31, 28, 31, 30, 31, 30, 31, 31, 30, 31, 30, 31};
        for(int month = startMonth; month <= endMonth; month++){
            if( month < 10 ){
                //          sprintf(IOFfilename,
                //          "/sample/precipi_avr_1hr_%4d0%d.dat",year,month);
                //          sprintf(IWOFfilename, "/dat/precipi_avr_1hr_%4d0%d.dat",year,month);
                //          sprintf(IWBOFfilename,
                //          "/dat/precipi_avr_1hr_%4d0%d.bin",year,month);
                sprintf(IOFfilename,
                "/m%03d/precipi_avr_1hr_%4d0%d_m%03d_pr.dat",ensemble,year,month,ensemble);    // For ASCII input format
                //          sprintf(IWOFfilename,
                //          "/dat/CC/sfc_avr_3hr_CC_%4d0%d_m%03d_rof.dat",year,month,ensemble);    // For ASCII output format
                sprintf(IWBOFfilename,
                "/bin/HPB/precipi_avr_1hr_%4d0%d_m%03d_pr.bin",year,month,ensemble);    //For Binary output format
            }
            else{
                //          sprintf(IOFfilename,
                //          "/sample/precipi_avr_1hr_%4d%2d.dat",year,month);
                //          sprintf(IWOFfilename, "/dat/precipi_avr_1hr_%4d%2d.dat",year,month);
                //          sprintf(IWBOFfilename,
                //          "/dat/precipi_avr_1hr_%4d%2d.bin",year,month);
                sprintf(IOFfilename,
                "/m%03d/precipi_avr_1hr_%4d%2d_m%03d_pr.dat",ensemble,year,month,ensemble);    // For ASCII input format
                //          sprintf(IWOFfilename,
                //          "/dat/CC/sfc_avr_3hr_CC_%4d%2d_m%03d_rof.dat",year,month,ensemble);    // For ASCII output format
                sprintf(IWBOFfilename,
                "/bin/HPB/precipi_avr_1hr_%4d%2d_m%03d_pr.bin",year,month,ensemble);    //For Binary output format
            }
            ifstream fin(IOFfilename); // declaring the input file
            if(!fin){
                cout << "Cannot open IOF file";
                exit(1);
            }

            ofstream fout(IWOFfilename); // declaring the output file
            outFile(IWBOFfilename, ios::out | ios::binary);

            if(month==2) dayMonth[1] = 28 + (1 / (year % 4 + 1)) * (1 - 1 / (year % 100 + 1)) +
            (1 / (year % 400 + 1));

            int nxy = 0 ;
            //          fout << "\t" << "\t" << "\t" << "Longitude" << "\t" ; // format arrangement of
            //          longitude.

            for( int nlat = 0 ; nlat < Row ; nlat ++ ){
                //          Col = 33, Row = 55

                for( int nlon = 0 ; nlon < Col ; nlon ++ ){
                    nxy += 1 ;
                    if( nxy < Row * Col ){
                        //          fout << lon[nlon] << "\t" ; // lon coordinates from
                        //          southwestern grid in eastward direction. Each value is separated with one tab space.
                    }
                    else{
                        //          fout << lon[nlon] << endl ; // end of the old line. Then,
                        //          going to the new line
                    }
                }
            }

            nxy = 0 ;
            //          fout << "\t" << "\t" << "\t" << "Latitude" << "\t" ;
            for( int nlat = 0 ; nlat < Row ; nlat ++ ){
                for( int nlon = 0 ; nlon < Col ; nlon ++ ){
                    nxy += 1 ;
                    if( nxy < Row * Col ){

```

```

//                                fout << lat[nlat] << "\t" ; // lat coordinates from
southwestern grid in northward direction. Each value is seperated with one tab space.
                                }
                                else{
//                                fout << lat[nlat] << endl ;
                                }
                                }
                                }

for( int day = 1 ; day <= dayMonth[month-1] ; day++){
for( int hour = 0 ; hour <24 ; hour++){ // hourly precipitation
// for( int hour = 0 ; hour < 8 ; hour++){ // 3-hourly total runoff
nxy = 0 ;
// fout << year << "\t" << month << "\t" << day << "\t" << hour + 1
<< "\t" ; // write year month day and hour. each one is separated by one tab space.
for(int nlat = 0 ; nlat < Row ; nlat++){ // Col=33, Row = 55
for(int nlon = 0 ; nlon < Col ; nlon++){
nxy += 1 ;
fin >> data ;
if( nxy < Row * Col ){
fout << data << "\t" ;
}
else{
fout << data << endl ;
}
}
outFile.write((char*)&data, sizeof(float));
}
}
}
}
outFile.close();
} // month
} // year
} // ensemble
} // end of main program

```