Project Progress Report[1]

(Final Year)

Project Reference Number: CRRP2018-06MY-Yanto

Project Title: Understanding Space-Time Variability of Climate Extremes for Societal Resiliency in Indonesia and India

[1] Remarks: Project progress report is required for all continuing multi-year projects, in lieu of the final project report. For completed projects, the APN Secretariat will provide a project review questionnaire (PRQ) before the official closure of the project contract.

Understanding Space-Time Variability of Climate Extremes for Societal Resiliency

1. Project information

1.1 Project duration

The project duration is 2 years (The project started from 1 October 2018 and should be completed by 30 September 2020) – extended 1 year to 30 September 2021

1.2 Funding, collaborators and key organizations involved

The project funding and in-kind support are listed below:

- APN Grant: US$ 72,315
- Jenderal Soedirman University in-kind contribution: US$ 12,000
- University of Colorado in-kind contribution: US$ 14,000
- Indian Institute of Technology in-kind contribution: US$ 10,000
- National Board for Disaster Countermeasure of Indonesia in-kind contribution: US$ 8,000

The investigators of the project are listed below:

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2. Project summary

This project were designed to provide applicable information on hydroclimate extremes variability in space and time useful for policy development and capacity building to enhance societal resiliency to floods and droughts. The project has four broad objectives:

- analyze the space-time variability of extreme rainfall and temperature events and, the large scale climate drivers in the ocean-atmosphere-land system that drive control their variability,
- translate these understandings to hydrologic variability in space and time,
- investigate the variability of climate and hydrologic extremes in a warmer climate, identify existing systems for managing floods and droughts in urban, agriculture and water resources management contexts – and,
- develop strategies for adaptation and mitigation of hydroclimate extremes; also develop a simple visualization tool to assist decision makers relating hydrologic extremes and societal resiliency.

This approach will be developed at two representative study regions - Serayu River Basin in Indonesia and Krishna River Basin in India.

In this reporting period, in accordance with the proposed activities and logical framework matrix, we have obtained an understanding on spatial and temporal variability of rainfall and temperature in the study area. Some results have been presented in the EGU Conference on 7 – 12 April 2019, in the Workshop and focus group discussion (FGD) in Hyderabad, India on 7 – 8 January 2020 and in Purbalingga, Indonesia on 9 – 12 August 2021. The manuscript for publication has been reformatted to take into account inputs from river basin stakeholders.

The project's current status:

X Complete

☐ Proceeding according to work plan and logical framework matrix

☐ Ahead of schedule

☐ Behind schedule

☐ Proceeding with some modifications (Please specify):.

2.1 Scientific finding

2.1.1 Societal information related to hydroclimatic extremes in Serayu and Krishna river basin

1. Summary

This study part aims to appraise the need level of watershed management stakeholders on climate information. Two watersheds are selected as the case, Serayu River Basin (SRB) in Indonesia and Krishna River Basin (KRB) in India. Evaluation was done based on the available climate information, level of interest, level of knowledge and level of engagement of the stakeholders. The data was gathered from workshop and focus group discussion that held in KRB and SRB with different approach. In KRB, FGD participant were given a specific topic without guided questions, while in SRB, guided questions were provided to the participants. The result shows that climate information is available at country level in Indonesia, but at diverse levels in India. Moreover, it is observed that the stakeholders exhibit great interest on the climate-impacts rather than climate information, except it is requested. It can also be noticed that the level of knowledge and engagement on climate information is low to medium in both watersheds. Accordingly, it is suggested that climate information at lower administrative level needs to be developed in Indonesia. Moreover, more efforts are required to provide better understanding on the role of climate on drought.

2. Background

In recent decades, scientists all around the world have struggled to develop climate forecasting model to response the sensed impact of heating earth surface on human life (Aryal et al., 2019; Huang et al., 2014; Song et al., 2020; Spinoni et al., 2020; Tabari, 2020; Verschuur et al., 2021; Yanto et al., 2016). Numerous models have been elaborated ranging from conceptual model, mathematical model, statistical model, computer model to physical model (Katz et al., 2002; Lazoglou et al., 2019; Nguyen-Huy et al., 2017; Rathinasamy et al., 2019; Regonda et al., 2013; Sutanto et al., 2020; Tan et al., 2016; Verdin et al., 2015; Yanto, Livneh, Rajagopalan, et al., 2017). The goal is to understand physical mechanism of interaction between warming climates and various aspects of life and environments including temperature, precipitation, streamflow, water quality, air quality, human health, disaster, etc (Doherty et al., 2017; C. Hong et al., 2019; Martius et al., 2020; Radhapyari et al., 2021). It is expected that the proper understanding on how the climate and natural systems work can be brought into planning and design of mitigation and adaptation strategies to minimize the impacts on human and environment.

Many studies suggest that the earth's warming process is unlikely stoppable but the heating rate can be slowed down (Martinich et al., 2018; Steffen et al., 2018). Moreover, the impacts of the global warming can vary in space, where some regions will be wetter and some others will be drier (Arnell et al., 2019). Drought and flood are two primary disasters anticipated due to climate change (Schiermeier, 2018; Wetherald & Manabe, 2002). A range of mitigation and adaptation strategies have been proposed to alleviate the impacts (IPCC, 2014b, 2014a; Martinich et al., 2018; Pollner et al., 2010). It involves development of low-emission and low-energy technology, less water irrigation system, flood early warning system and climate information system (IPCC, 2014a). To make the strategies useful, translation into climate policies, programs and actions is prerequisite.

To combat climate change impacts, the United Nation has set Sustainable Development Goals (SDGs) under Goal 13[2]. Low-income and least developed countries are priority target for this goal as they suffer more serious impacts compared to the middle-income and developed countries due to the constraints on economy, social, technology and culture (Miyan, 2015). In the SDG 13, each country is expected to develop national strategies to reduce disaster risks using natural resources to enhance human security[3]. To do this, disaster risk management is required. Moreover, to make an efficient disaster risk management, implementation of mitigation and adaptation strategies at low management level is compulsory.

As drought and flood are climate-triggered disasters, climate information plays an important role in the implementation of a better disaster risk management (Hellmuth et al., 2011; Pollner et al., 2010). For planning and design of mitigation and adaptation strategies, hence, truthful climate forecast is requisite. Due to region-specific characteristics of drought and flood, local climate forecast is sought. Unfortunately, nearly 100 countries undertake deficient climate information, forecast and early warning, particularly in the developing and least developed countries[4,5].

An effective governance is a key component in translating climate information into a policy. However, government itself is not sufficient to build an operative policy. Engagement of multi-stakeholders is vital in the climate-related policy making processes. Unfortunately, there is a gap between stakeholder's engagement and the recent knowledge on climate (Khatibi et al., 2021). Since the relationship between public knowledge and their engagement in the climate policy making processes is strong, enriching people with better knowledge on climate will enhance their engagement and subsequently succeed the climate policy planning, design and implementation (Creasy et al., 2007; Wibeck, 2014). To supply an appropriate climate information in a certain place, assessment of the existing climate information and public knowledge is needed (Scheraga & Furlow, 2012).

This paper presents a systematic study to evaluate the available climate information and the level of interest, knowledge and engagement of climate-related policy stakeholders in two developing countries, Indonesia and India. The study was conducted at watershed level as drought and flood are hydrometeorological disasters associated with hydrological processes within a basin. Some key findings are elaborated and some recommendations are proposed.

[2] https://sdgs.un.org/goals
[3] https://sdgs.un.org/topics/national-sustainable-development-strategies
[4] https://borgenproject.org/weather-prediction-technology/
[5] https://reliefweb.int/report/world/new-study-shows-socio-economic-benefits-weather-observations

3. Methodology

Data collection

The first step in data collection is identifying relevant stakeholders in the watersheds with respect to the climate-induced natural disasters. The second step is investigating the primary natural disaster types in each state for KRB and regency for SRB. This is done as many agencies responsible for the natural disasters are under separate administration. The key data to assess the existing climate information and the level of stakeholder's interest, knowledge and engagement were collected through a workshop and focus group discussion (FGD). For climate information, additional websites were reviewed to get the data.

Workshop and Focus Group Discussion

The workshop and FGD were organized as a series of activities to obtain the designated information. In the workshop, several speakers were invited to provide principal information on the climate related topics, whereas in the FGD, participants, which are stakeholders of the watersheds were asked to elaborate their knowledge and opinion on the issues related to their main duties. This activity was conducted in both watersheds, KRB and SRB. In KRB, the workshop and FGD was conducted in person for 2 full days, while in SRB, it was done online for 4 half-days (workshop in the day 1 and 3, FGD in the day 2 and 4) due to the Covid-19 pandemic situation. In KRB, participants were divided into 3 (three) groups to discuss the existing vulnerability and resiliency of the system as well as drawing new mitigation measures and strategies to increase resiliency to deal with climate extremes in the river basin. There was no guided questions given to the participants. On the other hand, in SRB, participants were divided into 2 groups per day whereby each group was guided with climate related questions

During the workshop in KRB and SRB, a broad range of climate and watershed management topics was presented including spatial and temporal variability of hydroclimate extremes and their relationship with global climate, weather forecast, climate forecast, flood and drought risk assessment as well as applicable policy in each watershed. The speakers invited in the workshop extends from local level (e.g. water manager, domestic water supply company) to national level (e.g. Central Water Commission of India, National Agency for Disaster Countermeasure of Indonesia) to world level scientists from the University of Colorado, Boulder, USA and World Bank.

Stakeholders invited in the workshop and FGD represent diverse components of watershed management. Table 1 summarize the organizations participating in the workshop and FGD for KRB and SRB

Table 1. Stakeholders invited into the workshop and FGD in SRB and KRB

Serayu River Basin	Krishna River Basin
• Serayu Opak River Basin Agency • Serayu Citanduy Water Resources Management Agency • Indonesian Agency for Meteorological, Climatological and Geophysic • Jenderal Soedirman University • Agricultural Agency of Purbalingga, Banyumas and Cilacap • Regional Disaster Countermeasure Agency of Wonosobo and Purbalingga • Farmer Association for Irrigation Water User of Banyumas • Public Works Agency of Purbalingga and Banyumas • Municipal Water Company of Banyumas and Cilacap • Energy and Mineral Resources Agency of the Middle Serayu	• Indian Institute of Technology Hyderabad • Central Water Commission of India • SaciWATERs • Indian Meteorological Department • Institute for Social and Economic Change • Krishna River Management Board • Telangana State Irrigation Department • Danish Hydraulic Institute • Advanced Centre for Integrated Water Resources Management • Osmania University • Maharasthra Irrigation Department • International Crops Research Institute for the Semi-Arid Tropics • Vassar Labs

Data analysis
The data collected during the FGD is analysed descriptively and qualitatively. Information acquired from the FGD is grouped according to the topic similarity. Existing climate information, level of interest, level of knowledge and level of engagement will be analysed from notes, recordings and recommendations collected during the FGD.

4. Results and Discussion

Climate information
Indonesian Agency for Meteorological, Climatological and Geophysic/Badan Meteorologi, Klimatologi dan Geofisika (BMKG) is a non-departmental government agency responsible for managing climate and weather data and information in Indonesia. BMKG publishes climate information in the form of map. The information contained in the map are number of days without rain, monthly precipitation, seasonal onset, monthly available water for plant and annual precipitation anomaly. Moreover, BMKG also provides climate forecast for monthly and annual precipitation, while weather forecast is available for daily, 3-daily and weekly time scale. In term

of climate impact, BMKG also supplies monthly flood and meteorological drought forecast. All climate information and forecast supplied by BMKG are available at country scale. There is no separate climate information and forecast on the province, regency and watershed level. In addition, some maps can be downloaded in the form of jpg/pdf file format. Detail information can be found in http://www.bmkg.go.id, http://wis.bmkg.go.id, and http://cews.bmkg.go.id.

Likewise, Indian Meteorological Department (IMD) is the government department responsible for managing climate and weather data and information of India. The climate information provided by IMD is quite similar to BMKG with some additional features. For example, IMD provides weather nowcasting (few hours), which is not available in Indonesia. Moreover, the information published by IMD cover several spatial scales: location, block, district, meteorological sub-division, river catchment, state and homogeneous regions. This includes forecast on drought and flood. The substantial works of IMD can be followed in https://mausam.imd.gov.in/.

Level of engagement

Around 30 people participating in each FGD representing various sectors of stakeholders from different management levels, scientists and companies. The FGD ran smoothly with all participants contributed in the discussion to explore issues, problems and experiences they have, indicating high enthusiasm. However, the level of engagement of the stakeholders is different. Some are dominant than others, as commonly happened in many group discussions.

Topics of interest and level of knowledge

It has been widely recognized that people tend to talk much on what they are interested (Ward, 2013). Moreover, people will talk more on the topic they know better (Searle, 1969; Tanner et al., 2015). This can be used to subjectively rate the level of interest and knowledge of the stakeholders of KRB and SRB on climate information.

The result highlights 27 points of recommendation from 3 groups in the KRB discussion, consisting of 13, 6 and 8 points for Group 1, Group 2 and Group 3 respectively. Most of the points recommended from the FGD in KRB are related to drought, water allocation, water management and water infrastructure. This is relevant to the characteristic of KRB where water shortage is the main problem they are facing. We found only 1 recommendation on the climate related information. However, the recommendation is on the climate measurement equipment.

In SRB, the output of the FGD is not shaped as recommendation points, but in the discussion notes that underline key points of the discussion. The main issue delivered by the stakeholders are flood related infrastructure and management. This is pertinent to flood events frequently occurred in SRB. However, it is found that climate related issues are discussed during the FGD in SRB. It includes available climate and weather information, status of climate and weather measurement tools and the use of climate information for flood early warning. This is the result of guided questions given to the FGD participants. However, there is no record on the discussion related to the relationship of global climate with natural disaster events in the region.

From the two FGDs in KRB and SRB, it can be underscored several inferences: i) the stakeholders show high interest in the climate-stimulated natural disaster pertinent in their own areas; ii) the interest on climate information and forecast emerges when the stakeholders asked to discuss it specifically; iii) the level of knowledge on the disaster-related topics in their areas is high; iv) the level of knowledge on the climate information and forecast system is equivocal in KRB but low-medium in SRB

Key findings

Based on the data on climate information system in Indonesia and India from various sources and the workshop, exploration of climate related disasters, water management and water infrastructure in SRB and KRB, the following key findings are concluded:

(1) There is a rising need of climate information system at various levels in Indonesia. While the climate information system available for the entire territory of Indonesia, it is difficult to obtain information and data for specific areas. The operating agency at low level requires climate information provided by BMKG can be accessed in the spreadsheet or comma separate value format such that they can perform an analysis for the specific region they work on.
(2) There is a difference in the response of SRB and KRB stakeholders on the climate information system. Even though FGD participants in SRB were guided with questions on climate, it is found that even in the topic of the disaster mitigation measures, discussion on the climate information appeared. This can be inferred that flood-prone area is more sensitive to climate rather than drought-prone area. This can be rationalized as the impact of climate extreme on flood is direct, obvious and happen in a short time.
(3) There is a need to provide better understanding to people living in the drought-prone areas that global climate dynamics are influential to the drought events. Accordingly, climate information is required for both flood and drought management.

5. Conclusion

This study assesses the level of requirement of watershed management actors on the climate information system in SRB, Indonesia and KRB, India based on the available climate information, level of interest, knowledge and engagement of all relevant stakeholders. It is found that climate information is available at country scale in Indonesia, but not at lower administration levels. On the other hand, climate information is available at various spatial level in India. The level of interest, knowledge and engagement of the watershed stakeholders on the climate information is low to medium both in KRB and SRB. This suggests the development of climate information system at various levels in Indonesia and better understanding on the climate impact on drought in KRB, India.

2.1.2 Hydroclimatic extremes study in Serayu river basin

1. Summary

This study presents the benefit of Copula for modelling correlation of tropical sea surface temperature (SST) and hydroclimatic extremes in Serayu river basin, Indonesia. Precipitation and streamflow dataset from ground-based measurement and sea surface temperature dataset from National Oceanic and Atmospheric Administration (NOAA) extending from 1985 to 2017 were analyzed in this study. Principal Component Analysis (PCA) was employed to extract the leading principal components (PCs) that explain more than 50% of data variance. Linear model and Copula model were utilized to detect tropical regions having strong correlation with hydroclimatic extremes. Having these regions, Bayesian Dynamic Linear Model (BDLM) was used to scrutinize the role of regional SST in the tropical region. To understand further on the spatial pattern of hydroclimatic extremes, Self Organizing Map (SOM) approach was exploited. Moreover, to show the applicability of the understanding of relationship between tropical SST and hydroclimatic extremes in the study area and its potential impacts on societal resilience, Nonstationary Extreme Value Analysis (NEVA) was implemented along with the traditional stationary approach. The result suggests increasing trend of hydroclimatic extremes and decreasing tendency of seasonal extremes over the period of 1985 – 2014, signifying intense floods and droughts in the study area. Furthermore, while typical regions owing to have powerful link with hydroclimatic extremes are detected from linear model, different regions are produced by Copula model. This indicates the complementary of Copula model to linear model, partially due to the ability of Copula model in gathering marginal distribution of the joint variables. Additionally, the larger areas spotted from Copula model strengthen the inference of influence of El Nino Southern Oscillation (ENSO) and Indian Oscillation Dipole (IOD) on hydroclimatic extremes in tropical regions, such as the river basin in this study. Moreover, it is found that the association of hydroclimatic extremes and IOD is stronger after 2007 while opposite feature is observed on ENSO. Using SOM, it is revealed that the hydroclimatic extremes in the study area show comparable attributes. Furthermore, precipitation extremes in some locations possesses higher return level estimates from nonstationary analysis, implying the important of incorporating climate drivers into return level estimation in flood design. Similar results are found for streamflow return level estimation. Hence, it can be supposed that integrating climate drivers into flood design will generate safer water infrastructures and subsequently helpful to ensure societal resilience. These findings conclude the benefit of proposed methodology on hydroclimatic extremes analysis, and the method should be applicable for other regions.

2. Introduction

During the last 50 years, the number of hydroclimatic disasters over the world has increased fivefold, killed 115 people and caused US$ 202 million per day ((WMO), 2021). Out of the number, developing countries contribute to more than 91% of death, which relates to the contribution of hydrometeorological disasters to all types of disaster ((WMO), 2021). While hydrometeorological disasters account for 50% of all disasters at global scale, it constitutes 90% to all disasters in Indonesia ((WMO), 2021; BNPB, 2020). While the total number of death decreased almost threefold during the period of 1970-2019, the economic losses increased almost sevenfold (WMO, 2021). Unfortunately, developing and least developed countries are more vulnerable to the disasters than developed countries due to limitation in economy, technology, human resources and culture (Miyan, 2015). Hence, it is reasonable to emphasize study on disaster mitigation and adaptation in developing and least developed countries to lessen the impacts on human and environment.

Hydrometeorological disasters in the form of floods and droughts are associated with hydroclimatic extremes (Dadson et al., 2019; Maggioni & Massari, 2019; Marengo et al., 2021). While flood is an event where relatively high streamflow exceeds the river capacity (Y. Hong et al., 2013), drought is defined as a lack of precipitation over a prolonged time period (usually season), causing water deficiency (Lloyd-Hughes, 2013). It implies that floods and droughts are linked with hydroclimatic extremes at daily and seasonal time scale respectively. Moreover, it has been widely understood that precipitation and streamflow expose spatial and temporal variability over a regional domain (Cristiano et al., 2017; Dabar et al., 2021; Fischer et al., 2019; Yanto et al., 2016; Yanto, Livneh, & Rajagopalan, 2017). Thus, understanding the sources of variability of precipitation and streamflow is fundamental for scrutinizing hydrometeorological disaster, which is valuable for planning efficient mitigation and adaptation measures.

Global climate variables change has been widely known to affect extreme precipitation and streamflow (Arnell et al., 2019; Haslinger et al., 2014; Liu et al., 2021; Schiermeier, 2018; Tabari, 2020). As global climate gets warmer, the frequency of extreme precipitation increases extensively (Myhre et al., 2019). In Southeast Asia, seasonal hydroclimatic extremes are projected to increase with intensification occur at one season (Shrestha et al., 2021). Over Indonesia, daily precipitation intensity increased significantly in the period of 1983 – 2012 (Supari et al., 2017). Moreover, precipitation intensity of 200 mm return level in Jakarta is found to have shorter return period during the time period of 2000 – 2010 than preceding decades (Siswanto et al., 2016).

Many studies relating hydroclimatic extremes and global climate drivers depend on the linear correlation (Dabar et al., 2021; Supari et al., 2017; Tabari, 2020), where normality assumption is applied (Casson & Farmer, 2014). While linear trend of precipitation dominates in warmer climate accounting for 80%, there is still nonlinearity which needs to take into account (Kazemzadeh et al., 2021). In addition, hydroclimatic extremes are found to follow extreme value distribution which is highly dependent on the distribution tail (Bracken et al., 2016; Miniussi & Marani, 2020; Ossandón et al., 2021). Modeling relationship of multivariate extremes distribution – e.g. precipitation and temperature extremes – requires understanding on the joint probability of the marginal distribution (Tawn, 1990).

A copula is a function that couple multivariate distribution into one dimensional marginal distribution (Nelsen, 2006). Hence, it is promising to model the link of hydroclimatic extremes and its climate drivers. It has been employed to demonstrate connection between various hydroclimatic extremes variables such as temperature, precipitation and streamflow within a specific region (Chen et al., 2015; Miao et al., 2016; Pandey et al., 2018). Moreover, it has also been used to model linkage between seasonal precipitation in Australia and El Nino Southern Oscillation (ENSO) and Inter-decadal Pacific Oscillation (IPO) (Nguyen-Huy et al., 2017), Borneo fire-prone areas and ENSO (Najib et al., 2021), and monthly precipitation in Texas, USA with ENSO and Pacific Decadal Oscillation (PDO) (Khedun et al., 2014). However, application of this method for precipitation and streamflow extremes in Indonesia, which is sitting on the warm pool region, is absent, which is primary motivation of this study.

This study presents a systematic approach to show the advantage of Copula model in diagnosing the tropical climates driving spatial and temporal variability of hydroclimatic extremes – i.e. precipitation and streamflow. A case study on Serayu river basin, Indonesia is established. We are convinced that this procedure will provide better knowledge on the climate drivers of hydroclimatic extremes in a certain region, and should be applicable widely.

3. Study Area and Data

Serayu Watershed is located in the southern part of Java island stretching from Wonosobo Regency to Cilacap Regency (Figure 1). The watershed has drainage area of 3,383 km2 and the river has length of 180 km with 11 tributaries. In the south of the watershed is Indian Ocean and in the north is a mountainous array with elevation ranges from 0 to 2,500 masl. The center of watershed is relatively flat with steep slopes in the surroundings. This makes the center regions are more susceptible to flood while the perimeter regions are more vulnerable to landslide which instigated by precipitation extremes (Figure 1). The annual rainfall extends from 2,800 mm in the downstream and 4,000 mm in the upstream.

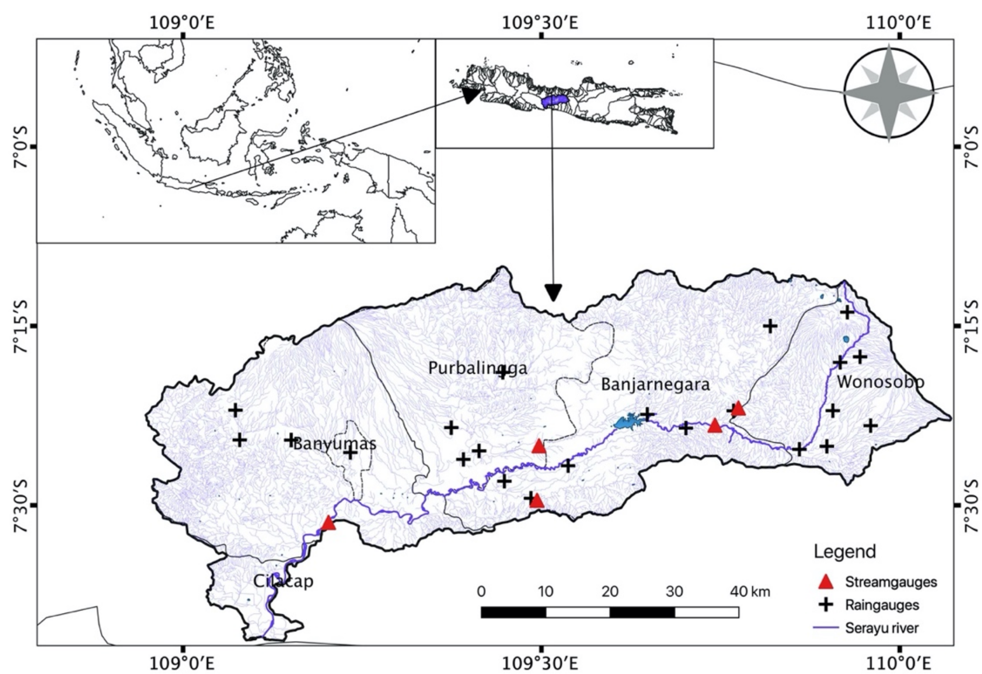


Figure 1. Serayu river basin along with location of rain gauges and stream gauges as well as regencies lie in within the basin.

Daily precipitation data from 22 rain gauges running from 1985 – 2014 were collected from the Center of Water Resources Research and Development, Ministry of Public Works, Indonesia as shown in black positive (+) sign (Figure 1). As shown in Figure 1, the stations spread across the entire watershed. However, there is no record in the most downstream of the watershed. Daily streamflow data were gathered from five stream gauges stretching from the upstream to the downstream of the Serayu river, marked with red triangle covering the period of 2007 to 2017. Monthly sea surface temperature (SST) over the tropical region (30° S to 30° N and 50° E to 50° W) at 1° x 1° spatial resolution was sourced from National Oceanic and Atmospheric Administration (NOAA) extending from 1985 to 2017 to mask the temporal coverage of precipitation and streamflow data (Reynolds et al., 2002). This is optimally interpolated SST from both in situ measurement and satellite products.

Three types of hydroclimatic extremes, annual maximum, dry season and wet season. In Indonesia, dry season is defined as the period of April to September, while wet season spans from October to March (Yanto et al., 2016). Table 2 presents statistical measures of the dataset including mean, range, standard deviation and variance. The range of streamflow is large as it covers streamflow data from upstream to downstream. Dry season has more variance in precipitation than wet season. Conversely, wet season streamflow dataset possess higher variance than dry season.

Table 2. Statistical measures of the hydroclimatic extremes and tropical SST

Variable	Unit	Extreme type	Mean	Range	Mean of Variance	Standard Deviation
SST	°C	Annual maximum	26.18	15.29 – 30.44	7.05	2.68
		Dry season	26.19	13.51 – 32.63	9.85	3.17
		Wet season	26.18	11.77 – 30.96	7.04	2.69
Precipitation	mm	Annual maximum	118	49 -350	200	38
		Dry season	969	114 – 3192	182222	512
		Wet season	2605	1096 – 5506	90118	586
Streamflow	m^3/s	Annual maximum	270	18 – 1537	7375	352
		Dry season	8360	659 – 67772	18194200	13567
		Wet season	12957	878 – 87989	29014258	19960

Figure 2 shows temporal trend of spatial average of tropical SST, precipitation and streamflow for the respective time period owing to data availability. As shown, similar trend between SST and precipitation can be observed in the period of 2000 to 2010, while likeness of trend between

SST and streamflow can be visibly seen during the period of 2007 – 2017 for annual maximum, dry season and wet season.

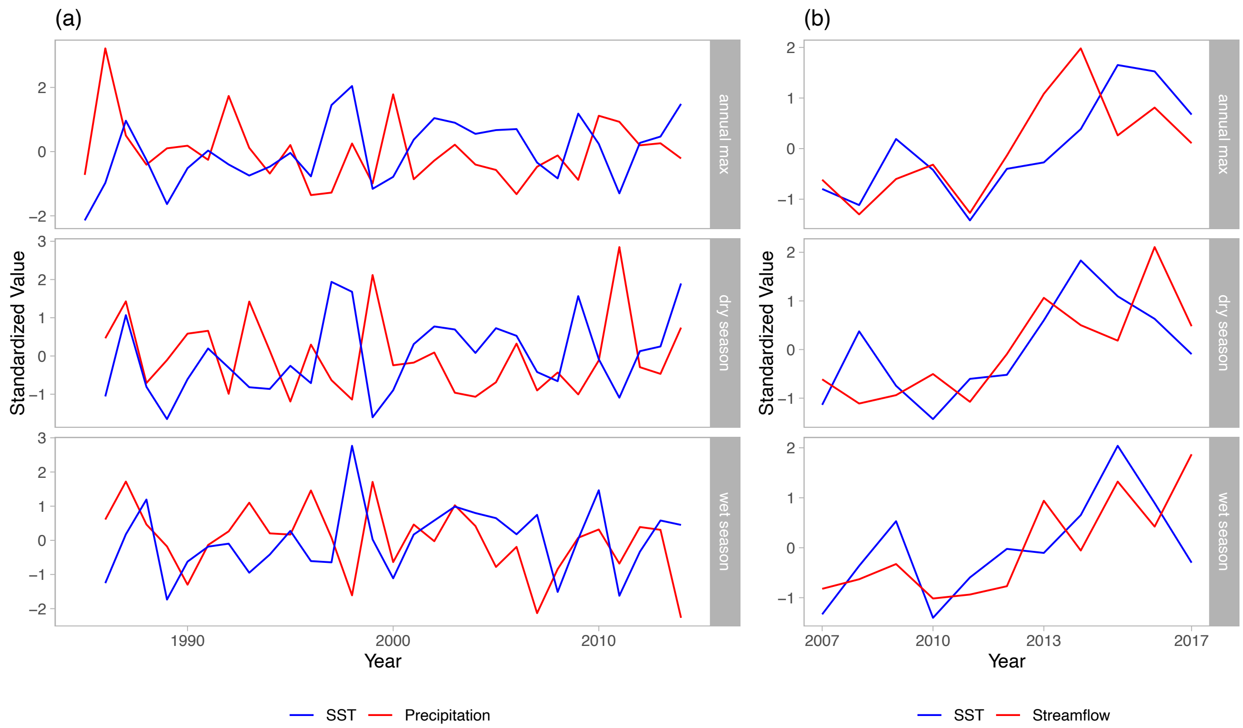


Figure 2. Temporal trend of precipitation (a) and streamflow (b) extremes compared to the tropical SST for annual and seasonal time scale

4. Methodology

Four sequential methods are proposed to sources of spatial and temporal variability of hydroclimatic extremes. Firstly, spatio-temporal variability of hydroclimatic extremes over the basin and sea surface temperature (SST) over the tropical region is profoundly elaborated using Principal Component Analysis (PCA). Secondly, linear correlation between hydroclimatic extremes and SST is developed, the correlation coefficient is computed. Thirdly, Copula model is constructed for hydroclimatic extremes and SST, correlation strength is calculated. Fourthly, temporal variability of this relationship is investigated using Bayesian Dynamic Linear Model (BDLM).

Principal component analysis to extract spatial representation of hydroclimatic extremes and tropical SST

Modeling relationship between hydroclimatic extremes and tropical SST, spatial-wise representations of those variables are required. PCA is a widely used technique to encapsulate variability of high dimensional data through separating uncorrelated dominant spatial and temporal modes from jointly concurrent data (Jolliffe & Cadima, 2016). This is done by projecting original data into new axes called Principal Components (PCs) whereby the first PC explains more variance than the second PC and so forth (Wilks, 1995). In hydroclimatic extremes studies, this method has been extensively utilized for both diagnosing (Drees & Sabourin, 2019; Jiang et al., 2020; Lovino et al., 2014; Puczko & Jekatierynczuk-Rudczyk, 2020) and forecasting (Chandimala & Zubair, 2007; Jewson, 2020). Here, PCA is exploited to generate basin attributes of hydroclimatic extremes and tropical feature of SSTs and diagnose the linkage between those variables.

Linear and Copula model for diagnosing correlation between hydroclimatic extremes and tropical SST

Linear model is a simple way of describing linear combination of the response and predictor variables. The model assumes that both response and predictor variables follow the normal distribution. One way to measure the goodness of fit of the linear model is computing correlation coefficient (ρ). The value of ρ ranges from -1 to +1 where the value of ±1 indicates strong correlation and the value of 0 indicates no correlation. Pearson's ρ is the most popular type of correlation coefficient for linear model among the available types of ρ, such that it is used in this study. Mathematically, Pearson's ρ is defined as below:

$$\rho_P = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$$

Where ρ_P is Pearson's correlation coefficient, x_i and y_i are the sample value of predictor and response respectively, $\bar{x}$ and $\bar{y}$ are the sample mean of predictor and response respectively. In this study, the response variable is hydroclimatic extremes and the predictor variable is tropical SST.

Copulas are mathematical functions capable of capturing the dependence structure among random variables due to its ability to separate marginal distribution from their joint distribution. Using Copulas, it is more flexible to develop multivariate stochastic model and expose the fallacies associated with correlation analysis (Durante & Sempi, 2010; Gudendorf & Segers, 2010). Copulas have been employed to model the dependency of precipitation on climate variables both locally and globally (Nguyen-Huy et al., 2017; Pandey et al., 2018; Yee et al., 2014). In here, Copulas are used to inspect tropical climate drivers of hydroclimatic extremes in the study region.

A number of families, distinguished by their dependence structure and the number of parameter (usually varying from 1 to 3), are available for Copulas model fitting, including Gaussian copulas, t-copulas, Archimedean copulas and extreme-value copulas (Mai & Scherer, 2014; Sadegh et al., 2017). For rare events such as hydroclimatic extremes, extreme-value copulas class can be considered as an appropriate model (Gudendorf & Segers, 2010). Within a copula family, there are several copula classes. Tawn copula is a class of Gumbel copula that asymmetrically extended using three parameters (Tawn, 1990). It has been successfully applied to model extreme events (Chen et al., 2015; Sadegh et al., 2017; Taillon et al., 2019), thus it is adopted in this study.

Recent studies detected non-linear pattern on global SST and precipitation (Kazemzadeh et al., 2021; Martinez-Lopez et al., 2020), which could be the case on our study area. For this reason, Pearson's ρ is no longer adequate to measure the correlation strength. Suitably, Spearman's ρ is chosen which is a nonparametric measure of dependence that compute correlation between pair of ranks and defined as below:

$$\rho_S = \frac{\sum(R_i - \bar{R})(S_i - \bar{S})}{\sqrt{\sum(R_i - \bar{R})^2 \sum(S_i - \bar{S})^2}}$$

Where ρ_S is Spearman's correlation coefficient, R_i and S_i are the sample rank value of predictor and response respectively, $\bar{R}$ and $\bar{S}$ are the sample rank mean of predictor and response respectively. To implement the method, we specifically used the Copula R Package (Kojadinovic & Yan, 2010; Yan, 2007). Detail computation and assumptions of the method can be found in Yan (2007). The ρ_P and ρ_S are computed for the leading PCs of hydroclimatic extremes and tropical SST of each grid, such that maps of ρ_P and ρ_S are produced. These maps are analyzed to investigate the tropical regions driving hydroclimatic extremes in the study region.

Time varying dependency of precipitation extremes

The link of climate variables and annual precipitation in Indonesia is time varying (Yanto et al., 2016). Hence, it is expected to be the case for hydroclimatic extremes. The changing relationship is uncapturable by traditional linear regression methods. On the other hand, Bayesian Dynamic Linear Model (BDLM) provides an option to modeling and identifying this nonstationary relationship (Petris et al., 2009; West & Harrison, 1997). While regression coefficient is retained fix over time in traditional regression, it varies with time in BDLM. BDLM has been applied to modeling inter-annual and inter-decadal precipitation variability over Indonesia and interesting insight on the strengthening ENSO signal in the period of 1980 to present was found. In this study, we applied this method to each precipitation extreme along with its respective global climate indices.

Spatial clustering of precipitation extremes using Self-Organizing Map

Considering the variety of topographical setting of the watershed, it is expected that precipitation extremes in the study area undergo spatial variability. To evaluate the spatial variability of precipitation extremes, we exploited Self-Organizing Map approach. This approach has been applied in many studies in the context of precipitation clustering (Cavazos, 2000; Gorricha & Lobo, 2013; Kohonen, 2013; Li et al., 2020; Loikith et al., 2017). SOM is an automatic data analysis applicable for clustering problems (Kohonen, 2013). In SOM, input data will be distributed into nodes of a regular grid in a way that data with similar features are automatically placed adjacently in the grid, whereas data with less similar features are situated farther away from each other in the grid (Kohonen, 2013). This procedure enables the model to provide an insight on the topographic association of the data, particularly for high dimensional data. SOM model can be constructed using unsupervised and supervised learning approach (Allinson et al., 2001; Papadimitriou et al., 2002), where supervised SOM has an ability to solve classification problem using very compact networks (Hagenbuchner & Tsoi, 2005). Accordingly, in this study we decided to exploit supervised SOM. To supervise the SOM model, we used SST anomalies indices yielded from the Copulas model fitting. In addition, we also utilized the SOM model to classify temporal trend of precipitation whether it will be above or below normal. To do this, we split the data into two groups. The first 70% of data are used for training while the rest 30% are taken for testing. Application of the method in this study was accomplished with the help of kohonen R package (Wehrens & Kruisselbrink, 2018).

Extreme value analysis for nonstationary return levels estimation

Return levels estimation is one of big interests in the analysis of precipitation extremes (Acero et al., 2018; Fischer et al., 2019). Extreme value analysis (EVA) is a statistical means for estimating the likelihood of extreme values occurrences (return levels) using observed data with a few basic assumption (Benstock & Cegla, 2017). Following the results from SOM model, we fitted the model using General Extreme Value (GEV) distribution and performed return levels estimation for each generated cluster, each precipitation extreme for 25, 50 and 100-year return periods (Coles, 2001; Gilleland & Katz, 2011). Nonstationarity of the return levels is established by incorporating covariates in the distribution fitting processes (Jakob, 2013). In here, we used climate indices associated with each precipitation extreme as model covariates. Using the fitted distribution, we then estimated return levels for the defined return periods. Under nonstationary assumption, return levels are changing as a function of time to preserve the occurrence probability of an extremal event constant which is known as effective return levels (Cheng et al., 2014; Katz et al., 2002). We applied the procedure on the precipitation extremes over the watershed and on each station to understand the return levels simulation at watershed and station scale. By doing this, we can show the spatial variability of return levels estimation. To this end, we employed extRemes 2.0 R package (Gilleland & Katz, 2016).

5. Results and Discussion

Temporal features of hydroclimatic extremes and tropical SST

The goal of PCA application is to generate PCs that capture the variability of dataset. This can be done by selecting PCs which explain more variances. Figure 3 displays the fraction of variance explained by each PC for SST (a), precipitation (b) and streamflow (c). PC1 of SST explains almost all variances in the data for all extreme types, indicating low variability. For precipitation, PC1 in dry season explains more variance that those in wet season and annual maximum, which is also the case of streamflow.

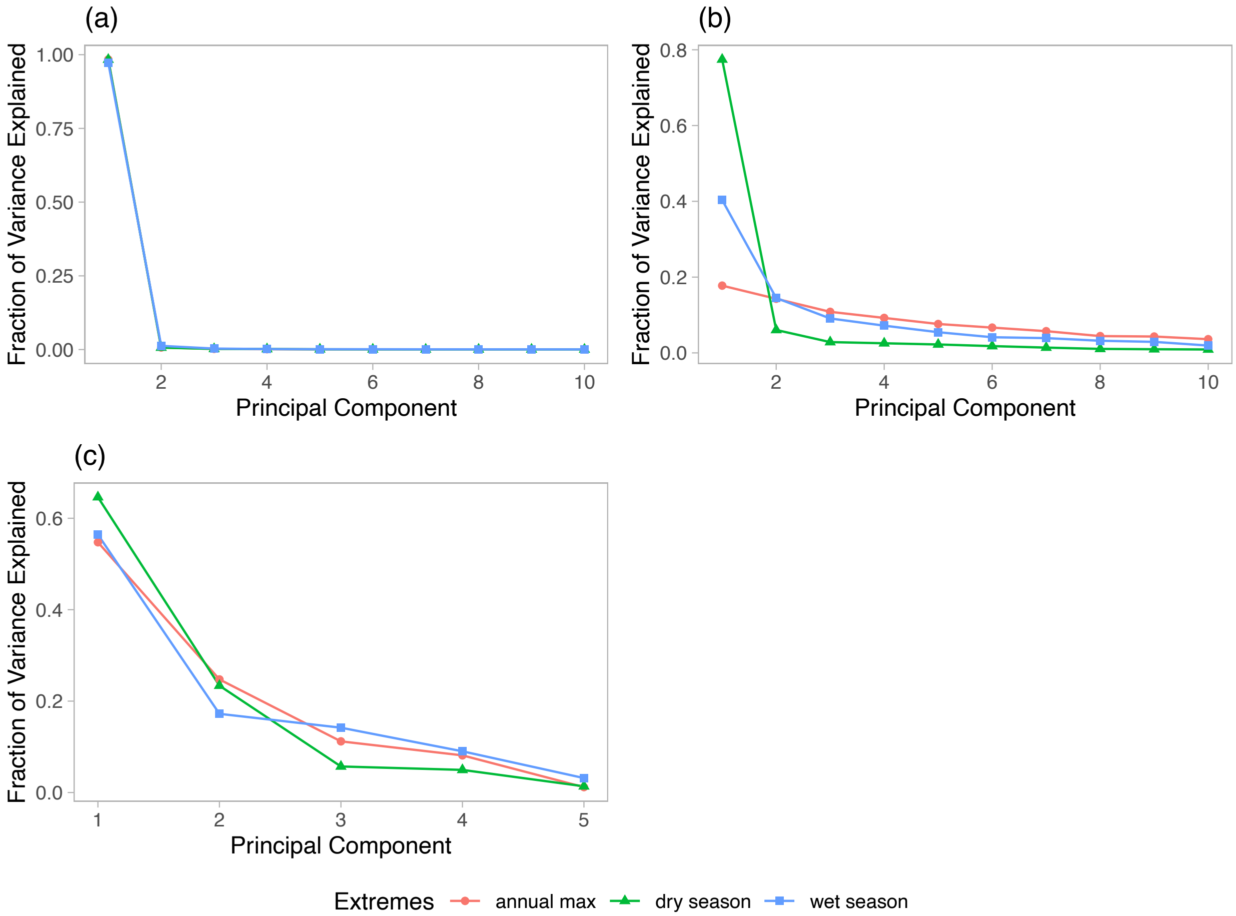


Figure 3. The fraction of variance explained by leading PCs for SST, precipitation and streamflow extremes for both annual and seasonal time window

To understand more on the variability of hydroclimatic extremes, biplots of PC1 and PC2 is helpful. Figure 4 shows biplots of PC1 and PC2 for annual maximum (a), dry season (b) and wet season (c). In biplot, PC scores of samples are denoted as dots and loadings of variables are marked with vectors. The further away these vectors are from a PC origin, the more influence they have on that PC. Loading plots also hint at how variables correlate with one another: a small angle implies positive correlation, a large one suggests negative correlation, and a 90° angle indicates no correlation between two characteristics. A scree plot displays how much variation each principal component captures from the data. If the first two or three PCs are sufficient to describe the essence of the data, the scree plot is a steep curve that bends quickly and flattens out. It can be seen annual maximum and wet season are influenced by positive PC1. Adversely, negative PC1 is dominant in dry season. Moreover, it can also be noticed positive correlation among stations in the study area (shown by angle of less than 90 degree) with variability in the correlation power. Small number of stations are detected to have negative correlation with others.

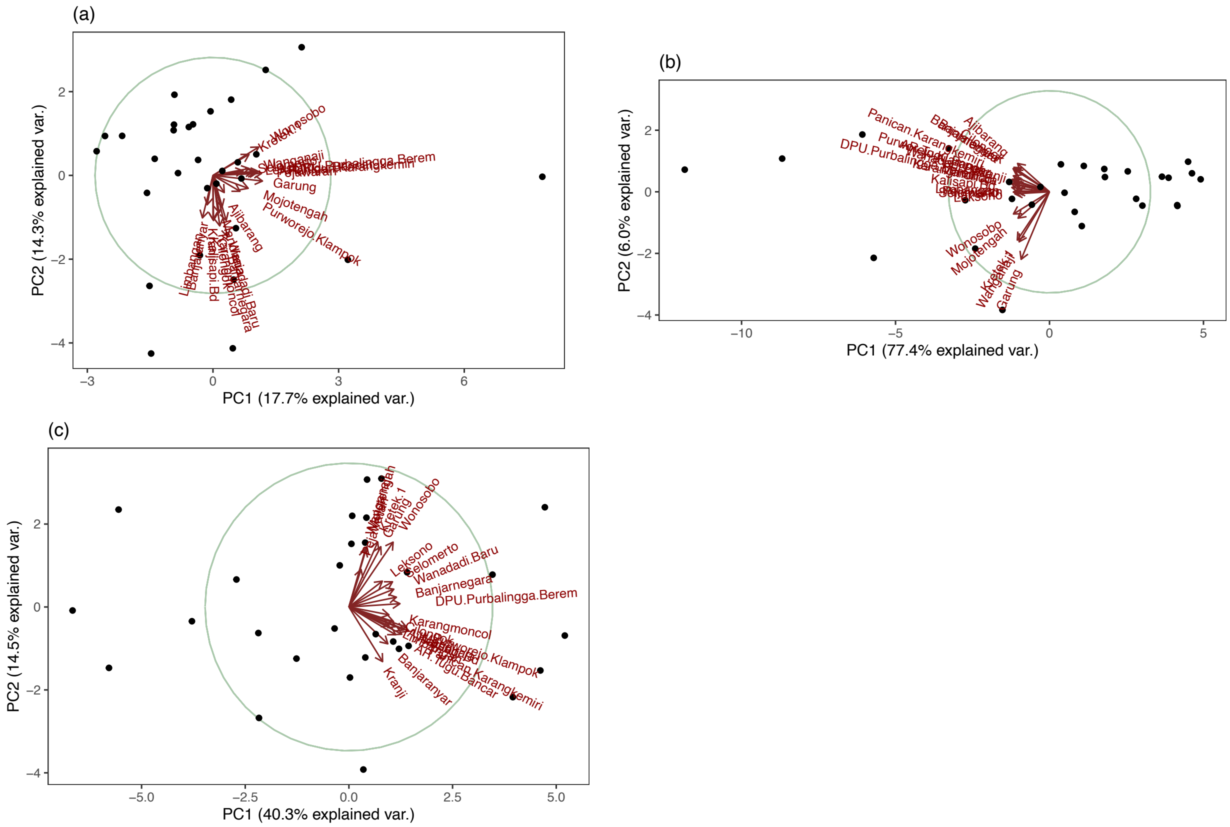


Figure 4. Biplots of PC1 and PC2 for precipitation extremes

Biplots of PC1 and PC2 for streamflow extremes exhibit similar feature for annual maximum and wet season, but not for dry season (Figure 5). In all extreme types, PC1 positively controls the variability of streamflow. While positive correlation is occurred among almost all stream gauges, Singomerto and Limbangan stream gauges expose negative correlation.

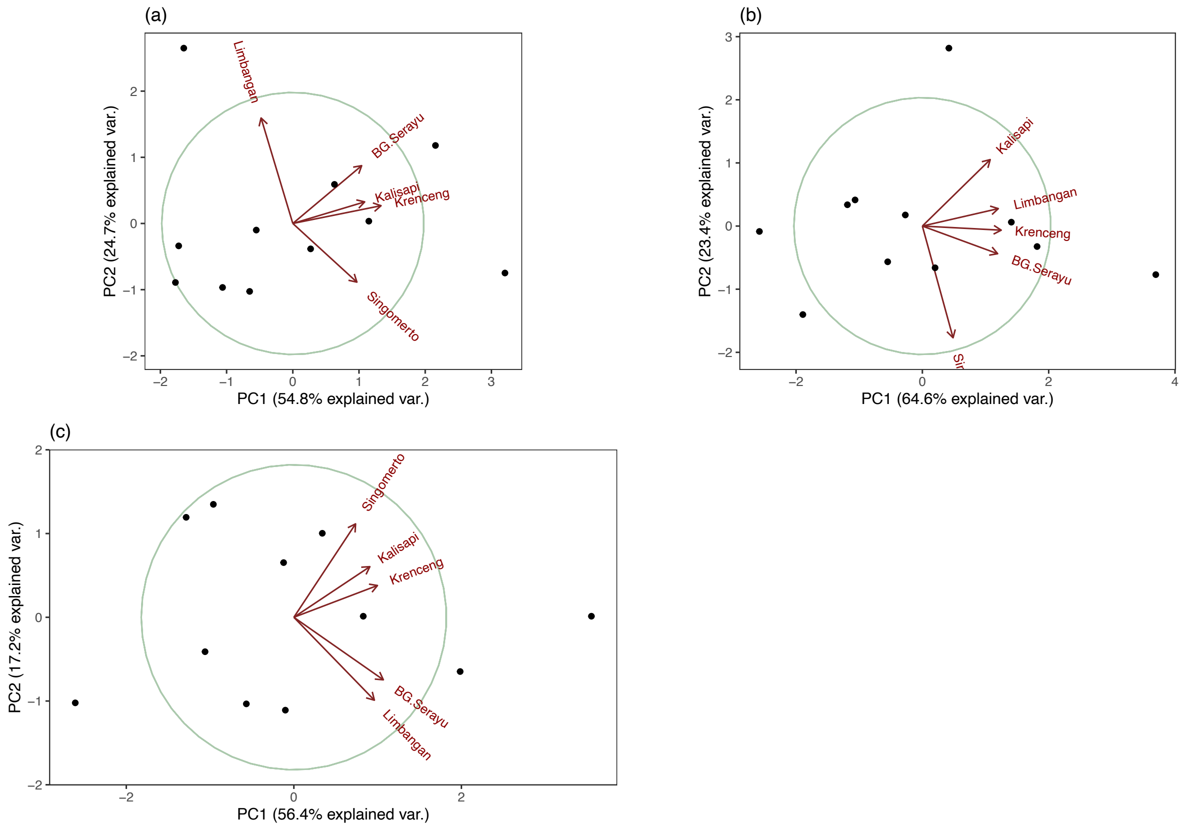


Figure 5. Biplots of PC1 and PC2 for streamflow extremes

To catch dataset variability in this study, PCs that capture more than 50% variance are selected. With this threshold, the chosen PCs are presented in Table 3.

Table 3. The leading PCs of hydroclimatic extremes and tropical SST selected for analysis.

Variable	Extreme type	PCs	Fraction of variance explained
SST	Annual maximum	PC1	98%
	Dry season	PC1	98%
	Wet season	PC1	98%
Precipitation	Annual maximum	PC1, PC2, PC3, PC4	51%
	Dry season	PC1	77%
	Wet season	PC1, PC2	54%
Streamflow	Annual maximum	PC1	55%
	Dry season	PC1	65%
	Wet season	PC1	57%

Using the selected PCs, temporal variability of hydroclimatic extremes and SST can be perceived. Figure 6 presents temporal variability of hydroclimatic extremes and SST along with the trend. While SST and streamflow reveals increasing trend for all extreme types, only annual maximum precipitation exhibits rising tendency. On the other hand, dry and wet season precipitation is declining over the period of 1985 – 2014 (Figure 6.b). Increasing annual maximum precipitation and decreasing seasonal precipitation relates to intensifying flood and drought events, which is the case of the study area.

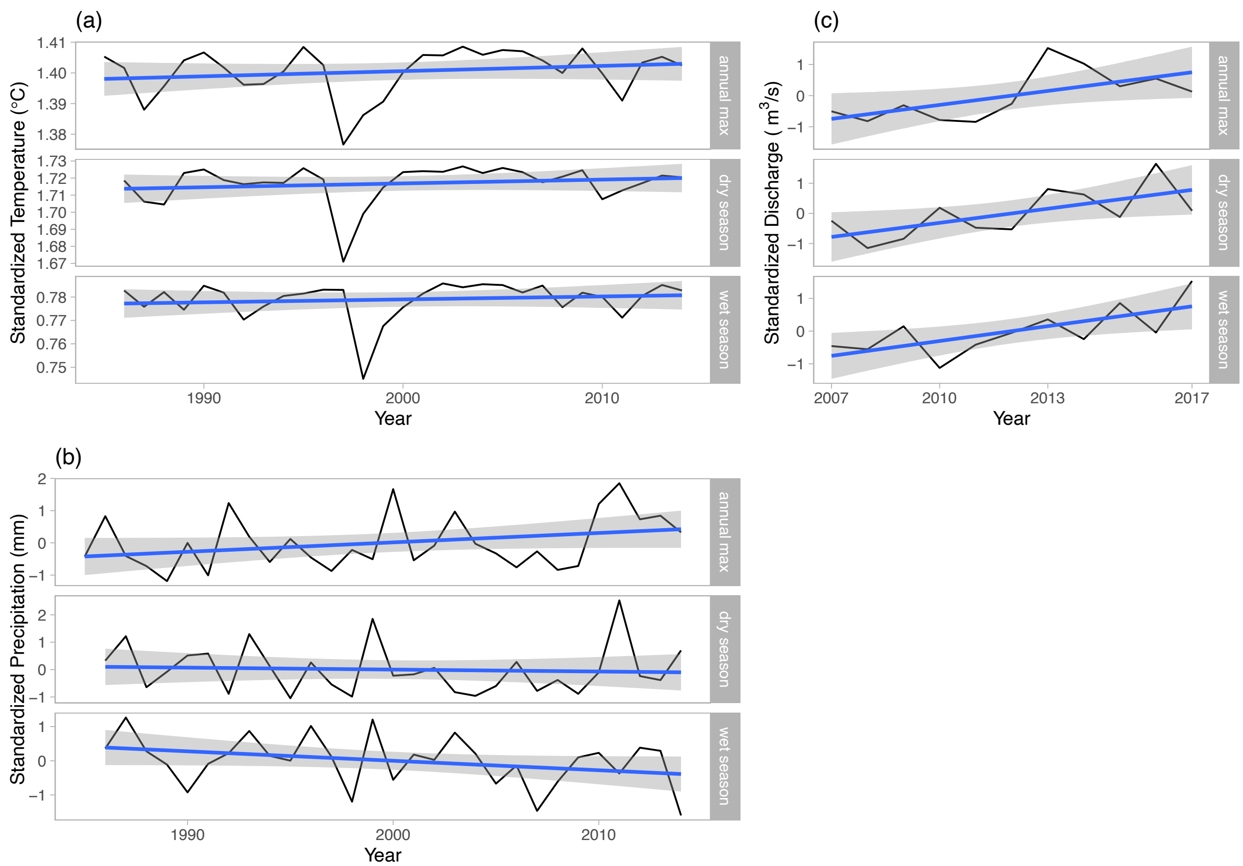


Figure 6. Temporal variability of leading PCs (black line) and its trend (blue straight line) along with 90% confidence interval (shadow area) for annual and seasonal time scale

Apparent difference between precipitation and streamflow trend should be discerned carefully as the figures show partial overlapping time period. While precipitation tends to decline during the period of 1985 – 2014, it rises in the period of 2007 – 2014, the intersecting period with streamflow record. Hence, it can be inferred that both precipitation and streamflow expose comparable temporal variability. However, precipitation data provide longer time coverage, such that it is used to conclude the temporal feature of hydroclimatic extremes, as mentioned above. Moreover, it can also be noticed from the fluctuation of precipitation and streamflow in the period of 2007 – 2014, when high precipitation and streamflow detected in dry season, the opposite attribute is noted in wet season, and vice versa.

Spatial variability of tropical SST is presented in Figure 7. As shown in Figure 7, most of tropical regions experience warming temperature. In the eastern Pacific Ocean, cooling temperature is detected. This is typical characteristic of ENSO. Figure 8 displays spatial variability of leading PCs of streamflow in the study area. Negative PCs are dominant in the annual precipitation, positive PCs are the foremost in wet season and neutral PCs are prevalent in dry season (Figure 8.a). The dominant pattern for streamflow is contradictory compared to precipitation as shown in Figure 8.b.

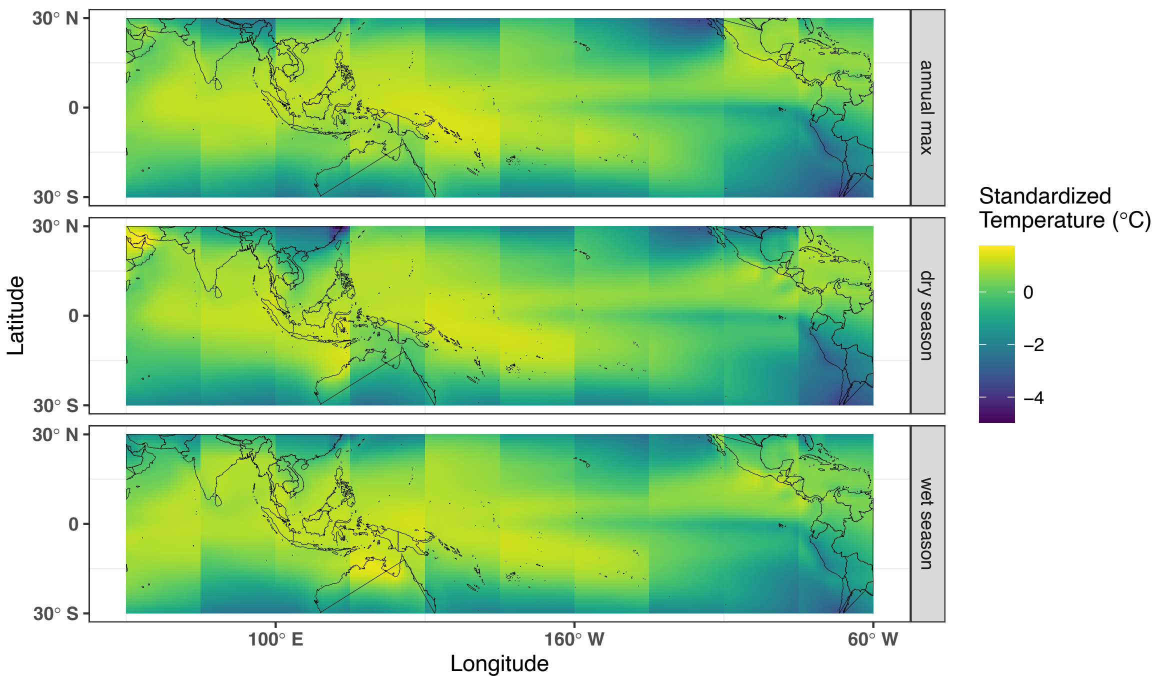


Figure 7. Spatial variability of leading PCs of SST within tropical regions

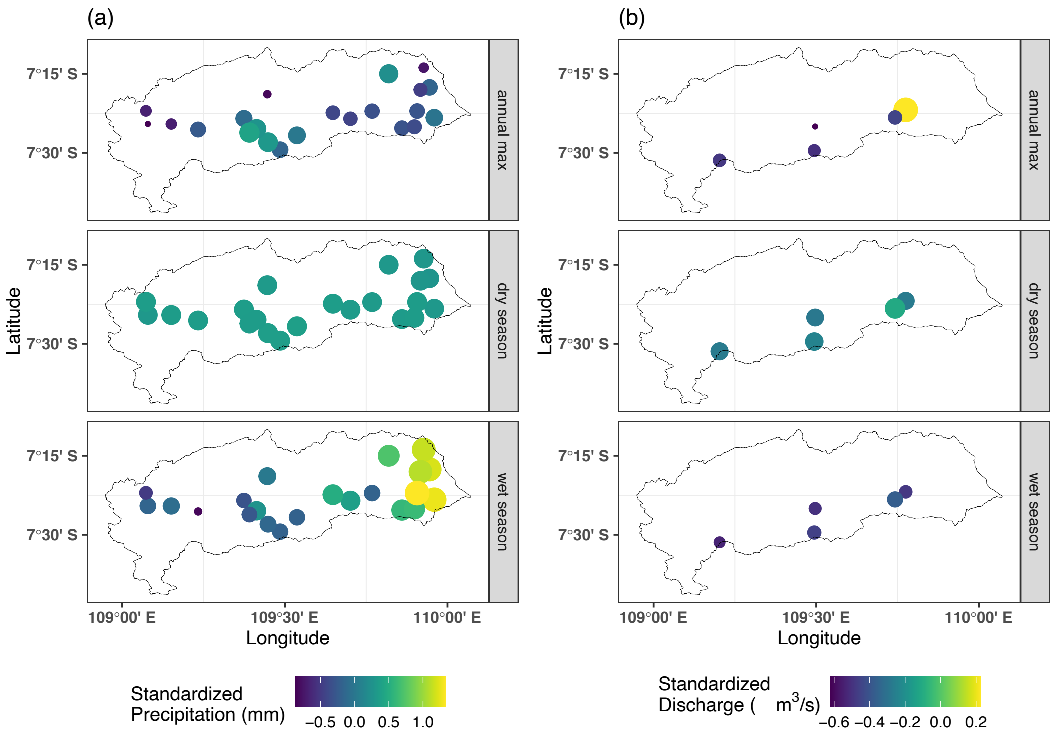


Figure 8. Spatial variability of leading PCs of precipitation and streamflow extremes within tropical regions

Tropical climate drivers of hydroclimatic extremes

Figure 9 shows maps of correlation strength of linear model between precipitation extremes and tropical SST, measured using Pearson's ρ for annual maximum, dry season and wet season. As presented, annual maximum precipitation is positively correlated with SST around Indonesia. It implies that if SST in these regions gets warmer, the annual maximum precipitation is higher. The regions with high Pearson's ρ signify the presence of ENSO and IOD indices. Larger areas of Pacific Ocean can be spotted to have strong negative correlation with precipitation, suggesting that the heating of this regions results in low dry season rainfall which causes drought. In wet season, the driving force of tropical SST on precipitation is weaker than it is in dry season.

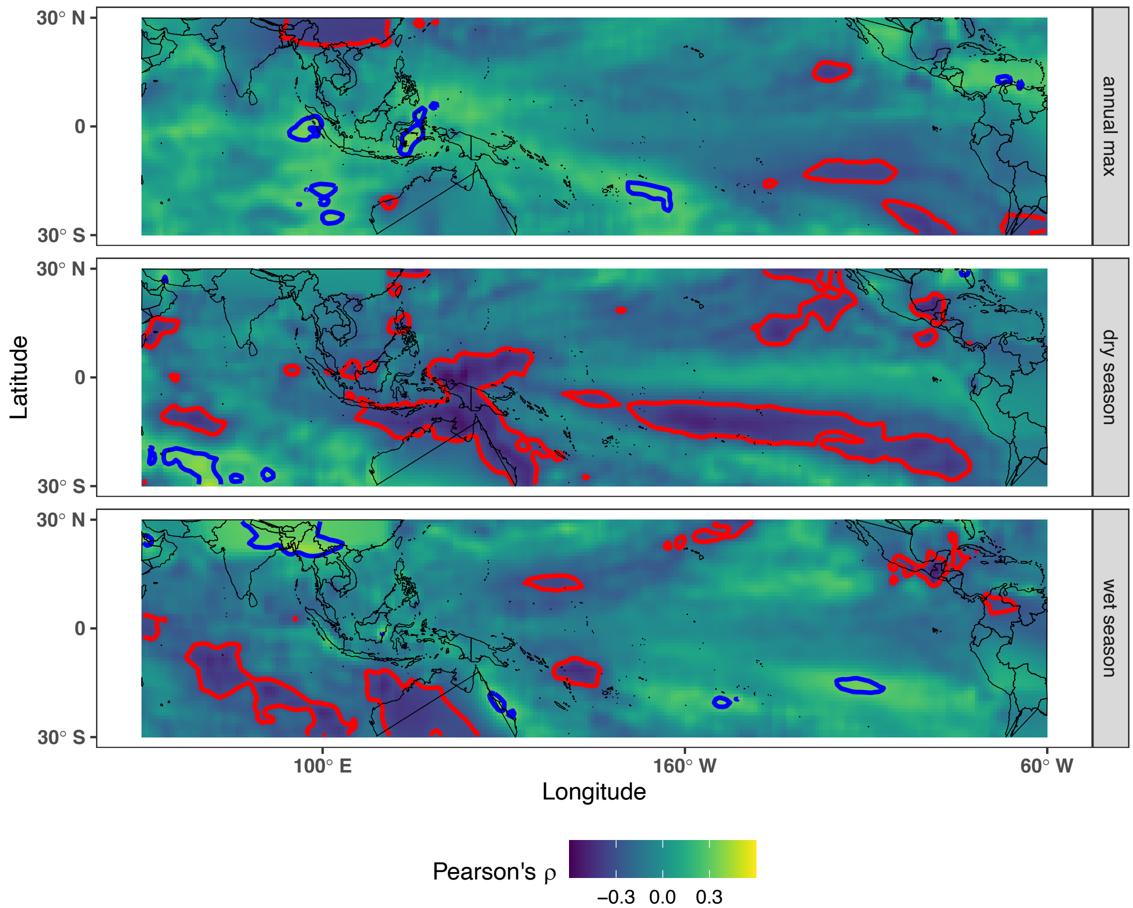


Figure 9. Maps of correlation power (Pearson's ρ) of linear model between selected leading PCs of precipitation and SST. Blue and red curved lines bound the area having Pearson's ρ of higher than 0.3 and lower than -0.3 respectively.

Different tropical regions to hold convincing correlation with precipitation extremes are detected using Copula model, quantified using Spearman's ρ (Figure 10). Positive correlation is dominant in the Copula model. As of the linear model, larger areas are found in dry season compared to annual maximum. However, wet season displays considerable zones with strong positive correlation, which is not the case of linear model. Moreover, it can be compared that the parts of tropical region having strong correlation from Copula model is different than that is from linear model. This can be deemed as the capability of Copula model to seize marginal distribution of the joint variables. Additionally, it can be surmised that the regions with high correlation from Copula model complements the linear model, demonstrating the benefit of Copula model.

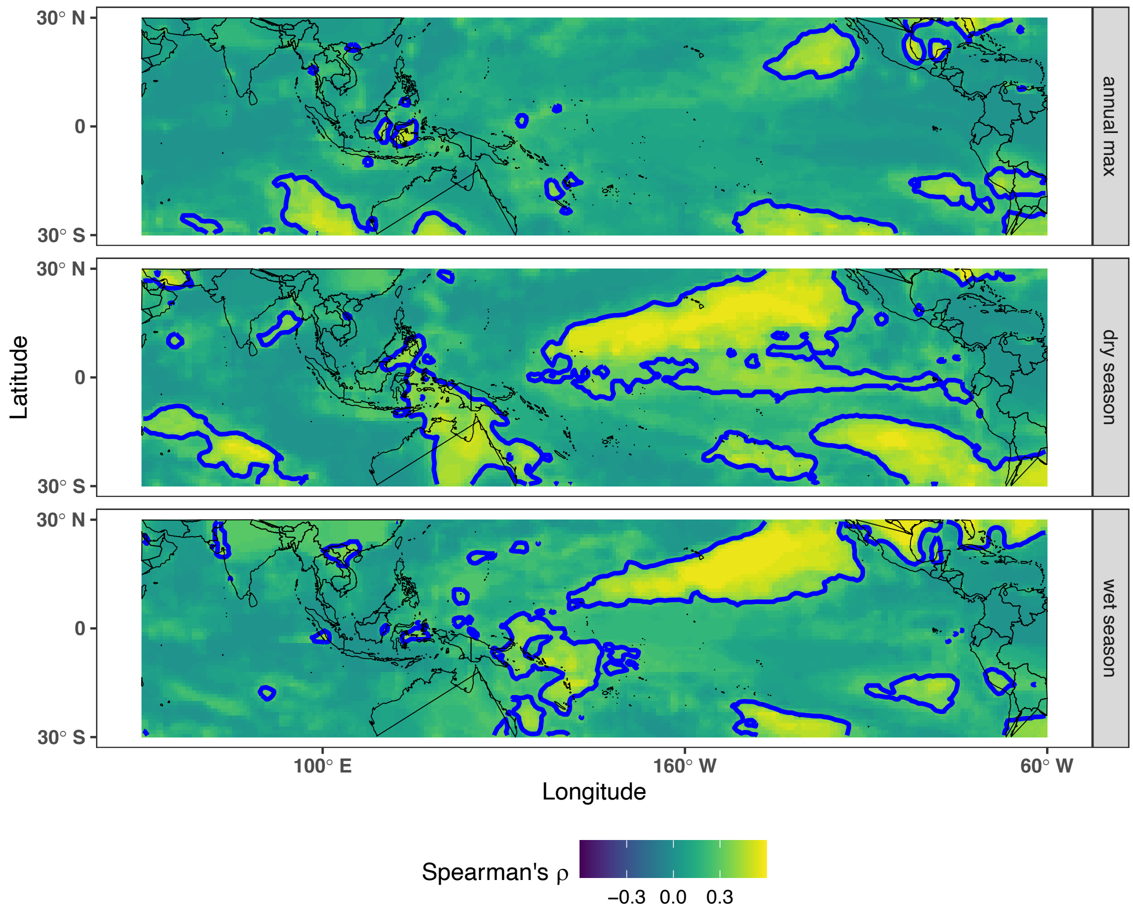


Figure 10. Maps of correlation power (Spearman's ρ) of Copula model between selected leading PCs of precipitation and SST. Blue curved lines bound the area having Pearson's ρ of higher than 0.3.

Figure 11 discloses spatial variability of correlation strength between tropical SST and streamflow extremes. In general, it can be viewed that streamflow extremes in the study area are strongly correlated with the most of tropical SST for annual maximum, dry and wet season. Strong positive correlation appears in nearly all Pacific Ocean and Indian Ocean. For dry and wet season, strong positive correlation can be noticed in the Pacific and Indian Ocean near Indonesia, whilst negative correlation emerges in the remote Pacific and Indian Ocean from Indonesia. Compared to the relationship between tropical SST and precipitation extreme, the influence of tropical SST on streamflow is meaningfully stronger and wider.

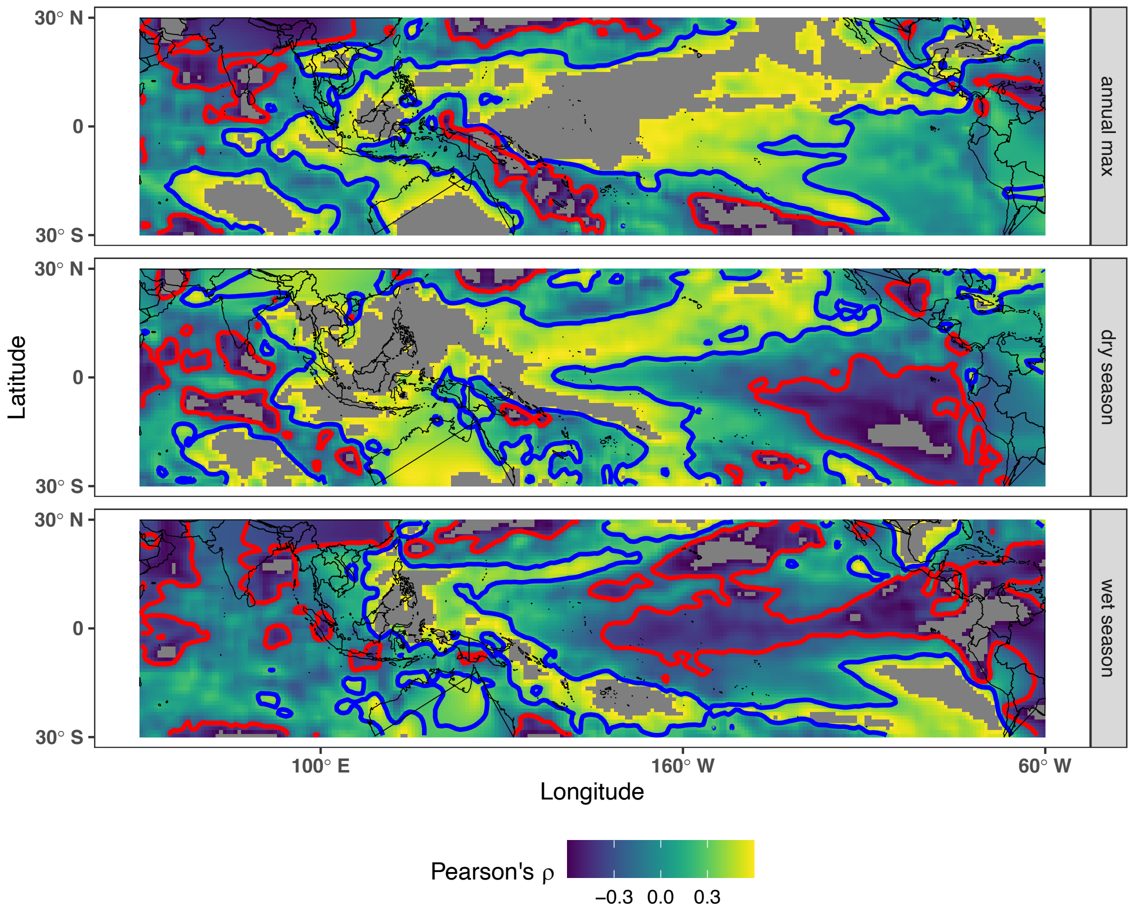


Figure 11. Maps of correlation power (Pearson's ρ) of linear model between selected leading PCs of streamflow and SST. Blue and red curved lines bound the area having Pearson's ρ of higher than 0.3 and lower than -0.3 respectively.

The connection of tropical SST and streamflow extreme modeled using Copula uncovers equivalent pattern as shown in Figure 12. Positive correlation dominates the effect of tropical SST on streamflow extreme, as the case of precipitation extreme. Moreover, while overlapping areas detected between linear and Copula model, some areas detected from Copula model accompanies the linear model. This denotes consistency of linear and Copula model for both precipitation and streamflow extremes.

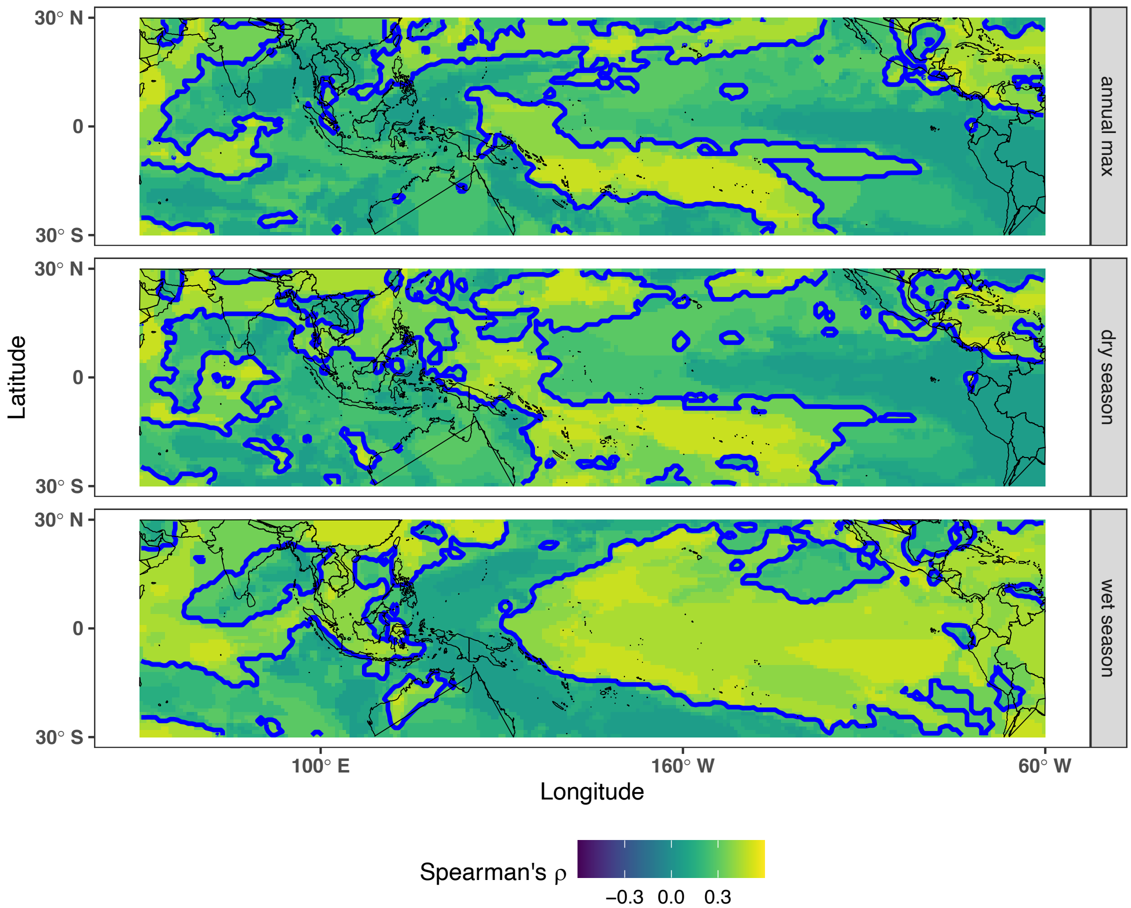


Figure 12. Maps of correlation power (Spearman's ρ) of Copula model between selected leading PCs of streamflow and SST. Blue curved lines bound the area having Pearson's ρ of higher than 0.3.

The maps of correlation between tropical SST and hydroclimatic extremes clarify that the heating SST in near Indonesia and cooling SST in distant areas steer mechanism of generating precipitation and streamflow extremes for annual and seasonal time scale. Physically, when SST near Indonesia is getting warmer, more air moisture produced near Indonesia. On the other hand, when SST faraway from Indonesia is getting cooler, higher pressure will be produced, creating greater pressure temperature gradient between eastern and western Pacific Ocean. The increasing pressure gradient creates more wind moving from east to west, bringing air moisture to Indonesia, resulting in intense precipitation and streamflow extremes. Moreover, the impact of cooling temperature in the remote areas is stronger in seasonal time scale than it is in annual time scale.

Time varying relationship of hydroclimatic extremes and tropical SST

The stronger linkage of tropical SST in the ENSO and IOD regions for streamflow can be justified from the data time range. As mentioned earlier, in the period of 2007 to 2017, noble similarity of precipitation and streamflow with tropical SST is obvious. This can be a sign of changing influence of tropical SST on the hydroclimatic extremes in the study area. BDLM is a suitable tool to investigate this. Here, Nino3.4 and IOD indices are used reflecting the results from correlation maps.

The result is presented in Figure 13 for precipitation extremes in forms of time varying correlation (curve line) for both slope (bottom) and intercept (top) of linear regression for each precipitation extreme and its corresponding Nino3.4 and IOD. The intercept represents the expected mean of precipitation extremes under neutral Nino3.4 and IOD, while the slope denotes the change of precipitation extremes in response to the change in Nino3.4 and IOD. Positive slope indicates parallel change, while negative slope implies opposite change. It shows that teleconnection power between precipitation extremes and their corresponding climate indices is increasing from the period of 2010 and afterward, except correlation between wet season precipitation and Nino3.4. As shown in Figure 13, the mean of precipitation extremes in the study area is originating from both Nino3.4 and IOD regions. Furthermore, the slope suggests that high precipitation extremes are more related to IOD (positive slope), while low precipitation extremes are dictated by Nino3.4 (negative slope) in the period of 2010 – 2014. It can be inferred that the teleconnection pattern of annual and seasonal precipitation extremes and Nino3.4-IOD indices is in agreement with teleconnection of annual precipitation and SST anomaly indices in ENSO and IOD regions at inter-annual and inter-decadal time scale (Yanto et al., 2016).

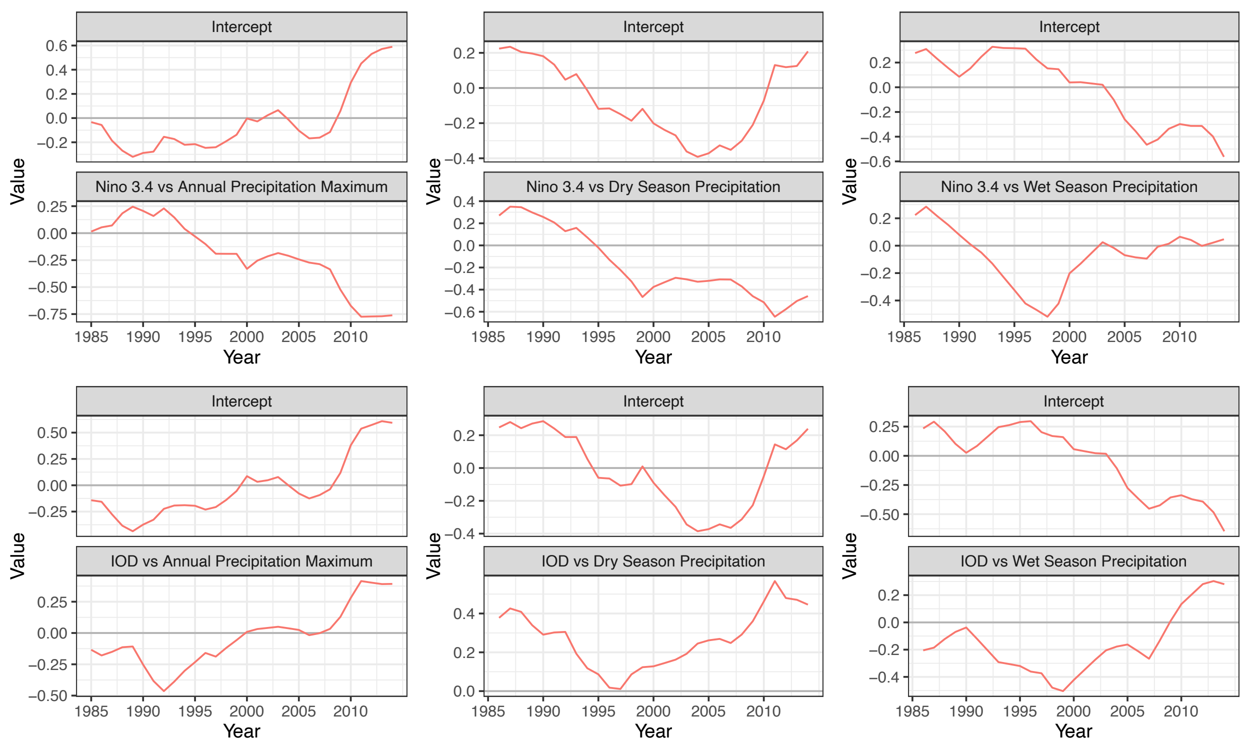


Figure 13. The change of linear model parameters (slope and intercept) between precipitation extremes and Nino3.4 (top) and IOD (bottom) for annual maximum (left), dry season (middle) and wet season (right)

Temporal dynamic change of link between streamflow extremes and Nino3.4-IOD indices demonstrate similar feature as for precipitation extremes and presented in Figure 14. As of precipitation extremes, Nino3.4 and IOD govern the streamflow extremes under neutral state. Warming SST in IOD and cooling SST in Nino3.4 regions marking the control of IOD on high streamflow, conforming the trend of precipitation extremes, in the period of 2007 - 2014.

Figure 14. The change of linear model parameters (slope and intercept) between streamflow extremes and Nino3.4 (top) and IOD (bottom) for annual maximum (left), dry season (middle) and wet season (right)

Hydroclimatic extremes patterns

Figure 15 illustrates the map the distribution of precipitation extremes for annual (a) and seasonal time scale (b,c), presented as codes or node weight vectors. Each weight vector is representative of similar samples mapped to the node. The nodes are grouped into three clusters indicating dominated low, medium and high value for each cluster. In annual precipitation, two nodes fall into cluster 3 (middle left and topright), one node in cluster 2 (bottomleft) and six nodes of cluster 1. Cluster 1, 2 and 3 covers 19, 1 and 2 stations respectively. In dry season, cluster 1 has 5 nodes with 12 stations, cluster 2 has 3 nodes with 8 stations and cluster 3 has 1 node with 2 stations. In wet season, cluster 1 comprises 4 nodes with 9 stations, cluster 2 has 3 nodes with 9 stations and cluster 3 has 2 nodes with 4 stations. The pattern of increasing cluster 2 and 3 as well as decreasing cluster 1 from annual to dry and wet season is detected.

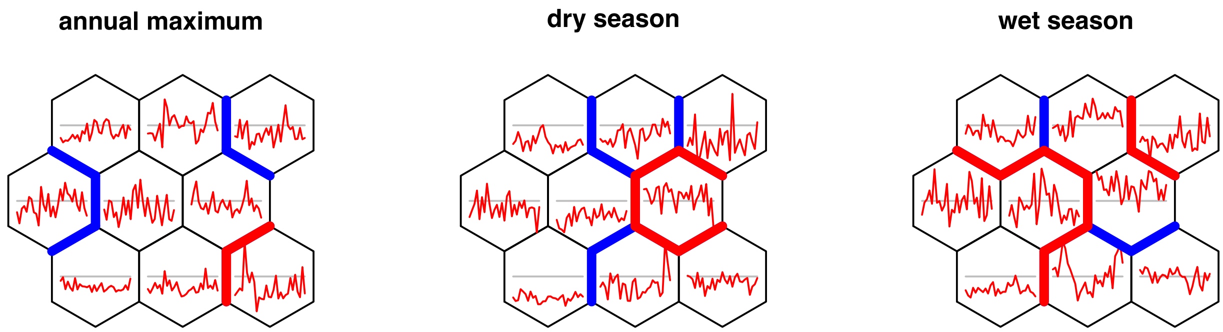


Figure 15. Codes plot of precipitation extremes showing three clusters representing low, medium and high values separated by blue and red lines.

The spatial distribution of precipitation clusters is presented in Figure 16. Echoing the codes plot, the annual precipitation map shows domination of cluster 1, decreasing in dry and wet season. It can also be observed that the change of cluster mainly occurs in the easter parts of the study area which are mountainous regions.

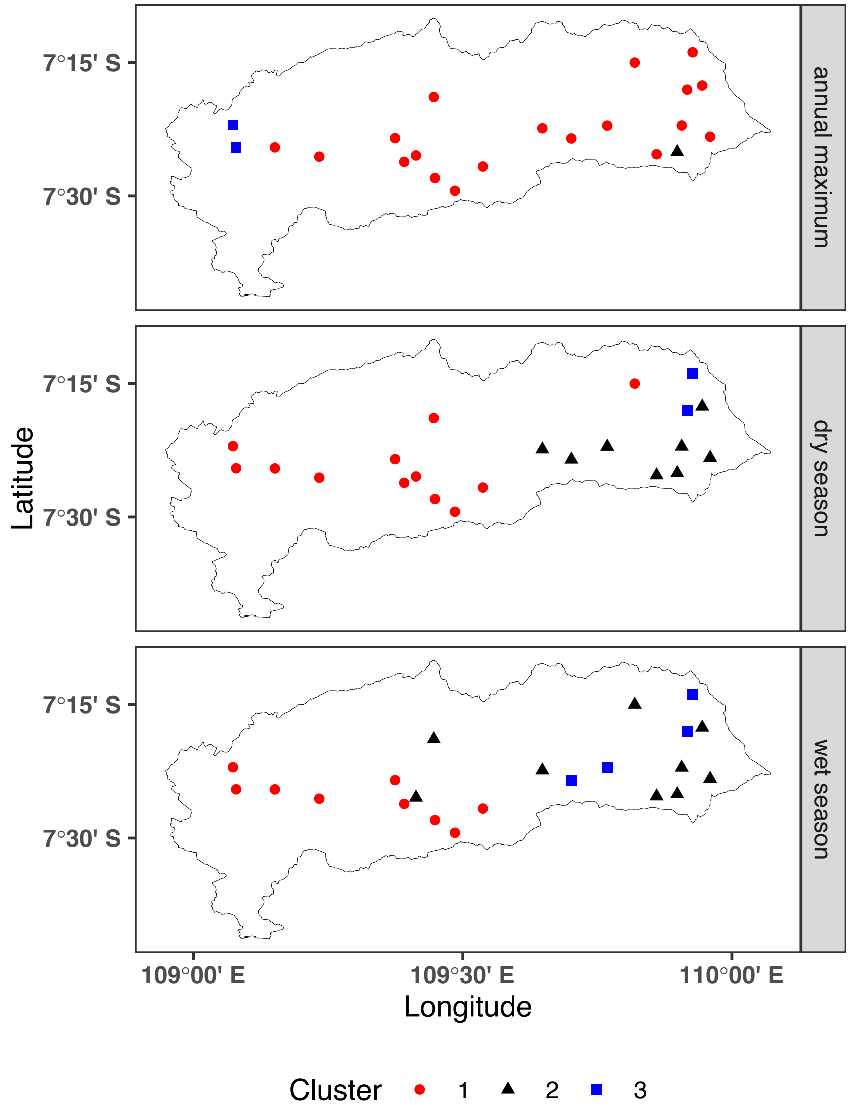


Figure 16. Maps of precipitation features enveloped in cluster.

The codes plot and map of clusters for streamflow are presented in Figure 17 and 18. Here, the nodes are separated into two clusters as the number of stream gauges in only five. The size of fan in Figure 17 represents the magnitude of streamflow, while the color of fan denotes contribution of temporal precipitation. It is shown that for the high cluster, all year in the observation contributes to the streamflow. On the other hand, in low cluster, only certain years contribute to the streamflow.

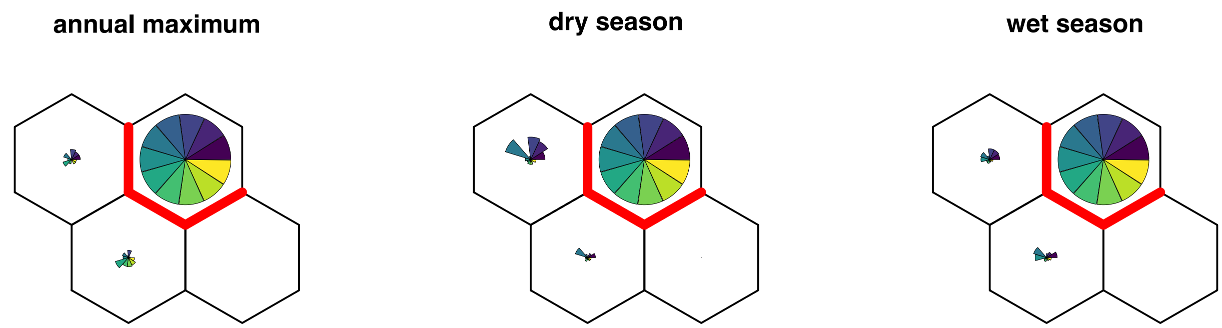


Figure 17. Codes plot of streamflow extremes showing two clusters representing low and high values separated by blue and red lines.

As shown in Figure 18, cluster 1 (low value) covers the stream gauges from upstream to middle stream, while cluster 2 (high value) is in the downstream. This is logic as flow accumulate in the downstream such that all areas In the basin contributes to the streamflow.

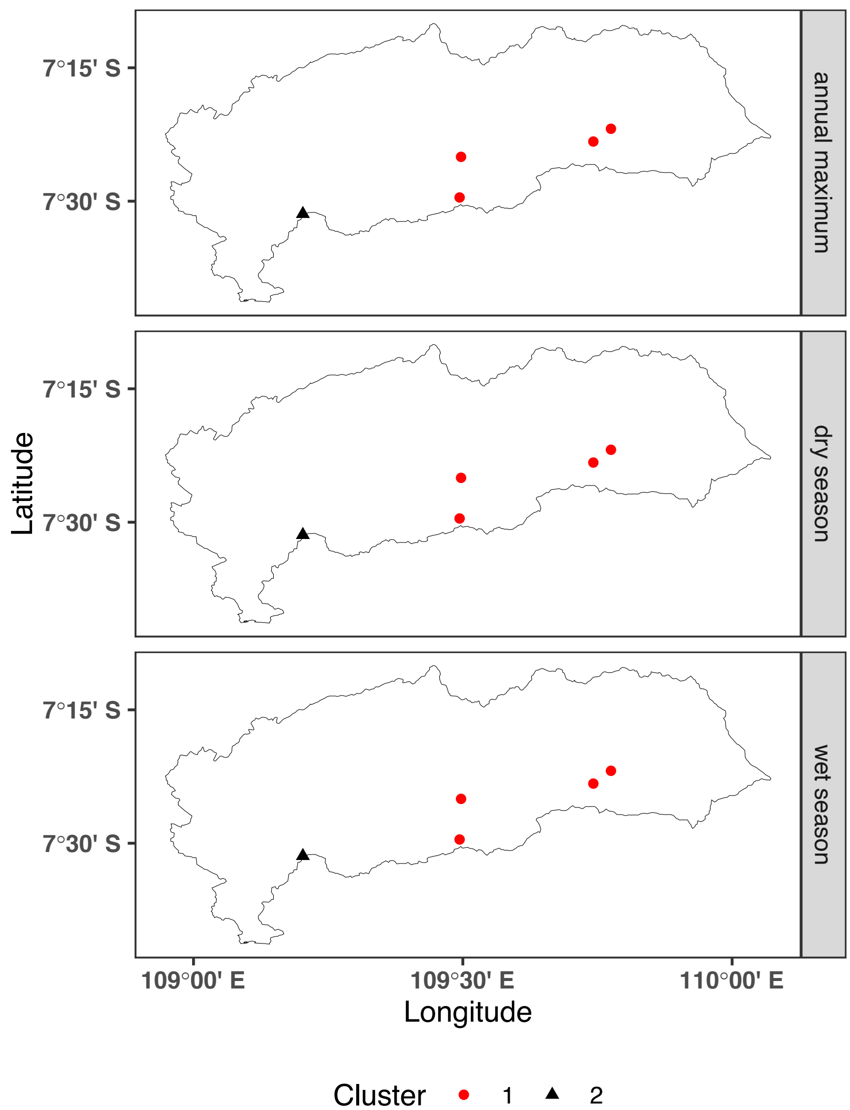


Figure 18. Maps of streamflow features enveloped in cluster.

Nonstationary return levels

To show the useful of the understanding the relationship between tropical SST and hydroclimatic extremes explained above, NEVA is used to estimate return levels of precipitation and streamflow extremes if climate drivers are incorporated. This is done as in practice, estimation of return levels for flood design has not considered the effects of global climate variables. Here, return levels of precipitation and streamflow extremes are computed using two approaches: stationary and nonstationary. Stationary is calculation of return levels using only the dataset, while nonstationary is computation of return levels using climate indices as covariates. Here, Nino3.4 and IOD are selected as covariates. The result is presented in Figure 19. It can be seen that some rain gauges produce high return levels, particularly for high return periods, in the case of stationary, while some others yield high return when nonstationary approach is used. This signifies the needs of incorporating climate drivers on the estimation of return levels for flood design to ensure the water infrastructures are designed using appropriate method. Similar features are noticed in estimation of return levels for annual streamflow extremes and shown in Figure 20.

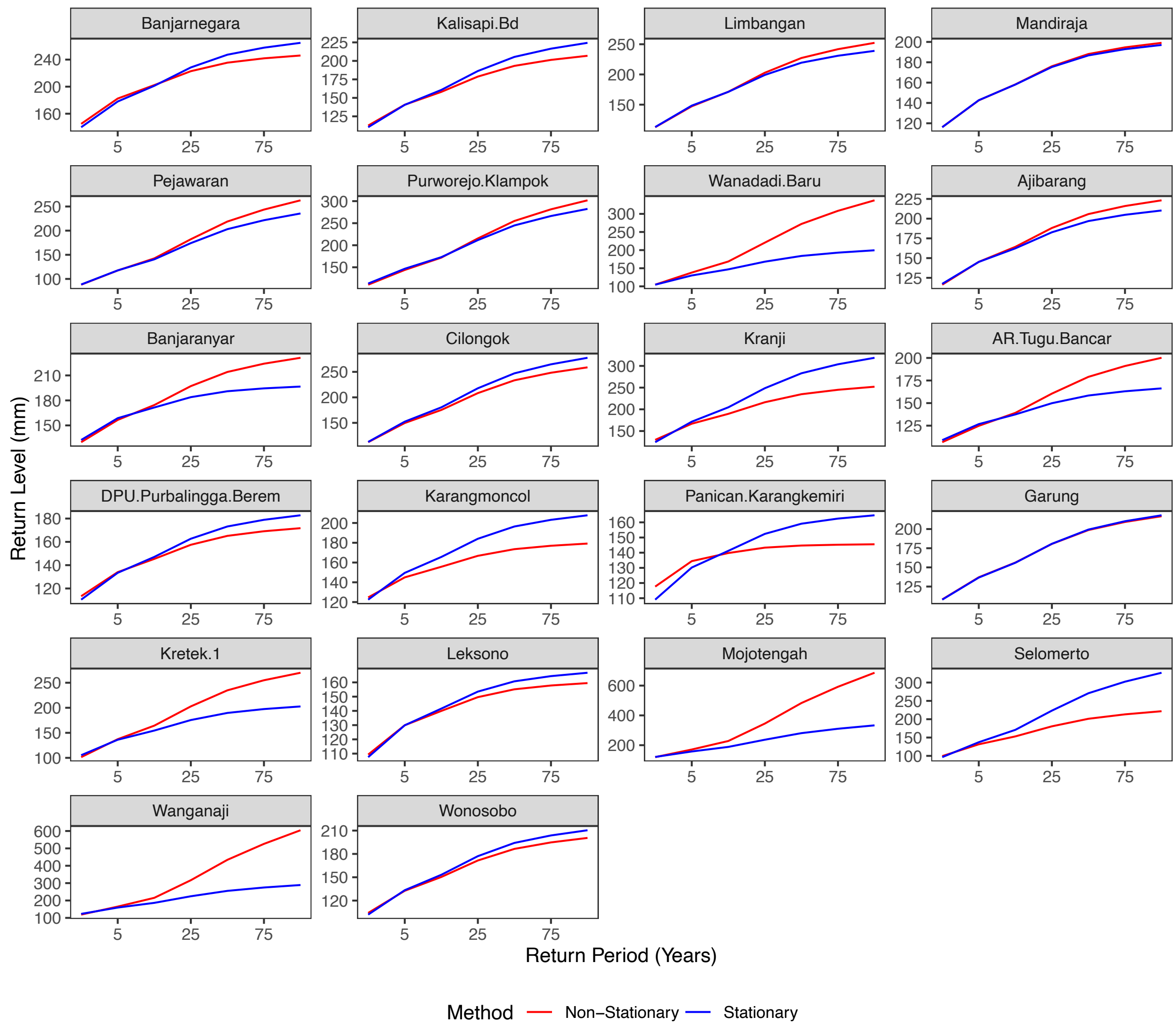


Figure 19. Return levels estimation using stationary and nonstationary extreme value analysis for annual maximum precipitation.

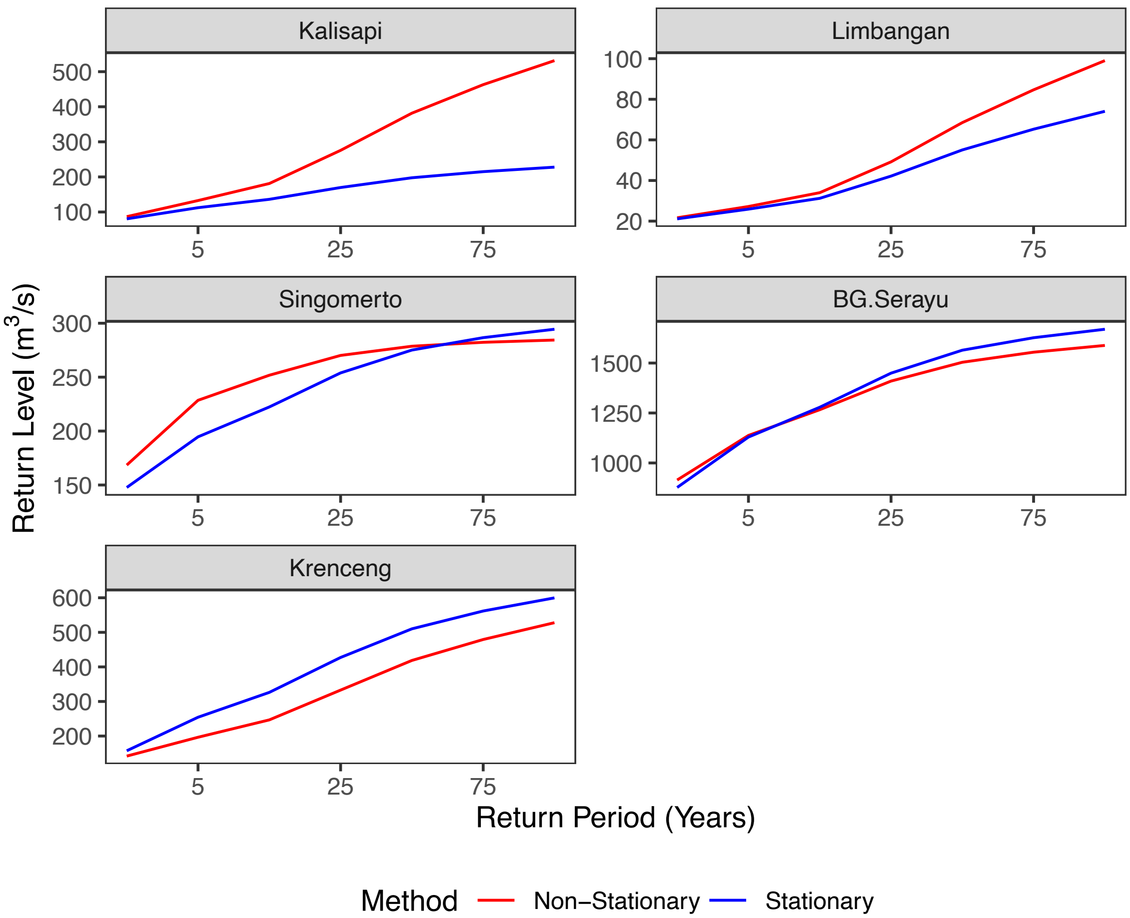


Figure 20. Return levels estimation using stationary and nonstationary extreme value analysis for annual maximum streamflow.

6. Conclusion

Copula is used to model relationship between tropical SST and hydroclimatic extremes in Serayu river basin, Indonesia. The hydroclimatic extremes, consists of annual maximum, dry season wet season precipitation and streamflow in the basin, are presented as the leading PCs which account for more than 50% variance generated from PCA. Over the period of 1985 – 2014, the annual precipitation extreme exposes increasing trend, while the seasonal extremes are declining. This conforms the trend in flood and drought intensity in the basin. Moreover, while linear model produces typical link of SST and hydroclimatic variables over tropical regions, Copula model provide alternative regions having strong correlation, signifying the advantage of Copula model where more spots in ENSO and IOD regions contributing to hydroclimatic extremes in Serayu river basin. Specifically, the presence of IOD effect on hydroclimatic extremes is verified using BDLM showing the increase of magnitude of influence of the linear model after 2007. Moreover, SOM is capable of visualizing spatial pattern of hydroclimatic extremes in a suitable way. It is found that precipitation extremes in the study area expose equitable features. Additionally, NEVA is able to produce return level estimates higher than it is from traditional method, which is important for flood design.

2.1.3 Hydroclimatic extremes study in Krishna river basin

1. Summary

Investigating spatio-temporal patterns of hydro-climatological extremes (e.g. floods and droughts) is necessary for multiple sectors which include water resources management, infrastructure, agriculture and energy and in the context of climate change this assessment holds high significance. This study examines variations in extreme precipitation and temperature over the Krishna River basin (KRB), India. As a preliminary assessment, daily precipitation, daily maximum, minimum and mean temperatures were looked upon to understand their variation over time. Precipitation extreme indices were evaluated in this study to understand precipitation's intensity, frequency and duration variations. This enables us to comment on the behaviour of flood and drought events on Krishna River Basin. Following the preliminary assessment, Principal Component Analysis (PCA) was performed on the gridded rainfall to understand the association of rainfall with global teleconnection indices, secondly the Principal Components (PC's) derived from this analysis were also correlated with Sea Surface Temperature (SST). The aim behind using the SST is to understand how temperatures over oceans influence extremes over KRB.

1. Introduction

The present climate change scenario has global socio-economic repercussions. The coupled system of global wind and hydrological cycle gets disturbed with the compounded actions of Earth's dynamics around the sun and the unwarranted actions of human industrial advancements. The increasing concen- tration of green house gases (GHG) in the atmosphere is leading to rise in global temperature, which in turns disturbs the global wind flows responsible for weather changes. This leads to change in the pattern of precipitation depending upon the regional topography and its interaction with the ocean body. The sixth assessment report (AR6) of Intergovernmental panel on climate change (IPCC) has highlighted the fact that the global surface temperature in the first two decades of the 21 st century, i.e., (2001-2020) was 0.99◦C and 1.09◦C in 2011-2020 more than 1850-1900 (Working Group I, 2021).

2. Study area

The Krishna River Basin (KRB) having an area of 258948 km^2 (Figure 21) is the second largest eastward draining river in peninsular India (Jain et al., 2007). The river originates from Mahadev range in western ghats and traverses a length of 1400 km before joining the Bay of Bengal, furthermore, this river has thirteen major tributaries. The Southwest monsoon happening in the months from June to September brings the majority of rainfall over KRB and high flows are observed between the months of August and November. The annual average rainfall in this basin is around 780 mm (Chanapathi et al., 2018). The deltaic portion of KRB is situated in latitudes between 15°42' to 16°30' N and longitudes of 80°30' to 81°15' E with its head at Vijayawada which is prone to flooding whereas some parts of Andhra Pradesh,Karnataka and Maharashtra are drought-prone areas. The basin has small- to large- scale reservoirs catering to a variety of needs including irrigation and hydropower generation.

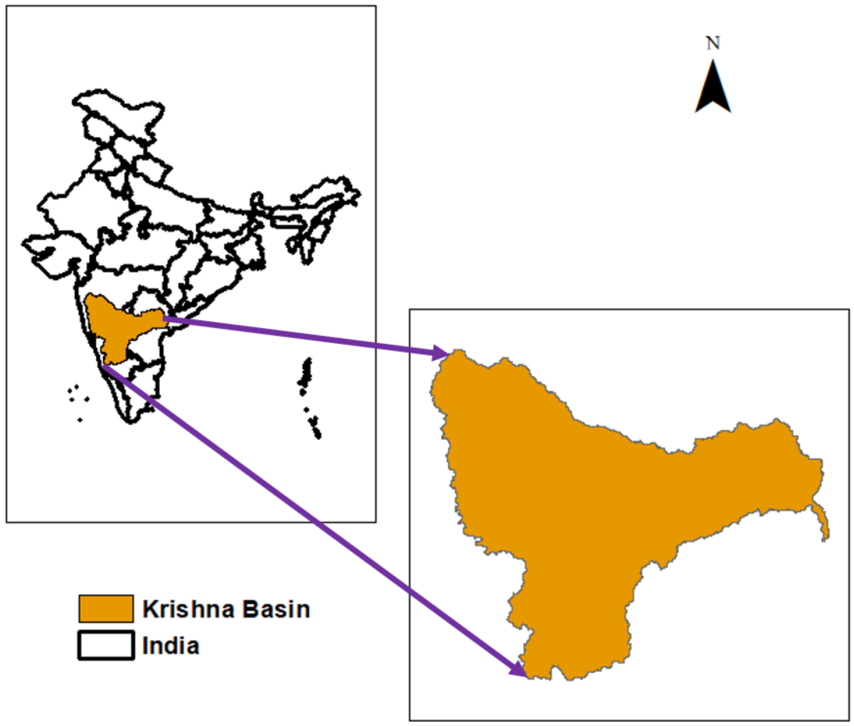


Figure 21. Krishna river basin service area map

3. Materials and methods

Gridded daily rainfall of 0.25° X 0.25° resolution (Pai et.al, 2014) and daily mean, maximum and minimum temperature data, which are widely used and well-known products from the Indian Meteorological Department (IMD), are used in this study. The gridded rainfall from 1901 to 2017 is used which is derived from observed rainfall amounts from rain gauge stations that are spread across India using inverse distance weighting method. The temperature data is available at 1° X 1° resolution. The following teleconnection indices are used : Antarctic Oscillation (AAO), Arctic oscillation, ENSO Precipitation index, Indian Ocean Dipole (IOD), Southern Oscillation Index (SOI), Caribbean Index, Nina 3.4, Nino 3.4, Nino 4, Tropical Northern Atlantic Index (TNA), Southern Annular Mode Index (SAMI), and Nino 3.4. The aforementioned teleconnection indices were obtained from https://psl.noaa.gov/data/climateindices/list/.

Methodology for identifying extremes

Identification of hydro-meteorological extremes is subjective for a given region, here rainfall thresholds are considered in identifying the extremes i.e., floods and droughts. To identify flood events, we first calculate the basin averaged rainfall and choose 5 mm/day as the threshold, and rainfall should persist above this threshold until rainfall remains below 1 mm for 4 days i.e., events are not separated unless this criteria is met (Andrews et al., 2011). We did not look into droughts as of now.

Advanced Statistical techniques

• Self-Organizing Maps (SOM)

SOM is typically an artificial neural network (Kohonen, 2013)which is useful in classifying synoptic circulation (Rousi et al., 2014). SOM is an unsupervised learning process that maps multivariate data on a 2-dimensional array or map.

• Copula Analysis

Copula based models allow for the derivation of joint distributions, given the marginal distribution. Copulas are useful for defining non-parametric measures for dependence.

• NEVA

Non-stationary extreme value analysis allows for the determination of the probability of exceedance of extreme values. It allows for the detection of the changes in the extreme values throughout the observation time.

4. Results

Preliminary data analysis

The variations of rainfall and temperature are examined as shown in Figures 22 and 23. Rainfall on a daily scale shown in Figure 22a shows periodicity i.e., rainfall being dominated in certain periods of the year. From the annual rainfall plot in Figure 22b, we see rainfall fluctuating between 500 and 1000 mm for most of the time; however, we see a peak in the year of 2005, which is attributed to flooding in the upper KRB (Kale, 2009). The monthly rainfall plot in Figure 22c indicates dominant rainfall in the monsoon season (June to October). The annual maximum rainfall in Figure 22d depicts a rising trend with peaks in certain years. Boxplots of mean, maximum and minimum temperatures in Figures 23a, 23b and 23c may not show large inter-annual fluctuations, nonetheless evident rising trend in the mean temperature over KRB in Figure 23d sheds light on changing climate. Thus, investigating hydro-meteorological extremes in the context of changing climate holds paramount importance.

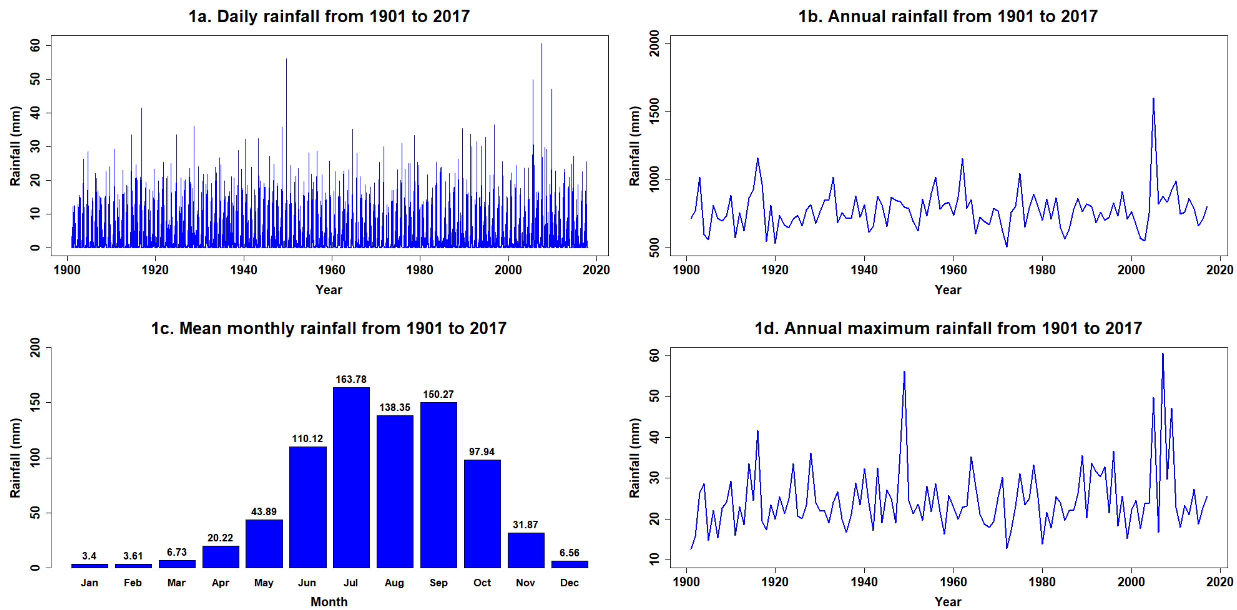


Figure 22. Rainfall variation at daily, monthly and annual timescales

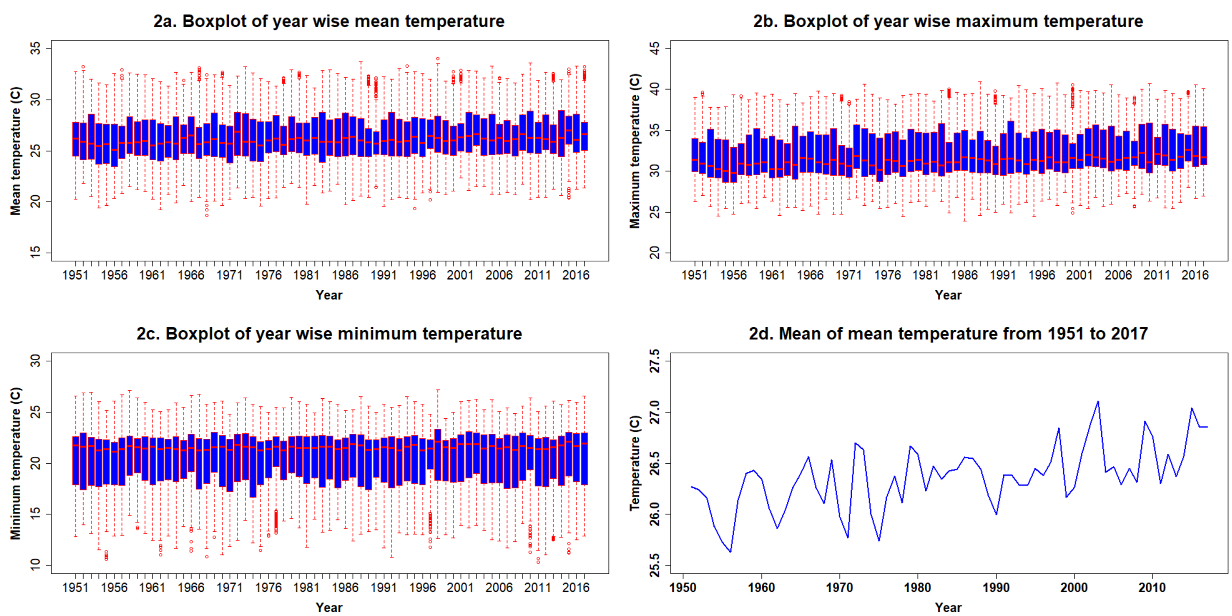


Figure 23. Boxplot of variations of mean, maximum and minimum temperatures

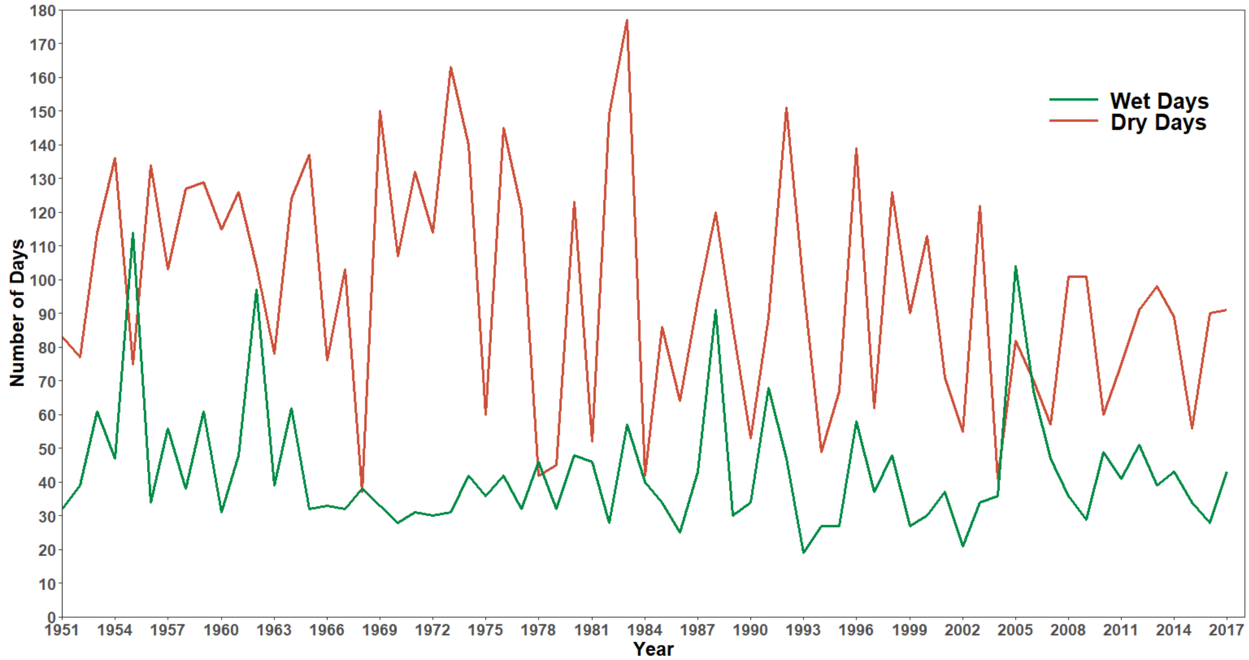


Figure 24. Consecutive wet and dry days over KRB

Analysis of precipitation indices

Consecutive Wet Days (CWD) imply the number of consecutive days when there has been a wet spell of rainfall exceeding 5 mm/day which should be persistent above this threshold until rainfall remains below 1 mm for 4 days. In Figure 24 we observe yearly variations in wet days, however no significant trend observed, interestingly Consecutive Dry Days (CDD) have shown a statistically significant decreasing trend (mann kendall test statistic (Z) = -2.25, p-value = 0.024). Specifically we observe a dip in the dry days after 1983.Spike in the CWD around 2005 is associated with floods in KRB, however spike in CDD in the years of 1984 and 1999 were a result of drought (Gaur et al., 2008). Three indices were evaluated to understand the intensity and frequency of precipitation over KRB, the three indices include Simple Daily Intensity Index (SDII), R95p (indicates annual contribution from very wet days i.e., days which have precipitation higher than 95 percentile of daily precipitation) and R10 (Number of days in a year when the daily precipitation exceeds 10 mm). These indices for precipitation are recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI, etccdi.pacificclimate.org/index.shtml) which were calculated for the period of 1951 - 2017.

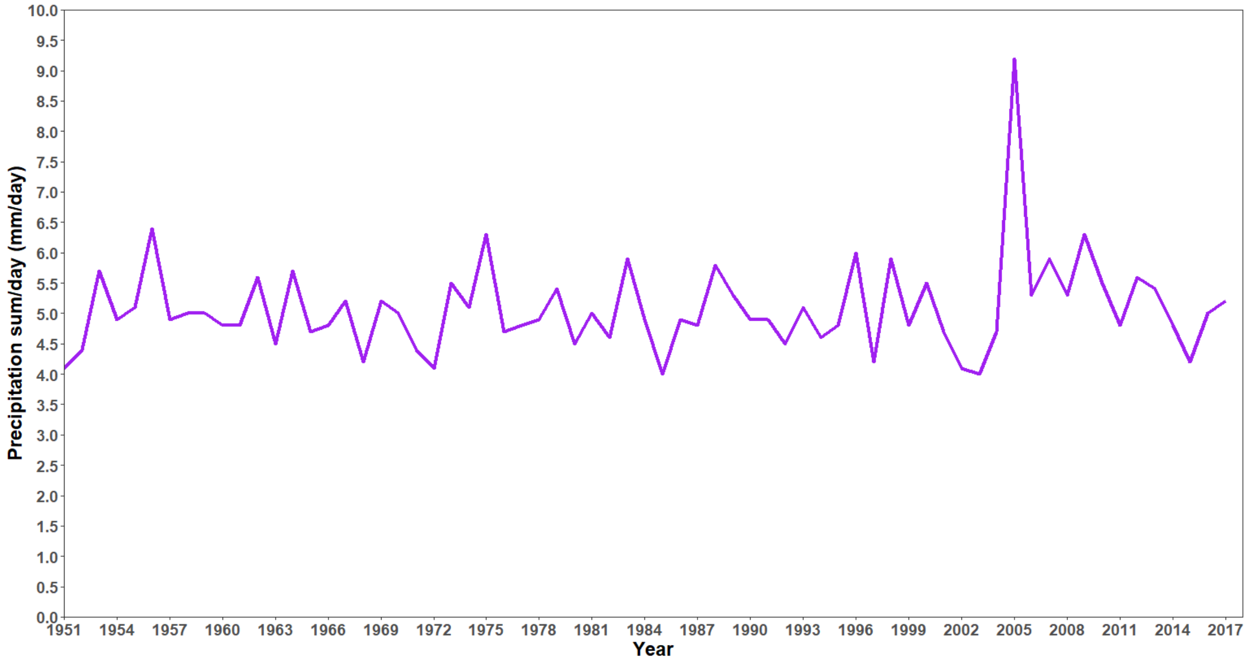


Figure 25. Simple Daily Intensity Index (SDII) over KRB

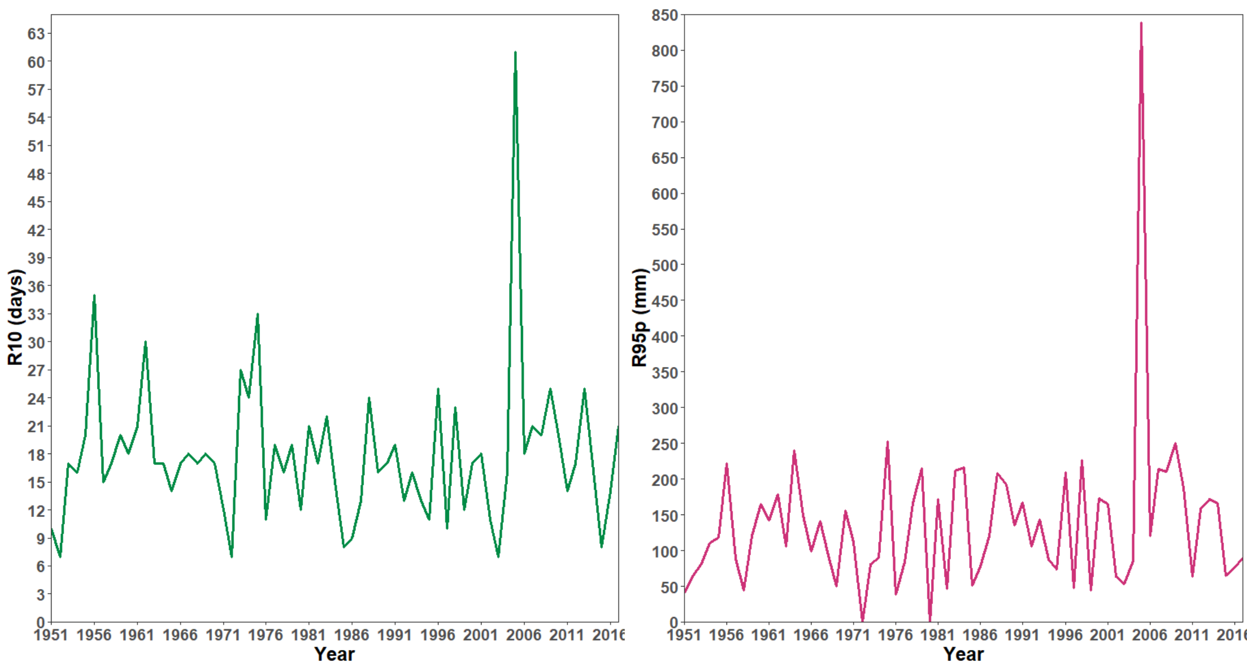


Figure 26.R10 index (left panel) and R95p (Right panel) in KRB

The Figure 25 describes intensity which is the ratio of annual precipitation and total number of days when precipitation is greater than 5 mm. As seen earlier, the year of 2005 which is the flood year shows a huge spike. The plot of R10 in Figure 26 has 61 days corresponding to year 2005 when rainfall is above 10 mm, moreover the contribution of R95p to the annual rainfall is highest for the year of 2005. It is to be noted that these indices are calculated using spatial averaged rainfall data thereby we are not talking about spatial variation of these indices.

Principal Component Analysis (PCA) and association of teleconnection indices

Principal component analysis is performed on the monsoon rainfall from 1943 to 2017, the first and second PC's explain 50% of variance in the data (The first PC explaining 38 % and the second one having 12 %), Figure 27 below depicts the percentage variance explained by all the principal components.

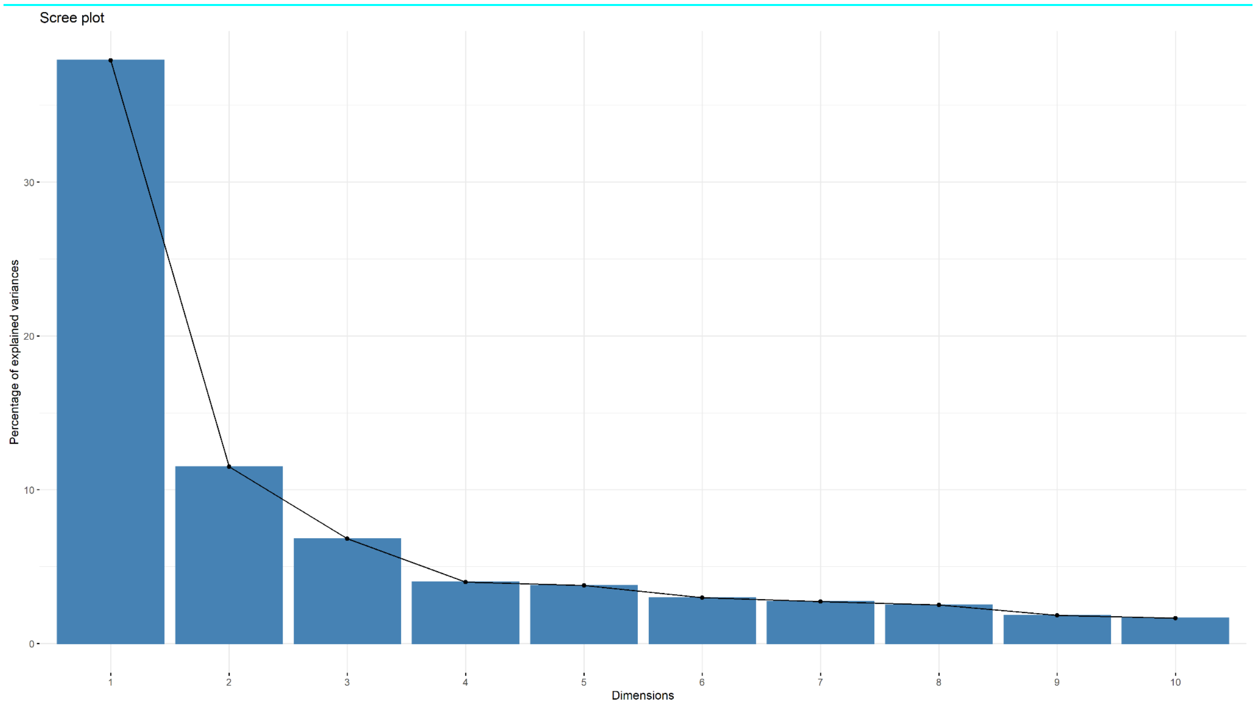
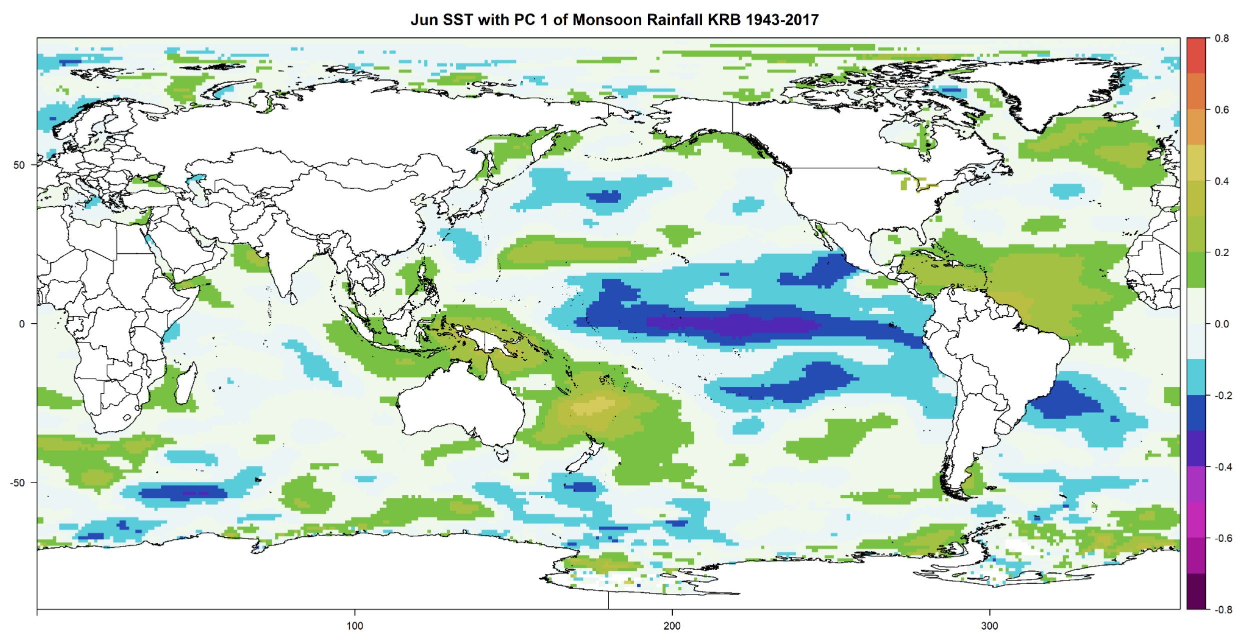


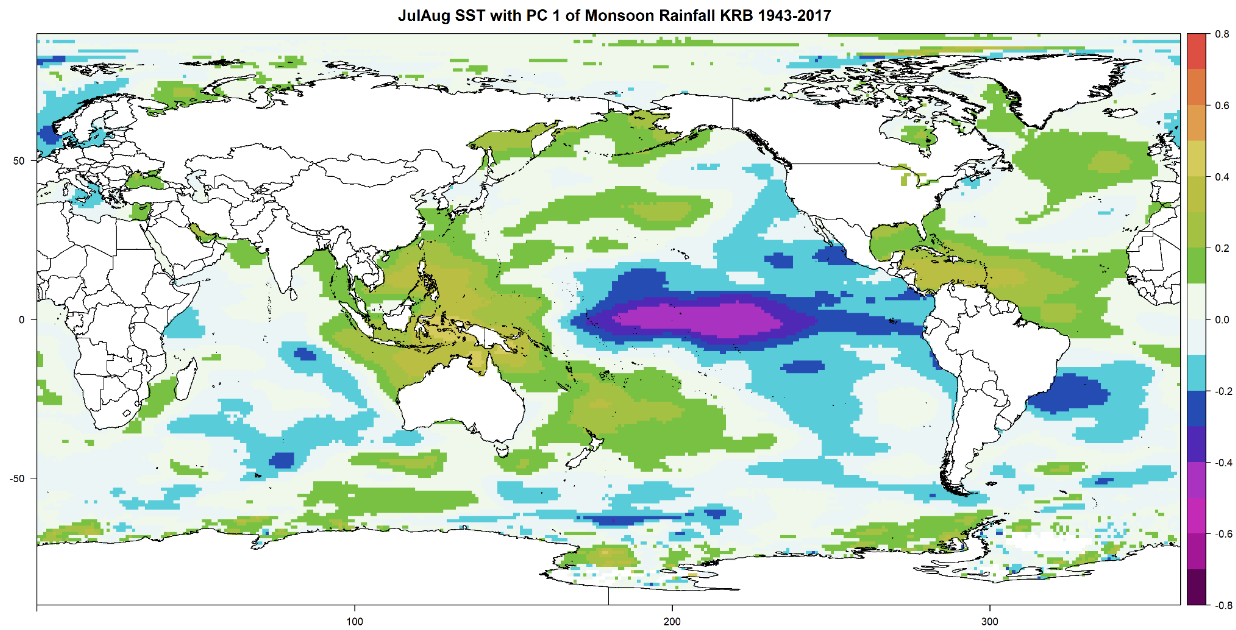
Figure 27. Scree plot providing percentage of variance explained by the principal components

The motive behind performing PCA is to find out the association between the principal components and the aforementioned global teleconnection indices. Lag-1 correlations were calculated between the two PC's and teleconnection indices, herein we only report the indices which showed higher association with the PC's. The PC1 showed highest association with Arctic Oscillation (AO) for the month of November which is 0.45, which implies that 20.25% of variance in the first PC of monsoon rainfall is explained by the AO of the preceding year November month. The other index i.e., Dipole Mode Index (DMI) exhibited a correlation of 0.45 with PC1 for the previous year November-December month combination and negative association is observed with the month of May of DMI. The Tropical Northern Atlantic Index (TNA) showed high correlation in the month of March (correlation coefficient: 0.39) of the current year with PC1 of monsoon. In regards to PC2, the AAO and SAMI exhibited higher association. The June and July combinations of the preceding year had its influence on the PC2 of monsoon. The AAO and SAMI of the preceding year of June and July month exhibited a positive correlation of 0.33 and 0.36 respectively.

Association of sea surface temperature and PC's of monsoon

The association between sea surface temperatures and monsoon PC's were evaluated, to understand how temperature over the oceanic surface influences monsoon over KRB. Correlations were assessed utilizing the data from 1943 to 2017. The June, July to August and September month SSTs are associated with monsoon PC's for the years from 1943 to 2017. Here we only present the correlations between PC1 and SST's and as seen from Figure 28, from all the plots we see region in the pacific ocean falling in the latitudes between 0° to 12° S and longitudes between 144° to 180° W has a higher negative association with monsoon season rainfall, indicating any rise or fall in the rainfall over KRB may be associated with fall or rise in the SSTs in the aforementioned region.





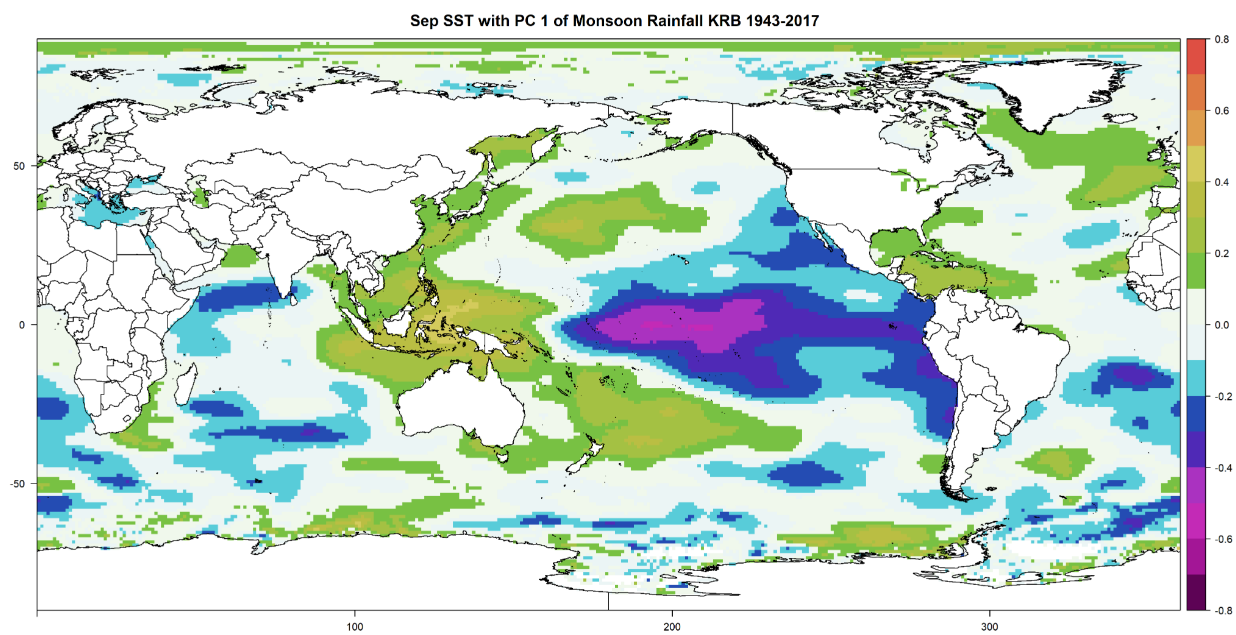


Figure 28. Correlation between SSTs of June (Top panel), July through August (Middle panel) and September (Bottom panel) with PC1 of monsoon

Advanced Statistical analysis

We considered annual daily maximum (top panel), annual 3-day maximum (middle panel) and annual 7- day maximum (bottom panel), and applied the following techniques. Below are shown plots for Copula , NEVA and SOM analysis.

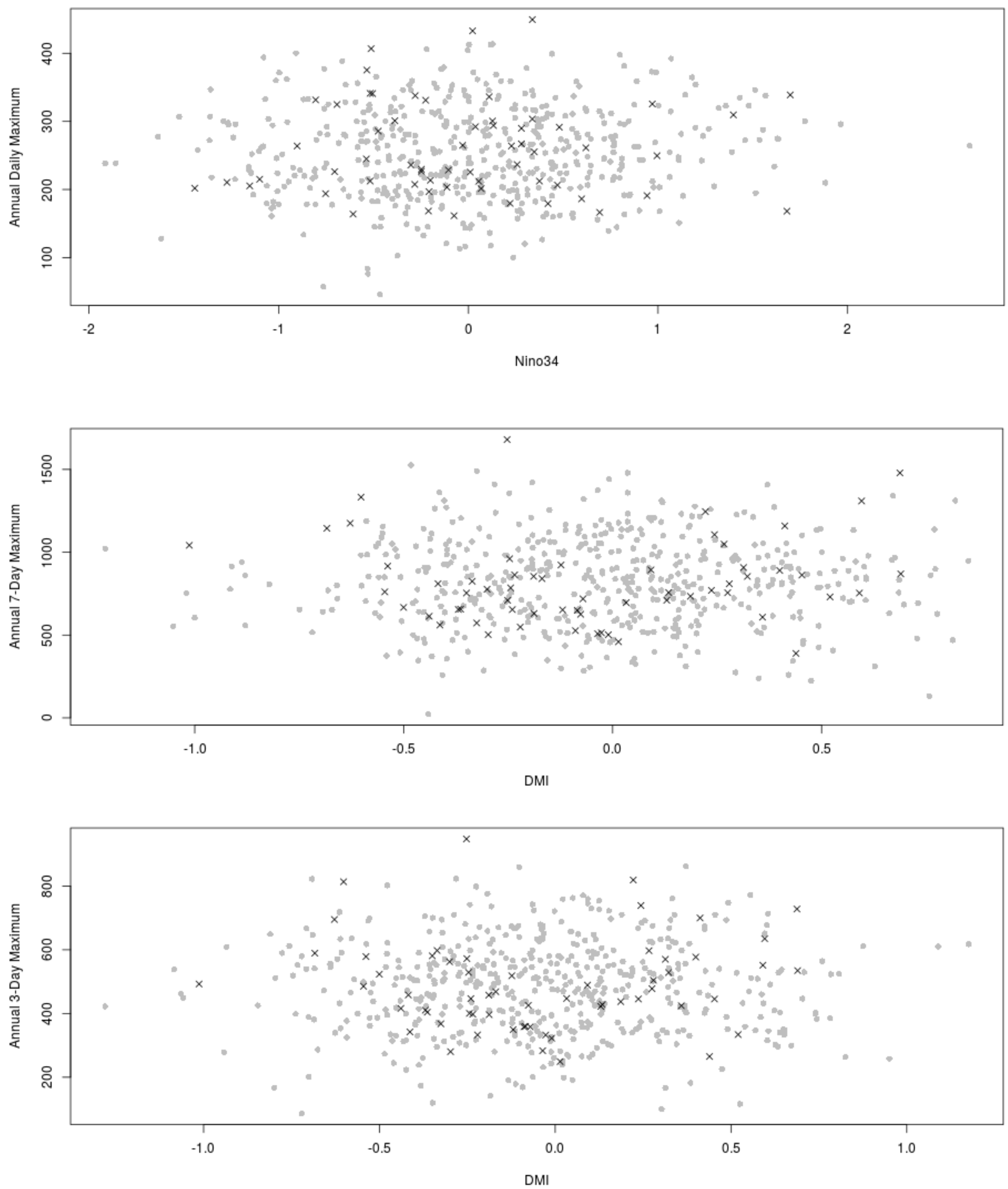


Figure 29. Copula analysis for Annual Daily Maximum (top panel), annual 3-day maximum (middle panel) and annual 7- day maximum (bottom panel)

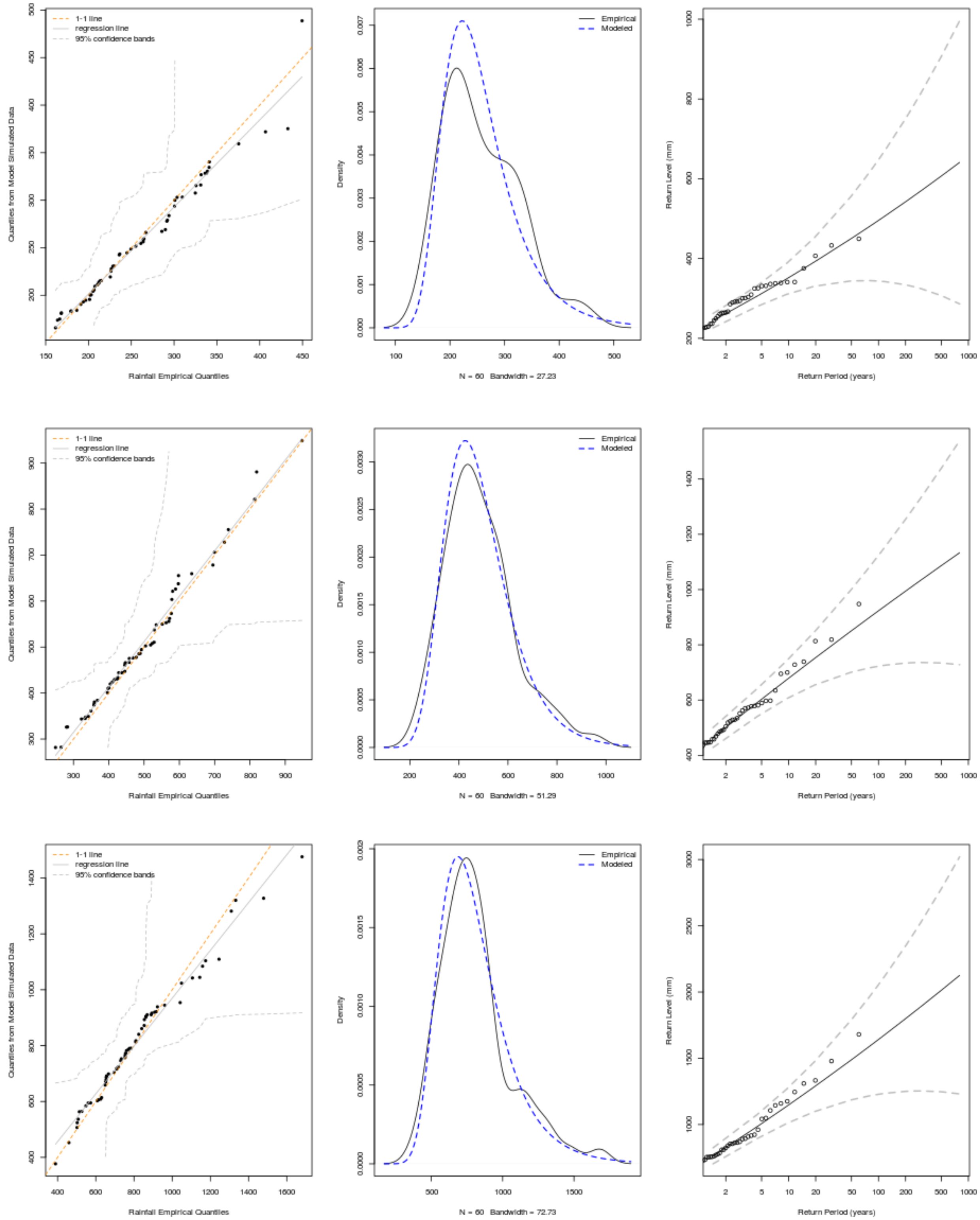


Figure 30. NEVA for Annual Daily Maximum (top panel), annual 3-day maximum (middle panel) and annual 7- day maximum (bottom panel)

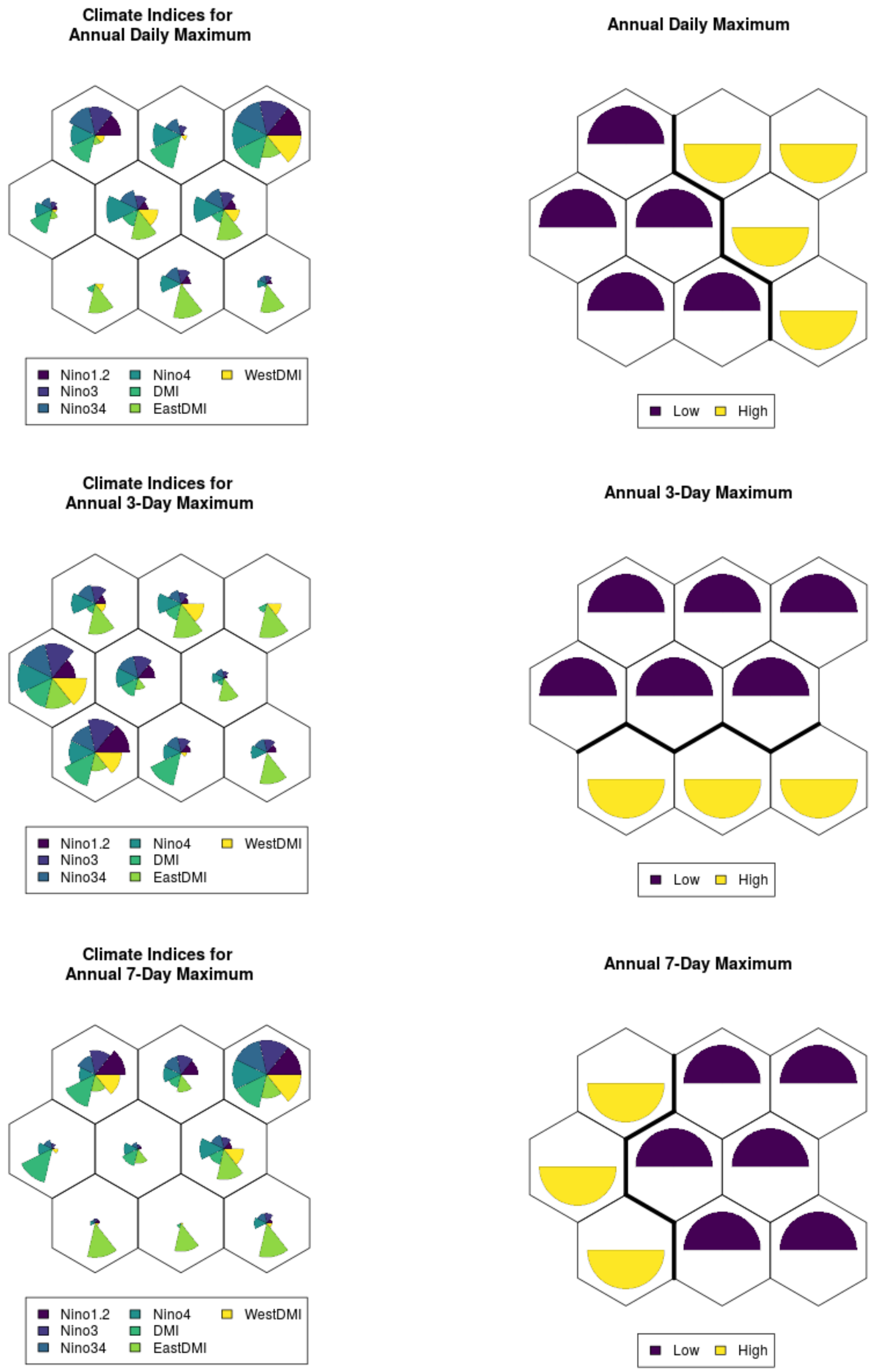


Figure 31. Self-organizing maps for Annual Daily Maximum (top row), annual 3- day maximum (middle row) and annual 7- day maximum (bottom row)

3. Project activities

Reporting period: October 2018 – September 2021

3.1 Activities completed

We have obtained fundamental hydroclimate data and performed hydroclimate analysis to achieve the first objective of the project. The Workshop and FGD have motivated the study to find simpler way to incorporate climate variables into river basin management is likely more favourable. One example is integration of climate variables into flood design, which has not yet been applied in the study area. Accordingly, we modified the second analysis on streamflow by directly connecting streamflow and global climate drivers using the specified approaches. By doing this, we provide a systematic approach to integrate climate variables into flood design, in a simple way. It is expected that the method can be easly applied by the watershed managers. The list of activities conducted in this reporting period are presented separately between Serayu and Krishna river basin

3.1.1 Serayu river basin

Project activities conducted in Serayu river basin are presented below:

- Obtained the shapefile of the Serayu river Basin
- Proposed Memorandum of Understanding between Jenderal Soedirman University and Meteorology, Climatology and Geophysics Agency of Indonesia to obtain more reliable data
- Obtained precipitation data from colleagues for 80 rainfall gauges over Serayu river basin for the period of 1997 – 2018
- Obtained streamflow data of the Serayu River Basins (source: Serayu-Citanduy Water Resources Management Office)
- Obtained data of Nino3,4 and IOD index for the period of 1985 – 2014
- Obtained historical hydrometeorological disasters within Serayu river basin including floods, droughts and landslides for the period of 2010 – 2019
- Obtained data on infrastructure related to societal resiliency such as evacuation route, roads, bridges, medical facilities etc.
- Developed an R-script to create rainfall extreme data, perform PCA analysis, SOM analysis, Copula analysis, BDLM analysis and NEVA for Serayu river basin
- Presented some of hydroclimate extreme analysis results in the 2019 European Geosciences Union (EGU) Conference held in Vienna, Austria on 7 – 12 April 2019
- Identified stakeholders of Serayu river basin who will participate in FGD and Workshop as follows:
    - Serayu-Opak Riverbasin Office (1 people)
    - Serayu-Citanduy Water Resources Management Office (1 people)
    - Public Work Service, District of Wonosobo, Banjarnegara, Purbalingga, Banyumas and Cilacap (5 people)

- Agricultural Agency, District of Wonosobo, Banjarnegara, Purbalingga, Banyumas and Cilacap (5 people)
- Environmental Agency, District of Wonosobo, Banjarnegara, Purbalingga, Banyumas and Cilacap (5 people)
- Association of Farmers, District of Wonosobo, Banjarnegara, Purbalingga, Banyumas and Cilacap (5 people)
- River Care Community, District of Wonosobo, Banjarnegara, Purbalingga, Banyumas and Cilacap (5 people)
- Climatology Service of Semarang, Central Java (1 people)
- Scientist from Civil Engineering and Agricultural of Unsoed, and UMP (5 people)
- Regional Disaster Countermeasure Board, District of Wonosobo, Banjarnegara, Purbalingga, Banyumas and Cilacap (5 people)

* Conducted workshop and FGD for Serayu river basin on 9 – 12 August 2021 by inviting the abovementioned stakeholders. The workshop and FGD was held online due to Covid-19 pandemic situation
* Adjusted study approaches to response findings from the workshop and FGD
* Reformatted manuscript for publication in response to the findings from the workshop and FGD

3.1.1 Krishna river basin

Project activities conducted in Krishna river basin are listed below:

* Obtained the shapefile of the Krishna river Basin from riverbasins.wateractionhub.org
* Obtained the gridded precipitation and temperature data from IMD for the period 1901 - 2017
* Obtained streamflow data for 36 locations in the Krishna River Basins (source: CWC, India WRIS)
* Developed an R-script that extracts areal average rainfall/temperature for any given region provided the shapefile of the region.
* Performed simple statistical analysis on the rainfall data
* Identified stakeholders of Serayu river basin (37 people) who will participate in FGD and Workshop as follows:
    - State Departments: AP, TS, Maharashtra, Karnataka
    - Central Department: http://agriculture.gov.in/, http://agricoop.nic.in/
    - State Departments: AP, TS, Maharashtra, Karnataka
    - Central Department: http://mowr.gov.in/, CWC,
    - Greater Hyderabad Municipal Corporation and Hyderabad
    - Hyderabad Metropolitan Water Supply and Sewerage Board
    - **Central Power Corporation**
    - Hydro Power ; Thermal Power

- State Departments: MIDC, KSIIDC, TSIIC, APIIC
- Central Department: COSIDICI
- https://www.india.gov.in/topics/agriculture/irrigation
- Central Department: Coastal AquaCulture
- *Rural Water Supply Departments*: AP, Mahabubnagar, Maharashtra, KRWSSA
- World Bank, https://www.indiawaterportal.org/author/department-drinking-water-supply-ministry-rural-development
- *Urban Water Supply* Department: https://jalshakti-ddws.gov.in/
- State Departments: AP, TS, Maharashtra, Karnataka
- Central Department: CPCC, ENVIS Center
- Hydel
- Non-Hydel
- Water Parks/ Amusement Parks, e.g., Haailand, Andhra Pradesh Tourism Department (e.g., Haailand)
- International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Hyderabad
- Water Users Associations in Local Bodies (consists of the local village head)
- SaciWATERS
- Center for Sustainable Agriculture
- Fisheries
- Animal Husbandry Department
- Short scale Industries which don't come under Industrial / Infrastructure
- Water Mobility (For Transferring Aqua Products)

- Organized workshop and FGD on 7 – 8 January 2020 with all abovementioned stakeholders

3.2 Adjustments or changes to the timeline of activities

During project implementation, we evaluated the effectiveness of separate Focus Group Discussion and Workshop in regard to data availability and stakeholders readiness to provide quality inputs for water resources management context relevant to disaster mitigation. As a result, we will implement Focus Group Discussion and Workshop at the same time such that we have sequence of discussion to explore current condition and future actions need by the stakeholders. We will conduct preliminary survey and interview to effectively design Focus Group Discussion and Workshop. We plan to conduct 3-day event of FGD and Workshop in January 2020 in India and August 2021 in Indonesia.

3.3 Challenges or issues

In Serayu river basin, acquiring precipitation and temperature data at a representative time window and spatial density is tough and could be very expensive. Even though the data is available, the amount of obtainable data is limited. We have requested the data from several government agencies that have precipitation and temperature data of Serayu River Basin as listed below:

- Public Works Service of Wonosobo, Banjarnegara, Purbalingga, Banyumas and Cilacap
- Serayu-Opak River Basin Office
- Serayu-Citanduy Water Resources Management Agency
- Climatology Service of Semarang, Central Java
- Center of Water Resources Research and Development, Ministry of Public Works, Indonesia

The quality of data is quite poor such that additional treatment must be performed to get more reliable data. We found 22 rainfall stations over Serayu River Basin from those government agencies. It is a daily rainfall data running from 1985 to 2014.

We have initiated a Memorandum of Understanding (MoU) between Jenderal Soedirman University and Indonesian Agency for Meteorology, Climatology and Geophysics to obtain high quality data over the study region. The MoU has been signed in August 26th, 2019. To get the data, a Memorandum of Agreement (MoA) should also be signed between the Faculty of Engineering, Jenderal Soedirman University and Climate Service, Semarang, Central Java following the undersigned MoU. The draft of MoA has been sent to Indonesian Agency for Meteorology, Climatology and Geophysics on December 6th, 2019. The process is quite challenging as the Indonesian Agency for Meteorology, Climatology and Geophysics is still reviewing the draft. We made intensive communication to the person in charge for the MoA draft reviewer in the Indonesian Agency for Meteorology, Climatology and Geophysics. However, we have not received good news on the MoA signing. Finally, we used the data we previously possessed.

4. List of project deliverables to date

1. A GUI based visualization tool to help policy makers and all relevant stakeholders in understanding hydrologic extremes as well as their linkages with social resiliency. The tool can be accessed here: https://satishregondaiith.shinyapps.io/ExtremeClimateAnalysis_Serayu_Krishna_RiverBasins/

5. List of pending project deliverables

The study approach has been reformatted to consider inputs from stakeholders during workshop and FGD. Moreover, we are unable to get good quality data from the Indonesian Agency for Meteorological, Climatological and Geophysic, even though many efforts have been done. It is mainly due to uncertain administrative process. Accordingly, the analysis is quite behind the schedule and the article has not been submitted yet.

- One paper on the hydroclimatic extremes correlation with tropical climate drivers and its effect on flood design in Serayu river basin, Indonesia has been drafted. We are now circulating the draft to all authors. It is expected that the manuscript can be submitted to Journal of Hydrology by the end of October 2021.

- One paper on the hydroclimatic extremes correlation with tropical climate drivers and its effect on flood design in Krishna river basin, India is in preparation. It is expected that the draft can be finished by the end of November 2021 and final manuscript can be submitted to Journal of Hydrology by the mid of December 2021.

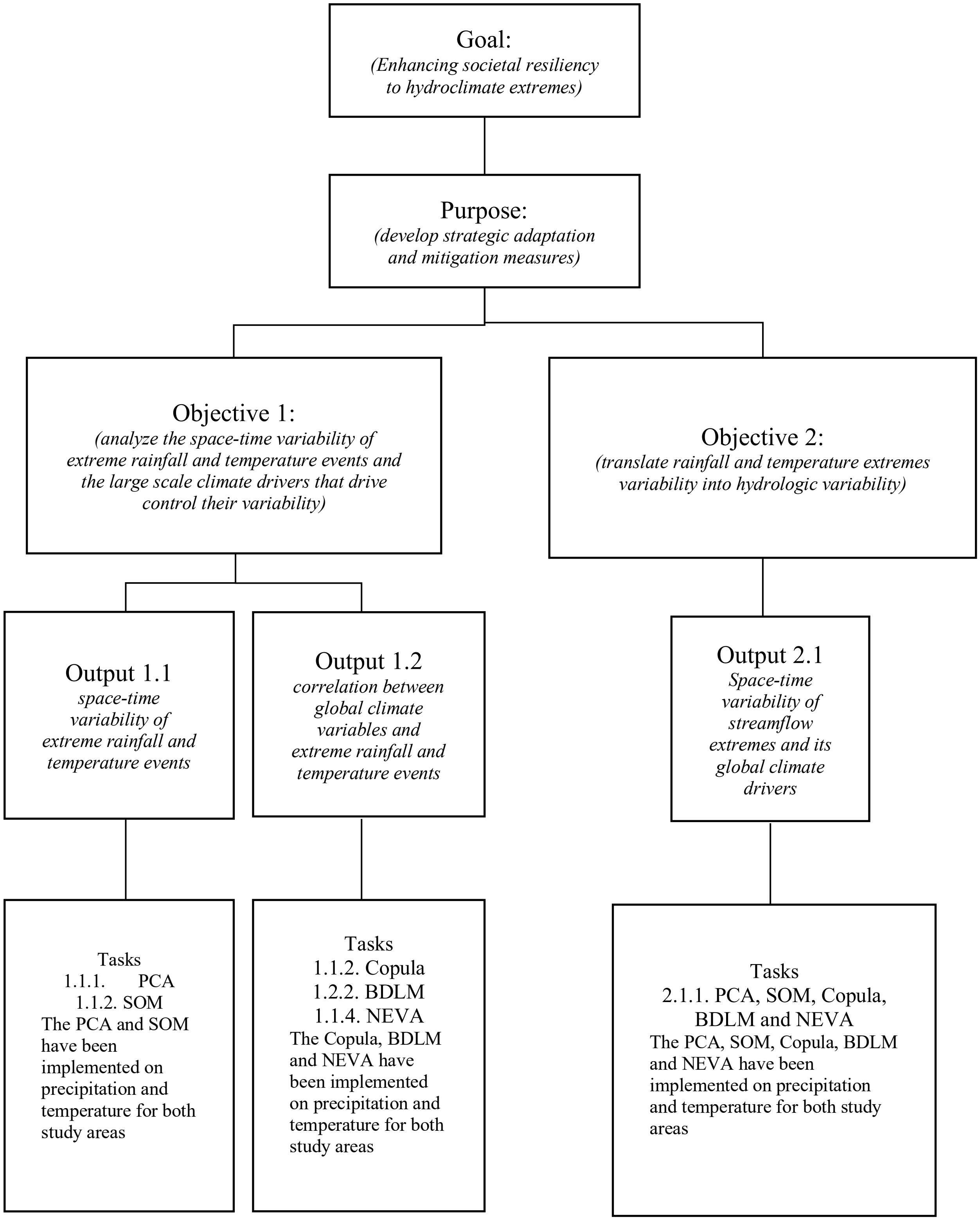
6. Future directions

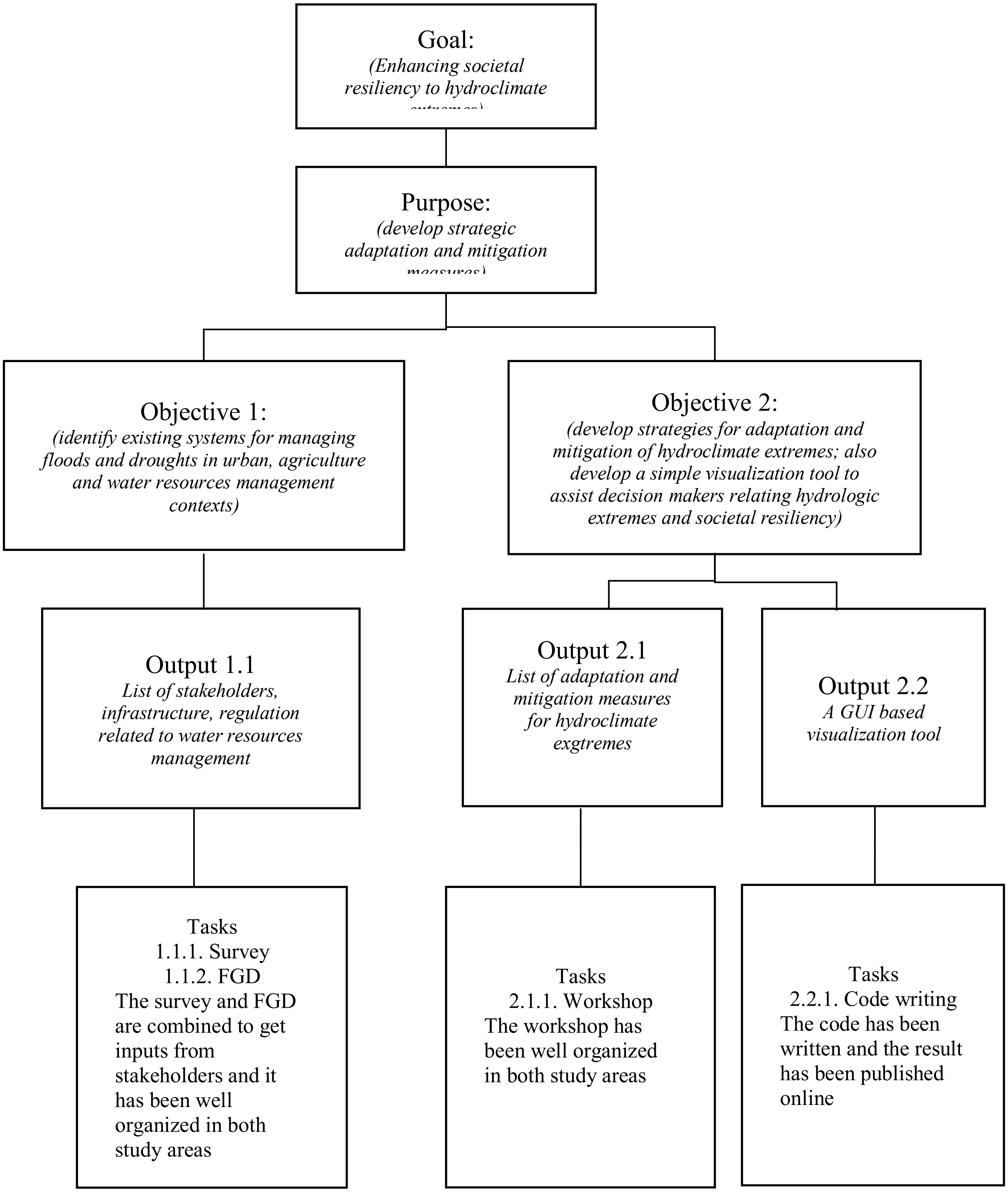
Through this project, we will produce some products that beneficial for stakeholders in both Serayu and Krishna river basin in form of: i) strategic adaptation and mitiation measures for hydroclimate extreme events; ii) a GUI based visualization tool to help policy makers and all relevant stakeholders in understanding hydrologic extremes as well as their linkages with social resiliency.

While GUI tool is good to provide climate information to stakeholders, advanced tool to implement the advanced statistic is required such that the approach is applicable in other regions. To do this, a web-based application where users can perform statistical analysis given their data is meaningful. Moreover, during the workshop and FGD in Indonesia, it is found that climate service is not available at watershed scale. Accordingly, the future direction of this project is developing climate service at watershed scale (particularly applicable for Indonesia) and a web-based application to help water managers perform required analysis specific to their river basin.

7. Special requirements

For continuing multi-year projects, please refer to your logical framework matrix and report your progress using the diagram below. You may add boxes as necessary.


Goal:
(Enhancing societal resiliency to hydroclimate extremes)
Purpose:
(develop strategic adaptation and mitigation measures)
Objective 1:
(analyze the space-time variability of extreme rainfall and temperature events and the large scale climate drivers that drive control their variability)
Objective 2:
(translate rainfall and temperature extremes variability into hydrologic variability)
Output 1.1
space-time variability of extreme rainfall and temperature events
Output 1.2
correlation between global climate variables and extreme rainfall and temperature events
Output 2.1
Space-time variability of streamflow extremes and its global climate drivers
Tasks
1.1.1. PCA
1.1.2. SOM
The PCA and SOM have been implemented on precipitation and temperature for both study areas
Tasks
1.1.2. Copula
1.2.2. BDLM
1.1.4. NEVA
The Copula, BDLM and NEVA have been implemented on precipitation and temperature for both study areas
Tasks
2.1.1. PCA, SOM, Copula, BDLM and NEVA
The PCA, SOM, Copula, BDLM and NEVA have been implemented on precipitation and temperature for both study areas


Goal:
(Enhancing societal resiliency to hydroclimate
Purpose:
(develop strategic adaptation and mitigation
Objective 1:
(identify existing systems for managing floods and droughts in urban, agriculture and water resources management contexts)
Objective 2:
(develop strategies for adaptation and mitigation of hydroclimate extremes; also develop a simple visualization tool to assist decision makers relating hydrologic extremes and societal resiliency)
Output 1.1
List of stakeholders, infrastructure, regulation related to water resources management
Output 2.1
List of adaptation and mitigation measures for hydroclimate exgtremes
Output 2.2
A GUI based visualization tool
Tasks
1.1.1. Survey
1.1.2. FGD
The survey and FGD are combined to get inputs from stakeholders and it has been well organized in both study areas
Tasks
2.1.1. Workshop
The workshop has been well organized in both study areas
Tasks
2.2.1. Code writing
The code has been written and the result has been published online

The activities, outputs and outcomes achieved to date.

We have obtained fundamental hydroclimate data and performed hydroclimate analysis to achieve the first objective of the project. In addition, we have also conducted additional activities to handle the issue on good quality data acquisition through developing MoU with climate agency in Indonesia. We have performed some primary analysis including PCA, Copula, SOM, BDLM and NEVA to understand the space-time variability of hydroclimate extreme events and its relationship with global climate indices. We have obtained an understanding on spatial and temporal variability of rainfall and temperature in the study area. Some results have been presented in the EGU Conference on 7 – 12 April 2019, in the Workshop and focus group discussion (FGD) in Hyderabad, India on 7 – 8 January 2020 and in Purbalingga, Indonesia on 9 – 12 August 2021. Important findings are found from the workshop and FGD which inspire the direction of this study. The manuscript for publication has been reformatted to take into account inputs from river basin stakeholders The GUI visualization tool has been created and published online, while two manuscripts for publication are prepared and expected to be submitted by the end of October 2021 (for Serayu) and mid of December (Krishna)

Acknowledgement

We thank to Center of Water Resources Research and Development, Ministry of Public Works, Indonesia for providing precipitation data used in this study, Indonesian Agency for Meteorological, Climatological and Geophysic and Jenderal Soedirman University for the arrangement of MoU, Indian Institute of Technology Hyderabad for providing GIS software and Indian Meteorological Department for providing precipitation data.

Appendices

List of young scientists involved in the project:

- Armia Faizal Sababa, Jenderal Soedirman University, armyids@gmail.com
- Thota Samba Siva Sai Prasad, Indian Institute of Technology, Hyderabad, ce15btech11022@iith.ac.in
- Sayantan Mandal, Indian Institute of Technology, Hyderabad, cc19mtech11006@iith.ac.in

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