ANALYSIS OF PRECIPITATION DATA USING SELECTED CLIMATE INDICES OVER THE HIMALAYAN REGION

Dissertation report

Submitted in partial fulfilment of

the requirements for the award of

the degree of

INTEGRATED MASTER OF TECHNOLOGY

In

GEOLOGICAL TECHNOLOGY

By

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Contents

Candidate's declaration

I hereby declare that the work which is being presented in the thesis entitles **"Analysis of precipitation data using selected climate indices over the Himalayan region"** in partial fulfilment of the requirements for the award of the Degree **INTEGRATED MASTER OF TECHNOLOGY** in **GEOLOGICAL TECHNOLOGY** and submitted in the Department of Earth Sciences of the Indian Institute of Technology, Roorkee is an authentic record of my own work carried out during a period from May 2020 to May 2021 under the supervision of **Dr Ajanta Goswami**, Associate professor, Department of Earth Sciences, Indian Institute of Technology, Roorkee.

The matter incorporated in this dissertation has not been submitted by me for the award of any other degree or diploma of this institute or any other university/Institute.

Tejas Warathe

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

Date: May 2021

Dr Ajanta Goswami

(Supervisor)

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Abstract

The Himalayas are a very important physical feature of the Indian Subcontinent, responsible for the monsoon season and origin of all the major river systems in India. The study of precipitation in the Himalayas hence is of utmost importance. This study uses Global Climate Models simulated by different research groups around the world to predict historical and future precipitation amount globally to analyse the historical changes till present in the precipitation pattern over the Himalayas and also analyse the future changes that we are going to see. This study uses simple analytical tools like climate indices to study the different extremes of precipitation and predict flood or drought conditions. This study also analyses the time series precipitation data over few major cities that are located in the Himalayan region. Statistical tools like the Modified Mann Kendall test and Sen's slope analysis is used to quantify trends in the climate indices over these cities. A difference between 2 future periods (2021-2060) and (2061-2100) with the historical (1981-2020) period for ten climate indices are calculated and plotted on a map. The differences plotted on the map help us to identify probable hotspots of a decrease in rainfall. It also helps up to identify other patches of increase in rainfall with a graphical colour scheme.

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Objective

The main objectives of the study are:

- To study the rainfall pattern in the Himalayan region, including the five major states and Union territories of Jammu and Kashmir, Ladakh, Himachal Pradesh, Uttarakhand, and Arunachal Pradesh over the past 40 years original data (1981-2020).
- Use ten different precipitation indices to analyse different conditions such as drought, flood, water abundance, and scarcity.
- To apply the same analysis to the next 80 years of generated synthetic data to study possible trends in the rainfall patterns in the region in future using statistical tests like the Mann Kendall trend test.

Introduction

Global climate change is one of the biggest challenges faced by humanity and is expected to have severe consequences for the environment in the twenty-first century (Agarwal et al. 2014; Immerzeel et al. 2012). In different parts of the world, climate change is affecting various sectors like water resources, agriculture, energy, and tourism. Climate change directly links changes in the precipitation, hydrological cycle, and atmospheric water content (Watts et al., 2015). Global warming will increase the earth's average temperature, which will lead to changes in the hydrological cycle, precipitation patterns, extreme conditions, melting of ice, changes in soil moisture, changes in the frequency and intensity of extreme events (Nicholls and Tol 2006; Xu et al. 2011; Menon et al. 2013). The monsoon season in India overcomes during June-September, and 80% of the annual precipitation occurs during monsoon months (Rao 1976; Reddy et al. 2014). The possible impact of global warming on the Indian summer monsoon is studied using the output of different climate models. However, there exist uncertainties in the regional climate projections due to biases in the global climate models. Different GCMs are used for local and regional level analysis and prediction of future climates.

The Himalayas act as an excellent climate divide affecting large amounts of air and water to circulate, they help determine meteorological conditions in the Indian Subcontinent. Due to their location and enormous height, the Himalayas blocks the passage of cold continental air from the north into India in the winter. The Himlayan range forces the southwesterly monsoon winds to give up most of their moisture before crossing the mountain range northward. Due to this, there is heavy precipitation on the Indian side but arid conditions in Tibet. The average rainfall on the south slopes varies between 1530 mm at Shimla, Himachal Pradesh, and Mussorie, Uttarakhand, in the western Himalayas and 3050 mm at Darjiling, in West Bengal state, in the eastern Himalayas. In the North, at places such as Skardu, Gilgit, and Leh in the Ladakh side of the Indus valley, only 75 to 150 mm of precipitation occur.

Local relief and location determine climatic variation in different parts of the Himalayas and even on different slopes of the same range. The town of Mussorie is situated on top of the mussorie range facing Dehradun city at an elevation of about 1,900 metres, It receives 2,335 mm of rainfall annually, compared with 1,575 mm in the town of Shimla, which lies some 145 km to the northwest behind a series of ridges reaching 2,000 metres. The eastern Himalayas, which are at a lower latitude than the western Himalayas, are relatively warmer.

The average minimum temperature for May, recorded in Darjiling at an elevation of 6,380 feet (1,945 metres), is 52 °F (11 °C).

There are two main periods of precipitation in India: the winter storms bring moderate amounts of precipitaion and the summer sees a heavier amount of precipitation, with its southwesterly monsoon winds. Heavy snowfall is caused by the advancing of low pressure weather system into the Himalayas from the West during winters. Over the high mountains, the precipitation is much more significant as the condensation occurs in upper air levels. Due to this precipitation is much more significant in the west than the east during this season with snow accumuating on the Himalayan high peaks. For example, Mussoorie town in Uttrakhand recieves 75 mm of rainfall in January whereas Darjiling in West Bengal recieves 25 mm. The meteorological conditions essentially reverse by the end of may. The moist air from the southwesterly monsoon when reaches the eastern Himalayas, rises, cools, and condenses to fall as rain or snow. In June, therefore, Darjiling receives about 600 mm and Mussoorie less than 200 mm. The rain and snow cease in September, after which the finest weather in the Himalayas prevails until the beginning of winter in December.

There are 19 major rivers that drain the Himalayas. The Indus, Ganges and Bramhaputra river systems are the three major river systems with their origins in the Himalayas. Five rivers form the Indus river system, including, the Chenab, the Beas, the Sutlej, the Jhelum, and the Ravi. They collectively form a catchment area of about 1,32,000 square km. The Indus river system is mainly responsible for providing freshwater reserves for the Punjab state in India and Pakistan. The state of Punjab, mainly being agriculture-dependent, requires the Indus river system to have an abundance of water throughout the year. Nine rivers collectively form the Ganges system, including the Ganges, Yamuna, Ramganga, Kali, Karnali, Rapti, Gandak, Bagmati, and Kosi rivers. The Ganges river system is mainly responsible for providing water in the northern plains of India, extending up to West Bengal in the East. The Northern plains are one of the most fertile lands in the Indian Subcontinent due to the deposition of alluvial soil due to the Ganges system. The northern plains are home to almost 40% of India's total population. The collective catchment area of the Ganges system is about 2,18,000 square km. The third main river system is the Brahmaputra river system, including rivers the Tista, the Raidak, and the Manas having a total catchment area of 1,84,000 square km.

The Himalayas also has few pockets of rich arable land, extensive grasslands and forests. Due to the high altitude of the Himalayas, the water draining away is harvested as hydro energy resources with projects like the Rampur Hydropower Project in the state of Himachal Pradesh.

Literature Review

Global Climate Model

Climate models are an essential tool to identify and improve our understanding of climate behaviour on a seasonal, annual, decadal and centennial basis. Climate models can predict climate changes that may have been caused by natural or human activity or a combination of both. They can be used as an essential measure to analyse and take precautionary measures to plan proper resource management, prevent scarcity and adverse calamities on a national, regional and local level.

The global climate model or GCM is a complex mathematical representation of the significant climate system components (sea ice, ocean, land surface, and atmosphere) and their interactions. The climate behaviour depends n the energy balance between these components.

The main climate system components are:

- Atmosphere: Includes clouds and aerosols responsible for the transport of heat and water around the globe.
- Ocean: Includes largest water bodies on the earth and their mixing, movement and biogeochemistry. It is also the primary heat and carbon reservoir in the system.
- Land surface: Characteristics such as vegetation, snow cover, soil water, rivers and carbon stores.
- Sea Ice: Includes solar radiation absorption and air-sea heat and water exchanges.

Climate models divide the earth into a 3-dimensional grid of cells, with each cell specifying a mathematical value corresponding to variables like temperature, precipitation flux etc. The different components also interact with each other by forming a coupled system that exchanges heat, moisture, and momentum.

Simulation of every component responsible, be it physical, chemical or biological in a single ideal model, would be close to impossible even with today's computational power available. Therefore, parameterisations and simplifications are made.

Atmospheric General Circulation Models (AGCMs) are used to simulate the atmosphere from weather forecasting models. Similarly, to simulate the oceans, Ocean General

Circulation Models (OGCMs) are used. Because Ocean and Atmosphere continuously transfer heat and moisture to and fro, using these models in a couples format is better. Hence, Atmosphere-Ocean General Circulation Models (AOGCMs) are used in modern-day simulations.

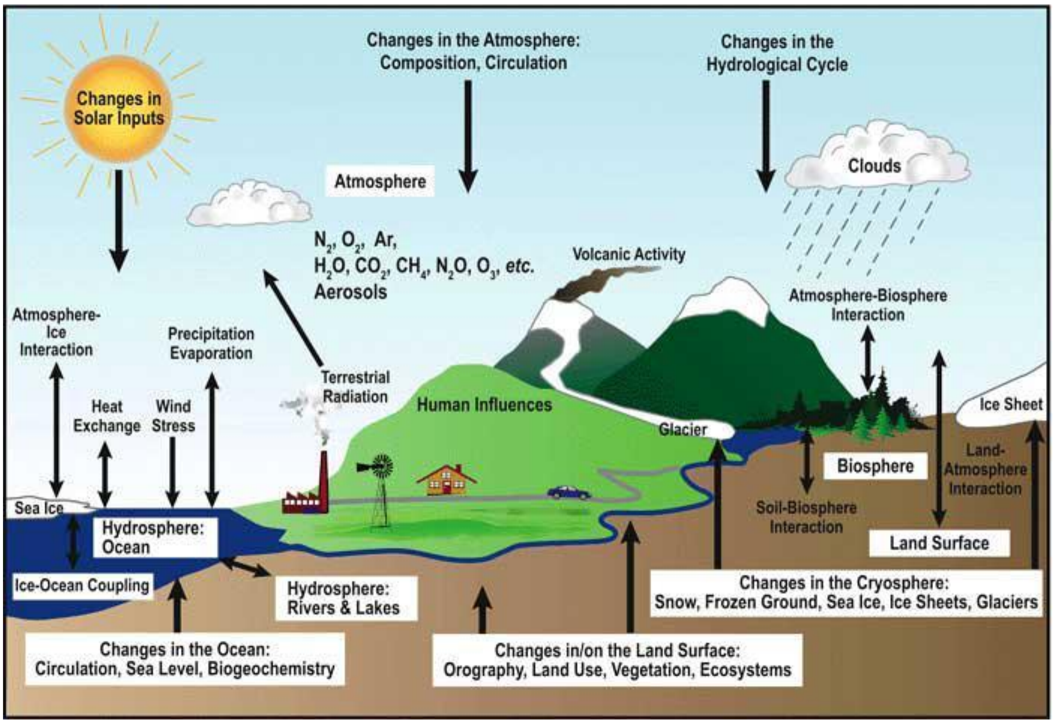


Figure 1: A schematic view of many of the processes and interactions in the global climate system (Le Treut et al., 2007)

These models use different physiological characteristic changes in the atmosphere, such as the change in the greenhouse gas concentration. Modern-day research centres worldwide assume a gradual increase in greenhouse gas concentration from present-day levels, using AOGCMs. These models show that the warming rate of oceans near the equator is higher than at higher latitudes near Antarctica. This causes an increase in the westerly winds, which has been observed in the 20th century (Salinger et al., 2005).

To have confidence in future predictions of these GCMs. Their predictions are first compared with observed climate data to see if they accurately simulate different climatic conditions. Confidence is the measure of the accuracy of global climate models to predict future climate based on globally accepted physical laws such as conservation of energy, momentum, and mass. They also consider empirical factors such as cloud reflectiveness or infrared absorptive properties of greenhouse gases.

Figure 2 shows an example of a comparison between observed surface temperatures with GCMs over the 20th century. These models were able to simulate the short term cooling followed by large volcanic eruptions, as shown.

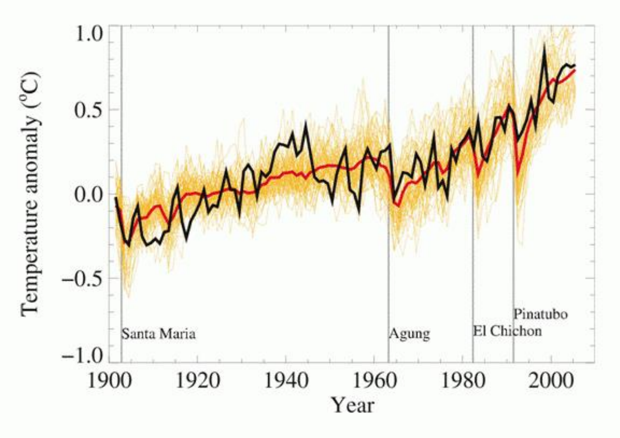


Figure 2: Global mean surface temperature, relative to 1901-1950 average, observation (black line), 58 simulations (orange lines) by 14 global climate models reported in the IPCC Fourth Assessment. Average of all models (red line) and dates of large volcanic eruptions (grey vertical lines). [Figure from IPCC (2007), Chapter 8, FAQ8.1].

Representative Concentration Pathways

To simulate different global climate models, different scenarios are taken into account. One such scenario is the measure of greenhouse gases in the atmosphere. Technological developments, change in land use and energy generations, global and regional economics and population growth are also considered. To make the research between different groups comparable and complimentary, a standard set of scenarios are formed that states starting conditions, historical data and projections across branches of climate science.

The Intergovernmental Panel on Climate Change (IPCC) is a body that publishes Assessment reports every few years that defines the set of scenarios. **Representative Concentration Pathways (RCPs)** are one such set of scenarios. There are four pathways: RCP2.6, RCP4.5, RCP6 and RCP8.5.

The different scenarios form possible pathways through which the future can be constructed by considering the varied amount of anthropogenic climate change. Scenarios consider many of the essential driving forces such as Physical, ecological and socio-economic impacts. These scenarios are important to form a better climate change policy. These are used as important factors globally in decision and policy-making (for example, preparing a water management infrastructure to combat future uncertainties). Having a standard also helps to consistently transfer information across different research areas.

An RCP scenario consists of a set of starting values and the estimated emissions till 2100, based on several assumptions regarding population growth, energy sources, economic activity and other socio-economic factors. This data also includes real-world historical data. RCPs is similar to high resolution global spatial datasets, which divides the earth into cells of latitude and longitude and time-series change of emissions for each cell every year.

Each of the four RCPs was developed by an Integrated Assessment Modelling (IAM) group.

The final agreed set of RCPs is:

RCP8.5: developed using MESSAGE model and Institute of Applied Systems Analysis (IIASA), Austria. Characterised by an increase in greenhouse gas emissions over time. (Riahi et al. 2007).

RCP6: developed by the National Institute for Environmental Studies (NIES), Japan, characterised by a stabilisation of total radiative forcing to around 6 W/m^2 shortly after 2100 by the application of technologies and reduction in greenhouse emissions. (Fujino et al. 2006; Hijioka et al. 2008).

RCP4.5: developed by GCAM modelling team at the Pacific Northwest National Laboratory's Joint Global Change Research Institute (JGCRI) in the US, characterised by stabilisation of total radiative forcing to around 4.5 W/m^2 shortly after 2100. (Clarke et al. 2007; Smith and Wigley 2006; Wise et al. 2009).

RCP2.6: developed by IMAGE modelling team of PBL Netherlands Environmental Assessment Agency, characterised by very low greenhouse gas emissions. It is a peak and decline scenario. Its radiative forcing reaches around 3.1 W/m^2 by mid-century and reduces to 2.6 W/m^2 by 2100. (Van Vuuren et al. 2007a).

Name	Radiative forcing	CO_2 equiv (p.p.m.)	Temp anomaly (°C)	Pathway	SRES temp anomaly equiv
RCP8.5	8.5 Wm^2 in 2100	1370	4.9	Rising	SRES A1F1
RCP6.0	6 Wm^2 post 2100	850	3.0	Stabilization without overshoot	SRES B2
RCP4.5	4.5 Wm^2 post 2100	650	2.4	Stabilization without overshoot	SRES B1
RCP2.6 (RCP3PD)	3Wm^2 before 2100, declining to 2.6 Wm^2 by 2100	490	1.5	Peak and decline	None

Table 1: Moss et al. 2010. Median temperature anomaly over pre-industrial levels and SRES comparisons based on nearest temperature anomaly, from Rogelj et al. 2012

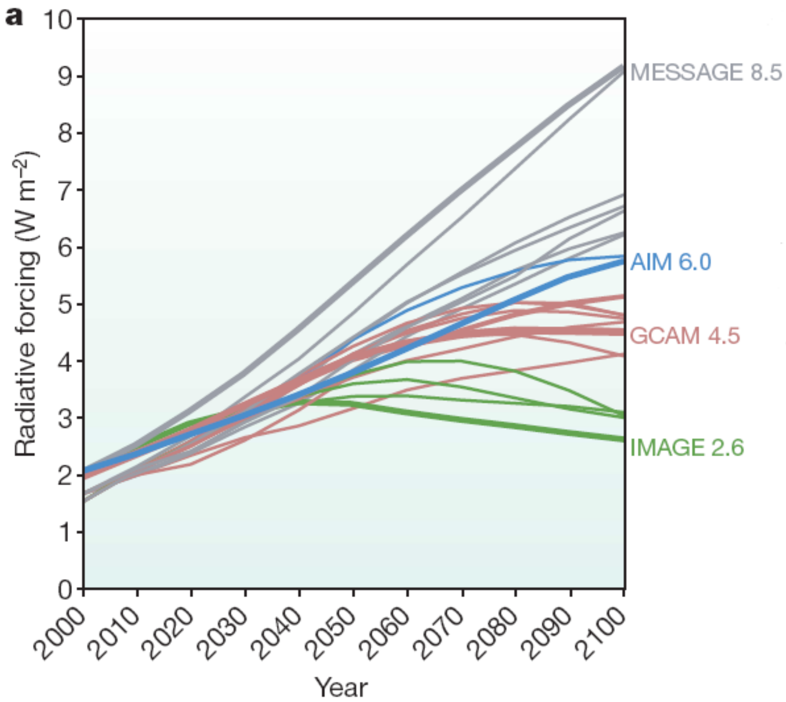


Figure 3: Changes in radiative forcing relative to pre-industrial conditions.

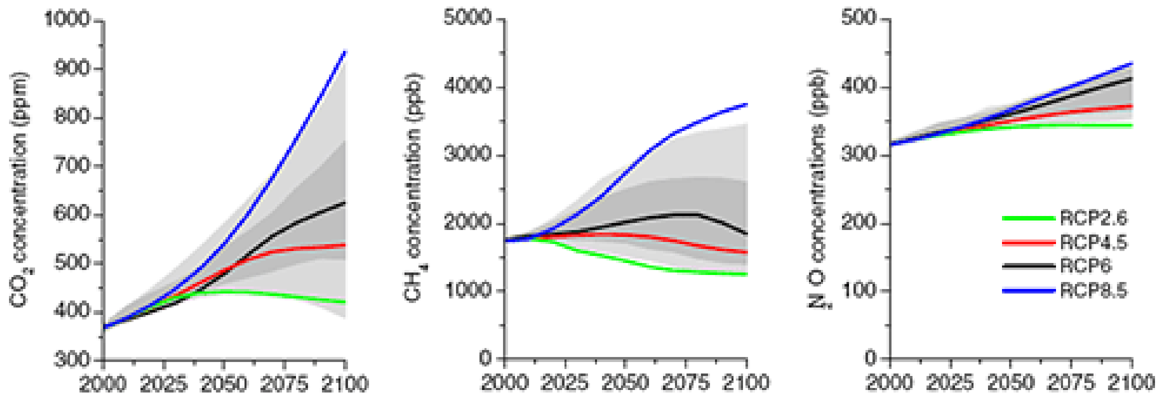


Figure 4: Change in concentrations of greenhouse gases (van Vuuren 2011).

GCM ensemble

Prediction of climate change from a GCM is highly dependent on the point of the control run at which increase in greenhouse gas emissions are introduced. For this reason, research teams' ensemble' a number of simulations with their climate model by keeping the historical and future changes in the greenhouse gases the same but changing the points of initiation of increase. The long term climate change from these experiments are very similar, showing that initial conditions are not very important in the long run. But they do have year by year and decade by decade differences. These are due to natural climate variability and are particularly large for some variables such as precipitation and at regional scales. These different results are then ensembled by averaging together to create a more robust estimate for climate change.

Climate Indices

Climate indices are a simple diagnostic quantity used to characterise an aspect of a geophysical system such as precipitation. The climate at a place is the average of the changes in atmospheric state over a long period of time, for example, months or years. Climate indices allow us to carry out a statistical study of different climatological aspects, such as analysis and comparisons of means, extremes, trends and time series.

Each climate index describes only a certain aspect of the climate. There are a variety of climate indices that have been defined. For each index, there is a defining mathematical equation. These equations use measurable parameters such as temperature, precipitation, solar radiation, air pressure to name a few.

Long term time series data from stations or remote sensing techniques can be used to calculate the climate indices of temperature and precipitation for that particular region. In comparison, air pressure climate indices calculate the pressure gradient between station; hence at least two station data are required.

Climate Base Period: A climate base period is used for calculations of some indices such as R95PTOT and R99PTOT. This base period should include 30 years of climate data as recommended by WMO (World Meteorological Organisation). The most used base period currently is 1961-1990.

10 Precipitation Indices

1. **CDD**: Consecutive dry days is a drought index defined as the maximum number of consecutive dry days per time period when the daily precipitation amount was less than 1 mm.
    - **Units**: Days
    - **Background**: This index is a measure of low precipitation days. When the values are high, it corresponds to long periods of low or no precipitation, which are potentially drought favouring conditions. An increase in CDD will be a sign of an increase in the chances of droughts.

2. **CWD**: Consecutive wet days is a flood index defined as the maximum number of consecutive wet days per time period when the daily precipitation amount was more than or equal to 1 mm.
    - **Units**: Days
    - **Background**: This index is a measure of precipitation days. When the values are high, it corresponds to long periods of precipitation which are potentially flood favouring conditions. An increase in CWD will be a sign of an increase in the chances of floods

      .

3. **PRCPTOT**: Average total precipitation in wet days. It is defined as the average total precipitation on days in a time period that has rainfall amount greater than or equal to 1 mm.
    - **Units**: mm
    - **Background**: This index is a measure of total rainfall received in a time period. A decrease in this index over time will lead to an overall decrease in the rainfall in a region and thus decreasing the water resources that are fed by rain.

4. **R95PTOT**: Heavy precipitation events. It is defined as the total amount of precipitation in a time period when the precipitation was at least 95th percentile of precipitation with respect to a base period (usually 1961-1990).
    - **Units**: mm
    - **Background**: This index is a measure of total rainfall when the daily precipitation is very high. An increase in this index will indicate that the rainfall contribution from very heavy precipitation days will increase, and hence there is a high chance of floods and reservoir overflow. Groundwater recharge is likely to decrease as the water tends to flow on the surface.

5. **R99PTOT**: Extremely heavy precipitation events. It is defined as the total amount of precipitation in a period when the precipitation was at least 99th percentile of precipitation with respect to a base period (usually 1961-1990).
    - **Units**: mm

- **Background**: This index is a measure of total rainfall when the daily precipitation is extremely high. An increase in this index will indicate that the rainfall contribution from extremely heavy precipitation days will increase, and hence there is a high chance of floods and reservoir overflow. Groundwater recharge is likely to decrease as the water tends to flow on the surface.

6. **Rx1day**: Highest one-day precipitation amount. It is defined as the maximum one-day precipitation in a period.
    - **Units**: mm
    - **Background**: This index is a measure of a single day heavy precipitation event. An increase in this index will increase the chances of flash floods in the region.

7. **Rx5day**: Highest 5-days precipitation amount. It is defined as the maximum total precipitation in a 5-day window in a given period.
    - **Units**: mm
    - **Background**: This index is a measure of heavy precipitation event in a five-day window. An increase in this index will increase the chances of flash floods in the region.

8. **R10mm**: Heavy precipitation days. It is defined as the number of days where the daily precipitation amount is at least 10 mm.
    - **Units**: Days
    - **Background**: This index is a measure of heavy precipitation days. An increase in this index indicates an increase in the chances of flood.

9. **R20mm**: Very heavy precipitation days. It is defined as the number of days where the daily precipitation amount is at least 20 mm.
    - **Units**: Days
    - **Background**: This index is a measure of very heavy precipitation days. An increase in this index indicates an increase in the chances of flood.

10. **SDII**: Simple Daily Intensity Index. Defined as the average daily precipitation on a wet day with precipitation of at least 1 mm in a given time period.
    - **Units**: mm
    - **Background**: This index is an indication of the spread of precipitation over a period. Higher values indicate that most precipitation is concentrated in a small amount of time which can lead to flood-like conditions.

Mann Kendall Trend Test

The Mann Kendall Trend test also called the M-K test, is a statistical tool to analyse data collected over time for consistently decreasing or increasing trends (monotonic). The test is a non-parametric test which means the data need not be a normal distribution. The test can be used for samples as low as four. However, the trend is more likely to be accurate if the number of data points is large. The minimum recommendation for the Mann Kendall test is therefore 8-10.

There are two hypotheses for the test:

- **Null Hypothesis:** A monotonic trend does not exist in the series.
- **Alternate Hypothesis:** A trend exists. The trend can be positive, negative or non-null.

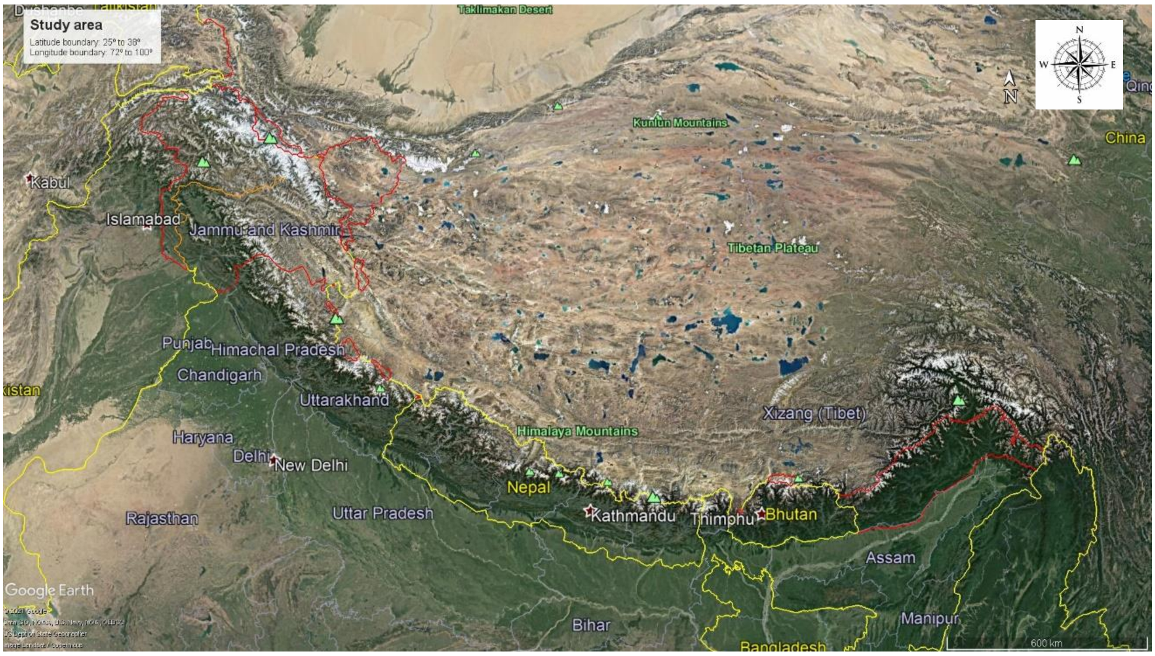
Points to ensure before running the test:

- **The data isn't collected seasonally**; the test won't work for alternating increasing and decreasing values. **Seasonal Kendall Test** can be used instead.
- **Data does not have covariates,** other factors which influence the data.
- **One data point per time period,** if multiple points available, the median value should be used.

Mann Kendall Trend test analyses the difference in signs between every pair of data points. The idea behind the test is that if a trend is present, the values will either increase or decrease constantly. If there are a total of 'n' data points, then the number of comparisons will be **n(n-1)/2.**

Study area and Data used

Study area



The study has been done between the latitudes 25° and 38° and longitudes 72° and 100°. The area covers the majority of the Himalayan range, which is present in the three north and north-eastern Indian states, Himachal Pradesh, Uttarakhand, Arunachal Pradesh and the Union territory Jammu and Kashmir. The study area also includes neighbouring countries of Nepal, Bhutan and parts of Tibet. The Himalayan range acts as a boundary for India from North and North-east and is home to the significant glaciers that are origins of the Main river systems of India.

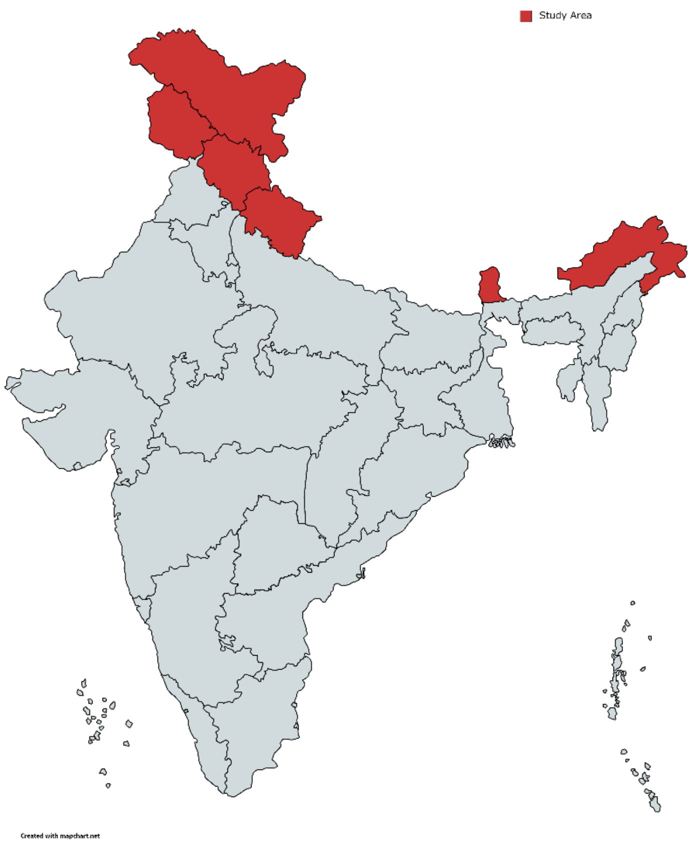
Some of the main Glaciers are:

- Arunachal Pradesh
    - Bichom Glacier
    - Kangto Glacier
    - Mazgol Glacier
- The UT of Ladakh
    - Siachen Glacier
    - Hari Parbat Glacier
    - Chong Kmdan Glacier

- Drang-Drung Glacier

- Himachal Pradesh
    - Bara Shigri Glacier
    - Beas Kund Glacier
    - Bhadal Glacier
    - Parvati and Dudhon
- Uttarakhand
    - Gangotri Glacier
    - Doonagiri Glacier
    - Kafini Glacier
    - Maiktoli Glacier
- Sikkim
    - Zemu Glacier
    - Rathong Glacier
    - Lonak Glacier

The rainfall analysis of the Himalayan region is of utmost importance as the amount of rainfall in the Himalayas determines the abundance of water in these river systems.



The Union territory of Jammu & Kashmir and Ladakh lies between 32º17' and 37º05' north latitude and 72º31' and 80º20' East longitude. They are the northernmost union territories of India. Both the UTs combined is spread in an area of 42,241 km^2. Major cities include Srinagar and Jammu in J & K, Leh in Ladakh.

Himachal Pradesh lies to the south of Jammu and Kashmir between 32º22'40 and 33º12'40 north latitude and 75º47'55 and 79º04'22 East longitude. Spread over an area of 55,673 km^2. Major cities include Shimla, Mandi, Manali etc.

The state of Uttarakhand is situated towards the east of Himachal Pradesh between 28º44' and 31º28' north latitude and 77º35' and 81º01' East longitude. Spread over an area of 53,483 km^2. Major cities include Dehradun, Rishikesh and Haridwar.

The state of Sikkim is present between 27º13' to 28º6' north latitude and 88º25' to 88º55' East longitude. Spread over an area of 7,096 km^2. Major cities include Gangtok.

The state of Arunachal Pradesh, situated in the northeast of India, is situated between 26º28' and 29º30' north latitude and 91º20' and 97º30' East longitude. It is spread over an area of 83,743 km^2. Major cities include Itanagar.

All the states and union territories present in the study area are predominantly mountainous. The major part of the study area consists of the Himalayan range with high altitudes.

Alternatively, studies have been done on the major cities of the five states of the Himalayan range, which includes: **Srinagar, Jammu, Leh, Shimla, Mandi, Dehradun, Haridwar, Rishikesh, Gangtok, and Itanagar.**

Data used

Global Climate models were acquired from Coupled Model Intercomparison Project 5 (CMIP5) database by the Working Group on Coupled Modelling (WGCM) under the World Climate Research Programme (WCRP). CMIP5 is considered to be a standard experimental protocol for studying the AOGCMs (Atmosphere-ocean general circulation models). CMIP project first began in 1995. Initially, it collected output from the control runs of models by keeping the climate forcing constant. Furthermore, iterations of CMIP have also considered ideal scenarios of global warming and a rate of 1% increase per year in atmospheric CO_2 until it doubles at about year 70.

For this particular study, experimental historical and future data models from the MIROC5 Global Climate Model, a version of the coupled model by Model for Interdisciplinary Research On Climate (MIROC), a Japanese research community, is being used. It is developed jointly by the University of Tokyo, Japan Agency for Marine-Earth Science and

Technology, National Institute for Environmental Studies (NIES), and Center for Climate System Research (CCSR).

Precipitation data from two different experiments of this model is used:

Historical: 01/01/1960 to 31/12/2009

RCP8.5: 01/01/2010 to 31/12/2100

Other characteristics of the model used:

Modelling Realm: Atmosphere

Time-frequency: Day

Ensemble : r1i1p1

The model has a resolution of about **1.4008 along latitude** with an extent of **-89^{0} to 89^{0}**; and about **1.40625 along longitude** with an extent of **-180^{0} to 180^{0}** on the Atmospheric grid.

Daily precipitation flux at each grid cell at the surface is available, which has contributions from both solid and liquid phases from all types of clouds for a calendar year with no Leap year (365 days), is available.

Precipitation Flux unit: **kg/m^2/s**

Methodology

Initially, the plan was to use a historical global daily dataset from Climate Hazards Group Infrared Precipitation with Station Data (CHIRPS) to analyse the precipitation patterns from 1981-2020. But due to huge differences in the value for future data by GCM used and CHIRPS data, historical data from GCM has been used instead.

Data sorting and Interpolation

The MIROC5 dataset consists of precipitation flux values acquired in the netcdf4 format is a global dataset, hence for processing only for the study area, the data was sliced using the Numpy library of Python. The data was then subsetted to Latitudes between **25^{0} and 38^{0}** and Longitudes between **72^{0} and 100^{0}**.

The MIROC5 dataset is a coarser dataset of latitude-longitude resolutions of about **1.4^{0}**. The MIROC5 dataset was then interpolated into a resolution of **.25^{0}x.25^{0}** using a quintic interpolation function. The function is available with the **scipy** library of Python. The code for Interpolation is given below:

```
newx = np.arange(71.875,100.125,.25)
newy = np.arange(24.875,38.125,.25)

def interpolate(data, oldx, oldy):
    global newx, newy
    newf = interp2d(oldx, oldy, data, kind='quintic')
    new_data = newf(newx, newy)
    return new_data
```

Here newx and newy are the sets of new longitude and latitudes, respectively. I have taken the starting and end values just outside the considered boundaries for latitudes and longitudes. The function interpolates the precipitation **data,** which is of the resolution 1.4^{0} (which is a 2-dimensional gridded data with each cell having values of precipitation flux corresponding to the lat/long location), **oldx** and **oldy** are the sets of corresponding old longitudes and latitudes, respectively. The function then uses the **interp2d** method from the **scipy library** to create a new function, **newf,** which is then used to interpolate the data into new sets of higher resolution latitudes and longitudes. The parameter **kind** given to the interp2d function tells us which interpolation function is used. Interp2d uses a polynomial smooth spline interpolation technique. The function has three types of interpolation methods available linear, cubic and quintic. In this study, I have used the **quintic function,** which is a polynomial function of degree 5. The function then returns a 2D grid of precipitation values with the news resolution.

After the Interpolation, the precipitation data available as precipitation flux is then converted to precipitation in mm/day by multiplying each value with **24*60*60**.

Code for Climate Indices

After the data acquisition, Python programming language was used to write code for the calculations of the 10 Climate Indices. The snippets for code are as follows:

1. **CDD (Consecutive Dry Days)**

   The maximum length of dry spell, the maximum number of consecutive days with RR < 1mm: Let RR_{ij} be the daily precipitation amount on the day *i* in period *j*. Count the largest number of consecutive days where:

$$RR_{ij} < 1mm$$

```python
def calculateCDD(precip, time_period):
    global cdd_matrix
    for y in range(53):
        for x in range(113):
            if(precip[y][x] < 1):
                current_cdd_matrix[time_period][y][x] += 1
            else:
                cdd_matrix[time_period][y][x] = max(current_cdd_matrix[time_period][y][x], cdd_matrix[time_period][y][x])
                current_cdd_matrix[time_period][y][x] = 0
            cdd_matrix[time_period][y][x] = max(current_cdd_matrix[time_period][y][x], cdd_matrix[time_period][y][x])
```

The function **calculateCDD** takes arguments *precip* which a 2D matrix data of precipitation for a day which has a shape of (53,113). The second argument is *time_period,* which is just the indication of which time period data are we calculating. The functions run through each cell in the 2D grid. The function then saves the maximum value for consecutive dry days in a 2D matrix *cdd_matrix* for the given time period. The resultant matrix *cdd_matrix* is a 53x113 matrix with each data point containing the CDD value for that latitude and longitude.

2. **CWD**

The maximum length of the wet spell, the maximum number of consecutive days with $RR \geq 1mm$: Let RR_{ij} be the daily precipitation amount on the day i in period j. Count the largest number of consecutive days where:

$$RR_{ij} \geq 1mm$$

```
def calculateCWD(precip, time_period):
    global cwd_matrix
    for i in range(53):
        for j in range(113):
            if(precip[i][j] >= 1):
                current_cwd_matrix[time_period][i][j] += 1
            else:
                cwd_matrix[time_period][i][j] = max(current_cwd_matrix[time_period][i][j], cwd_matrix[time_period][i][j])
                current_cwd_matrix[time_period][i][j] = 0
            cwd_matrix[time_period][i][j] = max(current_cwd_matrix[time_period][i][j], cwd_matrix[time_period][i][j])
```

The function **calculateCWD** takes arguments *precip* which a 2D matrix data of precipitation for a day which has a shape of (53,113). The second argument is *time_period,* which is just the indication of which time period data are we calculating. The functions run through each cell in the 2D grid. The function then saves the maximum value for consecutive wet days in a 2D matrix *cwd_matrix* for the given time period. The resultant matrix *cwd_matrix* is a 53x113 matrix with each data point containing the CWD value for that latitude and longitude.

3. **PRCPTOT**

Annual total precipitation in wet days: Let RR_{ij} be the daily precipitation amount on the day i in period j. If I represent the number of days in j, then:

$$PRCPTOT_j = \sum_{i=1}^{I} RR_{ij}$$

```
def calculatePRCPTOT(precip, time_period, year):
    global PRCPTOT
    for y in range(53):
        for x in range(113):
            if(precip[y][x] >= 1):
                PRCPTOT[time_period][year][y][x] += precip[y][x]
```

The function **calculatePRCPTOT** takes arguments *precip* which a 2D matrix data of precipitation for a day which has a shape of (53,113). The second argument is *time_period,* which is just the indication of which time period data are we calculating. The third argument is the *year* for which the PRCPTOT is being calculated. The functions run through each cell in the 2D grid. The function then saves the result for PRCPTOT in a 3D matrix *PRCPTOT* for all three periods. The resultant matrix *PRCPTOT* is a 40x53x113 matrix which is an array of 40 2D matrices corresponding to 40 yearly values of 53x113 dimension.

4. R95pTOT

Annual total PRCP when RR > 95p. Let RR_{wj} be the daily precipitation amount on a wet day w $(RR \geq 1.0mm)$ in period i and let $RR_{wn}95$ be the 95th percentile of precipitation on wet days in the 1961-1990 period. If W represents the number of wet days in the period, then:

$$R95p_j = \sum_{w=1}^{W} RR_{wj} \ where \ RR_{wj} > RR_{wn95}$$

```
def calculateR95pTOT(precip, time_period, year):
    global r95PercentileInterpolated, r95pTOT
    for i in range(53):
        for j in range(113):
            if(precip[i][j] > r95PercentileInterpolated[i][j]):
                r95pTOT[time_period][year][i][j] += precip[i][j]
```

The function **calculateR95pTOT** takes arguments *precip* which a 2D matrix data of precipitation for a day which has a shape of (53,113). The second argument is *time_period,* which is just the indication of which time period data are we calculating. The third argument is the *year* for which the R95PTOT is being calculated. The functions run through each cell in the 2D grid. The function compares each value on the cell with the 95th percentile of precipitation values in *r95PercentileInterpolated* for the base period 1961-1990, which is calculated beforehand. The function then saves the result for R95PTOT in a 3D matrix *r95pTOT* for all three periods. The resultant matrix *r95pTOT* is a 40x53x113 matrix which is an array of 40 2D matrices corresponding to 40 yearly values of 53x113 dimension.

5. R99pTOT

Annual total PRCP when RR > 99p: Let RR_{wj} be the daily precipitation amount on a wet day *w* $(RR \geq 1.0mm)$ in period *i* and let $RR_{wn}99$ be the 99th percentile of precipitation on wet days in the 1961-1990 period. If *W* represents the number of wet days in the period, then:

$$R99p_j = \sum_{w=1}^{W} RR_{wj} \ where \ RR_{wj} > RR_{wn}99$$

```
def calculateR99pTOT(precip, time_period, year):
    global r99PercentileInterpolated, r99pTOT
    for i in range(53):
        for j in range(113):
            if(precip[i][j] > r99PercentileInterpolated[i][j]):
                r99pTOT[time_period][year][i][j] += precip[i][j]
```

The function **calculateR99pTOT** takes arguments *precip* which a 2D matrix data of precipitation for a day which has a shape of (53,113). The second argument is *time_period,* which is just the indication of which time period data are we calculating. The third argument is the *year* for which the R99PTOT is being calculated. The functions run through each cell in the 2D grid. The function compares each value on the cell with the 99th percentile of precipitation values in *r99PercentileInterpolated* for the base period 1961-1990, which is calculated beforehand. The function then saves the result for R99PTOT in a 3D matrix *r99pTOT* for all three periods. The resultant matrix *r99pTOT* is a 40x53x113 matrix which is an array of 40 2D matrices corresponding to 40 yearly values of 53x113 dimension.

6. **Rx1day,** *Monthly maximum 1-day precipitation*:

Let RR_{ij} be the daily precipitation amount on the day i in period j. The maximum 1-day value for period j is:

$$Rx1day_j = \max(RR_{ij})$$

```
def calculateRx1day(precip, time_period, month):
    global Rx1day
    for i in range(53):
        for j in range(113):
            Rx1day[time_period][month][i][j] = max(precip[i][j], Rx1day[time_period][month][i][j])
```

The function **calculateRx1day** takes arguments *precip* which a 2D matrix data of precipitation for a day which has a shape of (53,113). The second argument is *time_period,* which is just the indication of which time period data are we calculating. The third argument is the *month* for which the Rx1day is being calculated. The functions run through each cell in the 2D grid. The function then saves the result for Rx1day in a 3D matrix *Rx1day* for all three periods. The resultant matrix *Rx1day* is a 480x53x113 matrix which is an array of 480 2D matrices corresponding to 480 monthly values of 53x113 dimension.

7. **Rx5day,** *Monthly maximum consecutive 5-day precipitation*:

Let RR_{kj} be the precipitation amount for the 5-day interval ending k, period j. Then maximum 5-day values for period j are:

$$Rx5day_j = \max(RR_{kj})$$

```python
def calculateRx5day(precip, time_period, month):
    global Rx5day

    max_of_5day_till_here = np.zeros([len(precip),53,113])

    firstWindowSum = np.zeros([53,113])
    monthlyMax = np.zeros([53,113])

    # first window sum end at index 4
    for k in range(5):
        for i in range(53):
            for j in range(113):
                firstWindowSum[i][j] += precip[k][i][j]

    max_of_5day_till_here[4] = firstWindowSum
    monthlyMax = firstWindowSum

    # from next window ending at index 5
    for m in range(5,len(precip)):
        for i in range(53):
            for j in range(113):
                max_of_5day_till_here[m][i][j] = max_of_5day_till_here[m-1][i][j] - precip[m-5][i][j] + precip[m][i][j]
                monthlyMax[i][j] = max(monthlyMax[i][j], max_of_5day_till_here[m][i][j])

    Rx5day[time_period][month] = monthlyMax
```

The function **calculateRx5day** takes arguments *precip* which a 2D matrix data of precipitation for a day which has a shape of (53,113). The second argument is *time_period,* which is just the indication of which time period data are we calculating. The third argument is the *month* for which the Rx5day is being calculated. The functions run through each cell in the 2D grid. The function then saves the result for Rx5day in a 3D matrix *Rx5day* for all three periods. The resultant matrix *Rx5day* is a 480x53x113 matrix which is an array of 480 2D matrices corresponding to 480 monthly values of 53x113 dimension.

8. R10mm,

Annual count of days when PRCP≥ 10mm: Let RR_{ij} be the daily precipitation amount on the day *i* in period *j*. Count the number of days where:

$$RR_{ij} \geq 10mm$$

```python
def calculateR10mm(precip, time_period, year):
    global R10mm
    for i in range(53):
        for j in range(113):
            if(precip[i][j] >= 10):
                R10mm[time_period][year][i][j] += 1
```

The function **calculateR10mm** takes arguments *precip* which a 2D matrix data of precipitation for a day which has a shape of (53,113). The second argument is *time_period,* which is just the indication of which time period data are we calculating. The third argument is the *year* for which the R10mm is being calculated. The functions run through each cell in the 2D grid. The function then saves the result for R10mm in a 3D matrix *R10mm* for all three periods. The resultant matrix *R10mm* is a 40x53x113 matrix which is an array of 40 2D matrices corresponding to 40 yearly values of 53x113 dimension.

9. R20mm

Annual count of days when PRCP≥ 20mm: Let RR_{ij} be the daily precipitation amount on the day i in period j. Count the number of days where:

$$RR_{ij} \geq 20mm$$

```
def calculateR20mm(precip, time_period, year):
    global R20mm
    for i in range(53):
        for j in range(113):
            if(precip[i][j] >= 20):
                R20mm[time_period][year][i][j] += 1
```

The function **calculateR20mm** takes arguments *precip* which a 2D matrix data of precipitation for a day which has a shape of (53,113). The second argument is *time_period,* which is just the indication of which time period data are we calculating. The third argument is the *year* for which the R20mm is being calculated. The functions run through each cell in the 2D grid. The function then saves the result for R20mm in a 3D matrix *R20mm* for all three periods. The resultant matrix *R20mm* is a 40x53x113 matrix which is an array of 40 2D matrices corresponding to 40 yearly values of 53x113 dimension.

10. **SDII,** *Simple precipitation intensity index*:
Let RR_{wj} be the daily precipitation amount on wet days, w *(RR ≥ 1mm)* in period j. If W represents the number of wet days in j, then:

$$SDII_j = \frac{\sum_{w=1}^{W} RR_{wj}}{W}$$

```
def calculateSDII(precip, time_period):
    global SDII, precipitationInWetDays, numberOfWetDays
    for i in range(53):
        for j in range(113):
            if(precip[i][j] >= 1):
                numberOfWetDays += 1
                precipitationInWetDays[time_period][i][j] += precip[i][j]

SDII[time_period] = np.true_divide(precipitationInWetDays[time_period], numberOfWetDays)
```

The function **calculateSDII** takes arguments *precip* which a 2D matrix data of precipitation for a day which has a shape of (53,113). The second argument is *time_period,* which is just the indication of which time period data are we calculating. The functions run through each cell in the 2D grid. The function return *numberOfWetDays* (total number of wet days) and *precipitationInWetDays* (total precipitation in those wet days (wet days is defined as days with precipitation greater than 1 mm)). Each cell value in the total precipitation matrix is then divided by the number of wet days to get the SDII value. The resultant matrix *SDII* is a 53x113 matrix with each data point containing the SDII value for that latitude and longitude.

Utility functions

Calculating percentile for the base period (1961-1990)

To calculate the percentile values for comparison in R95PTOT and R99PTOT climate indices, precipitation data from 1961 to 1990 is used. Numpy library has a predefined function called percentile, which calculates the n^{th} percentile value from a given set of values.

```
r95Percentile = np.percentile(totalPeriod, 95, axis=0)
r99Percentile = np.percentile(totalPeriod, 99, axis=0)
```

The two functions above take *totalPeriod* (precipitation from 1961-1990), *95 or 99* (as n value nth percentile), and *axis* (parameter which tells the function to calculate along the 0^{th} axis, i.e. time, in this case, the other two axes are latitude and longitude respectively). Returns a 2D matrix of n^{th} percentile values.

Calculations for Climate Indices

The database was divided into three periods of 40 years each:

1. **Historical:** 1^{st} January 1981- 31^{st} December 2020
2. **Period 1:** 1^{st} January 2021 - 31^{st} December 2060
3. **Period 2:** 1^{st} January 2061 – 31^{st} December 2100

Ten precipitation indices mentioned above were calculated for each of the three periods separately.

For precipitation indices, PRCPTOT, R95PTOT, R99PTOT, Rx1day, Rx5day, R10mm, and R20mm, a spike removal process was carried out before taking averages of 40 years, since these indices are calculated on an either annual or monthly basis.

Spike removal method

To remove the spikes before calculating averages, standard deviation and mean value for each of these indices were calculated over 40 year period.

The data between the values **mean $\pm$ 3 Standard Deviation** was kept as it is, and the data points beyond these were replaced by the mean value of 40 years. This spike removal was done for each cell of the 2D grid.

A mean of 40 years was then calculated, and a single 2D grid was formed.

The choice of 3 Standard Deviation was taken, keeping in mind that not more than 3-5% of data is removed.

Difference between future and historical values

After getting a single 2D grid values for each of the 10 indices in 3 distinct periods, the difference between two future periods and historical was calculated for each of these indices.

Difference 1 = Period 1 – Historical

Difference 2 = Period 2 – Historical

Difference 1 and Difference 2 are then plotted on the map of the study area using python libraries called Basemap and Matplotlib.

Mann Kendall Trend analysis

Along with spatial data, a trend analysis was carried out on 10 major cities of the Himalayan states, namely: **Srinagar, Jammu, Leh, Shimla, Mandi, Dehradun, Haridwar, Rishikesh, Gangtok, and Itanagar.**

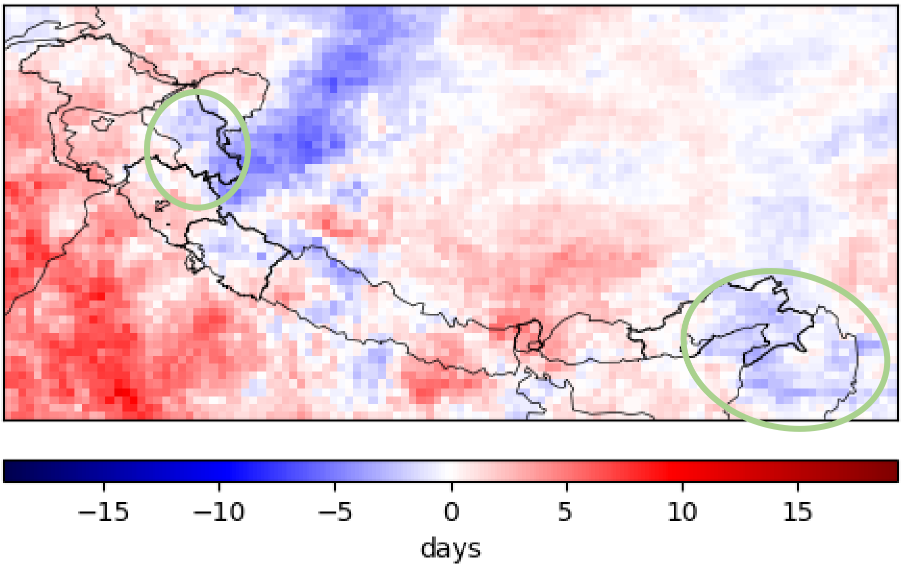
The nearest grid cell to the latitudes and longitudes of these cities were found, and trend analysis for those cell's climate index values for 120 years was carried out. Along with the index values, the Mann Kendal trend line was plotted on a time series graph to show a possible change in the index values on these 10 cities.

Results

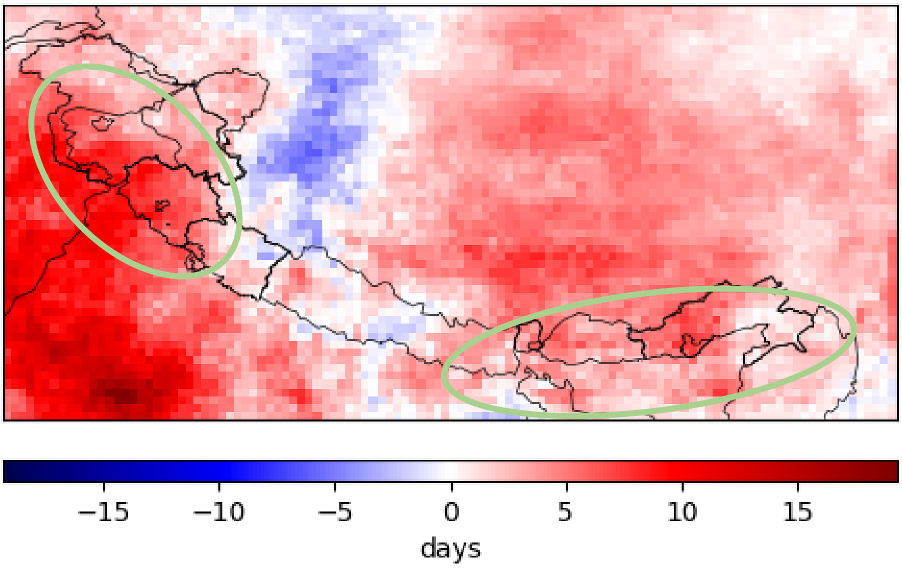
Change in Climate Indices

1. **CDD (Consecutive Dry Days)**

(a) Change in CDD in Period 1 (2021-2060)



(b) Change in CDD in Period 2 (2061-2100)



The above two plots represent the average changes in CDD per year in Period 1 (2021-2060) and Period 2 (2061-2100) with respect to the historical period. From the plots, we observe that dry days are likely to increase in the northwestern Himalayas in J&K and Himachal Pradesh for Period 1. There is a slight decrease in dry days in Ladakh and Uttarakhand. Coming to the eastern side, we observe an increase in the state of Sikkim and a decrease in Arunachal Pradesh. In Period 2, we observe that almost all Himalayan states are likely to have more consecutive dry days than before, with the highest increase in J&K and Himachal Pradesh. In Arunachal Pradesh, where CDD decreased during Period 1, saw a significant increase in Period 2, with eastern Arunachal Pradesh showing low or no change.

City	Trend	z value	Mann Kendall score	Sen's slope	Intercept
Srinagar	increasing	8.103295114	1174	0.0625000000	23.28125
Leh	no trend	1.886430732	455	0.0199009901	22.81589109
Jammu	increasing	5.909132827	1180	0.0659136048	27.57814052
Shimla	increasing	7.485543158	885	0.0526315789	26.36842105
Mandi	increasing	8.531077601	1245	0.0701754386	25.3245614
Dehradun	increasing	7.660604676	866	0.0454545455	26.29545455
Rishikesh	increasing	7.484631651	688	0.0363636364	26.83636364
Haridwar	increasing	10.82330645	988	0.0520833333	25.90104167
Gangtok	increasing	6.957925452	1051	0.0604235122	22.40480102
Itanagar	increasing	3.738136923	1104	0.0526315789	20.86842105

Table 2: Yue and Wang Modified MK Test Results for CDD

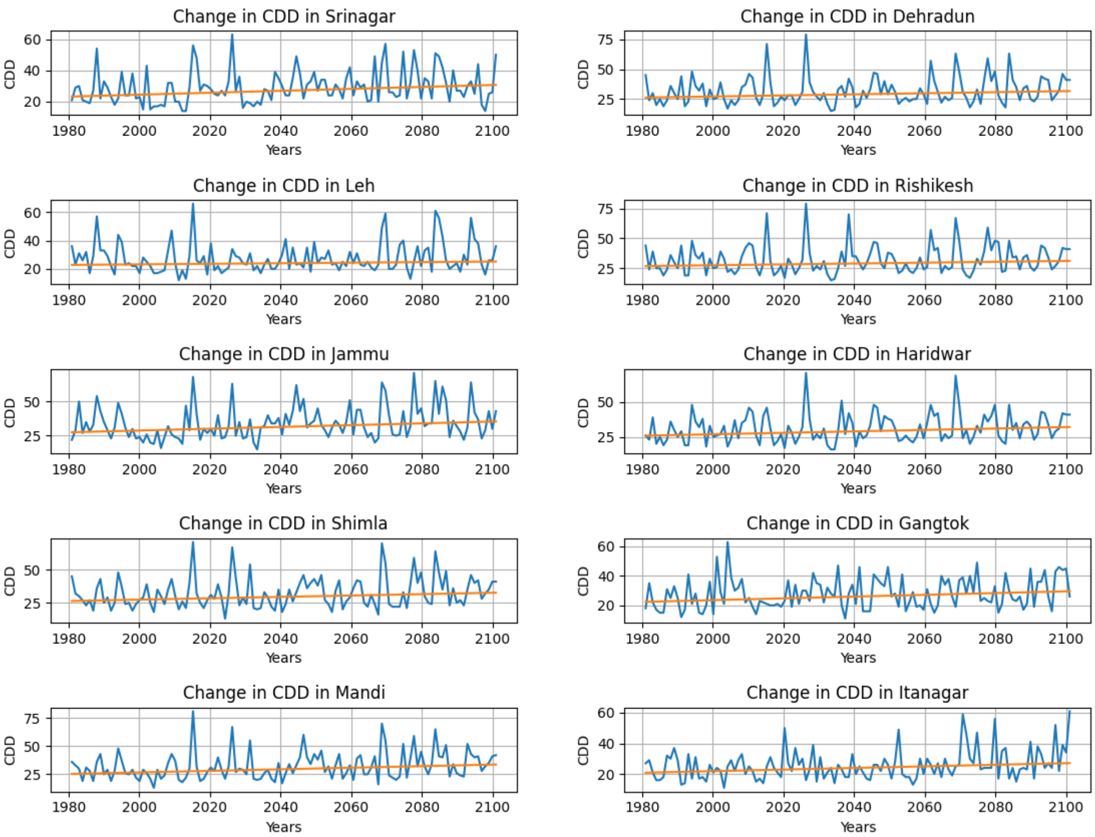
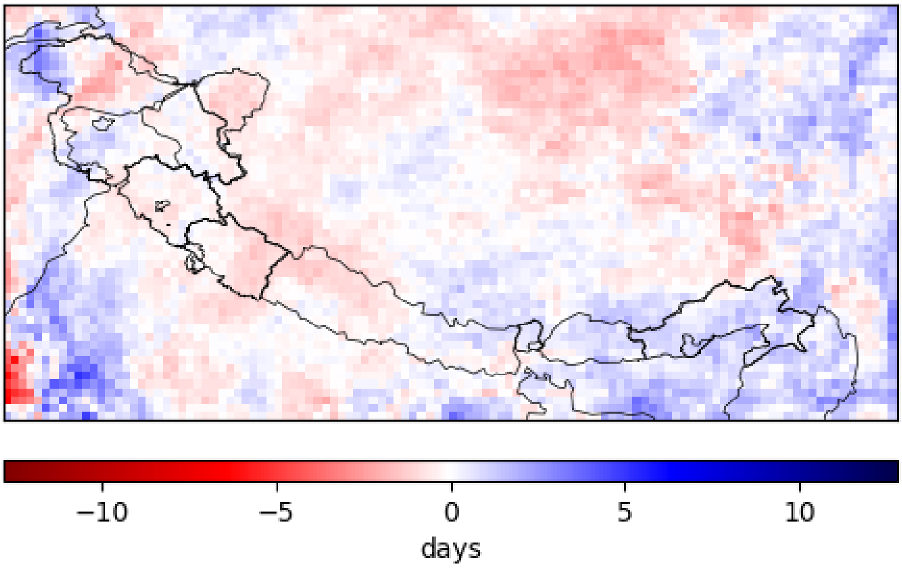


Figure 5: Time series and trend plots of CDD in 10 different cities

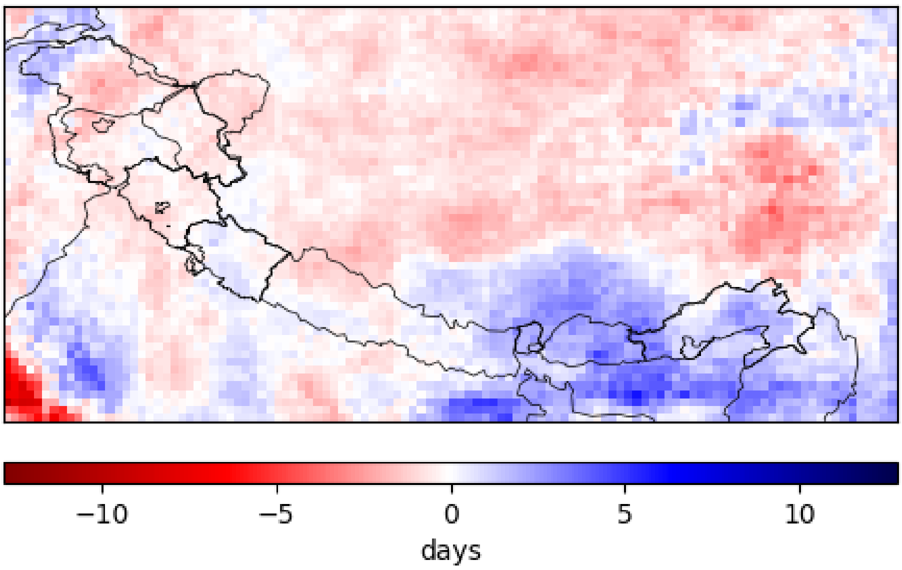
If we look at the trend plot of major cities, we notice a significant increase in CDD in Srinagar, Jammu, Shimla, Mandi, Haridwar, Gangtok and Itanagar. The increasing trend is also evident from the Sen's Slope values of these cities for CDD. Sen's slope tells us the magnitude of a monotonic trend if present. Leh has no monotonous trend present as it decreases for the first period and increases in the second.
An increase in CDD would increase the chances of drought-like conditions.

2. CWD (Consecutive Wet Days)

(a) Change in CWD in Period 1 (2021-2060)



(b) Change in CWD in Period 2 (2061-2100)



The above two plots represent the changes in CDD in Period 1 (2021-2060) and Period 2 (2061-2100) with respect to the historical period (1981-2020).

In Period 1, we see a varied amount of changes throughout the Himalayas. In J&K, CWD slightly increases, whereas, in Ladakh, we notice an increase and decrease in different areas. In Himachal Pradesh and Uttrakhand, we see an overall decrease in CWD. Towards the east, In Sikkim and Arunachal Pradesh, we see an increase in CWD.

In Period 2, we only notice a change in J&K where initially CWD was increasing is now less than historical. We notice a larger increase in the eastern part of the Himalayas.

City	Trend	z value	Mann Kendall score	Sen's slope	Intercept
Srinagar	decreasing	-3.106475773	-828	-0.0166666667	11.99166667
Leh	no trend	-0.088745539	-16	0.0000000000	9
Jammu	no trend	-1.71915584	-449	0.0000000000	8
Shimla	no trend	-1.071253595	-344	0.0000000000	9
Mandi	no trend	-1.419289617	-565	0.0000000000	9
Dehradun	no trend	0.246374585	53	0.0000000000	9
Rishikesh	no trend	-1.845562831	-300	0.0000000000	9
Haridwar	decreasing	-2.692906508	-336	0.0000000000	9
Gangtok	increasing	4.689208591	793	0.0178571429	10.9375
Itanagar	no trend	-0.446723197	-77	0.0000000000	11

Table 3: Yue and Wang Modified MK Test Results for CWD

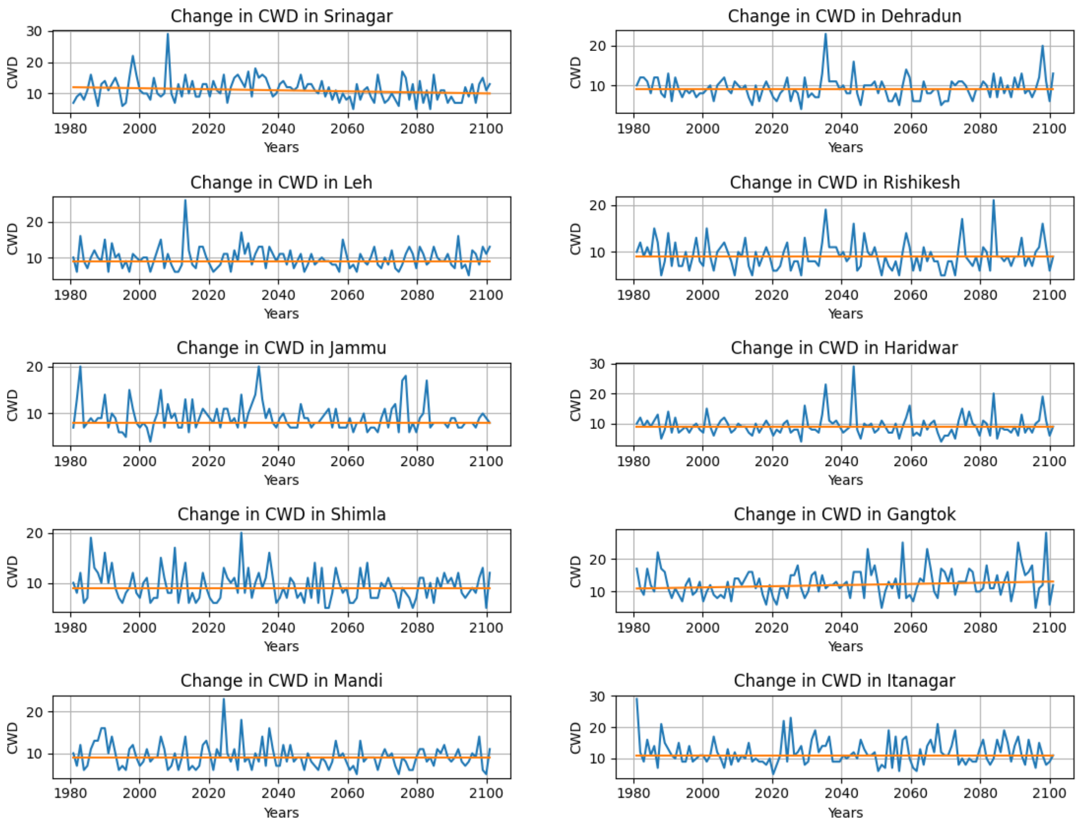
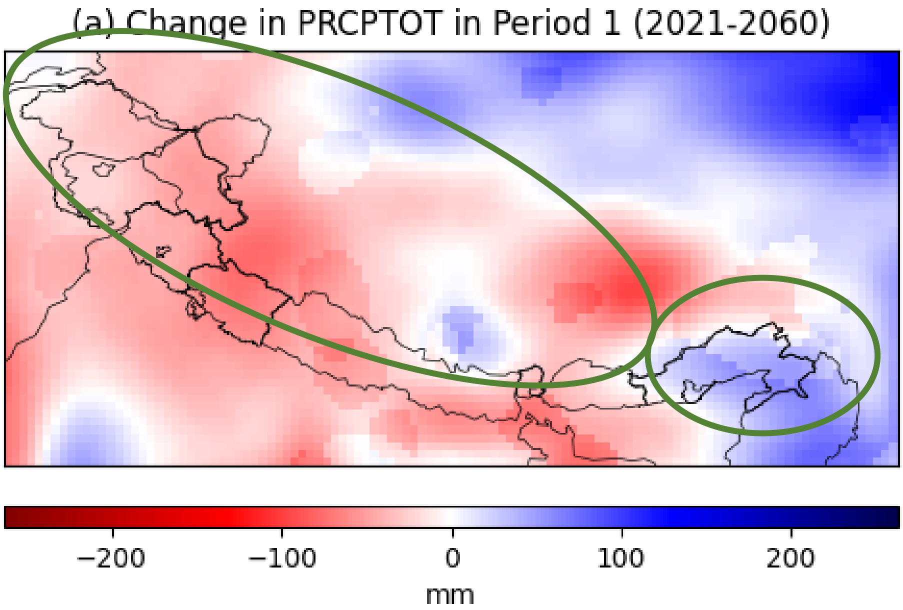
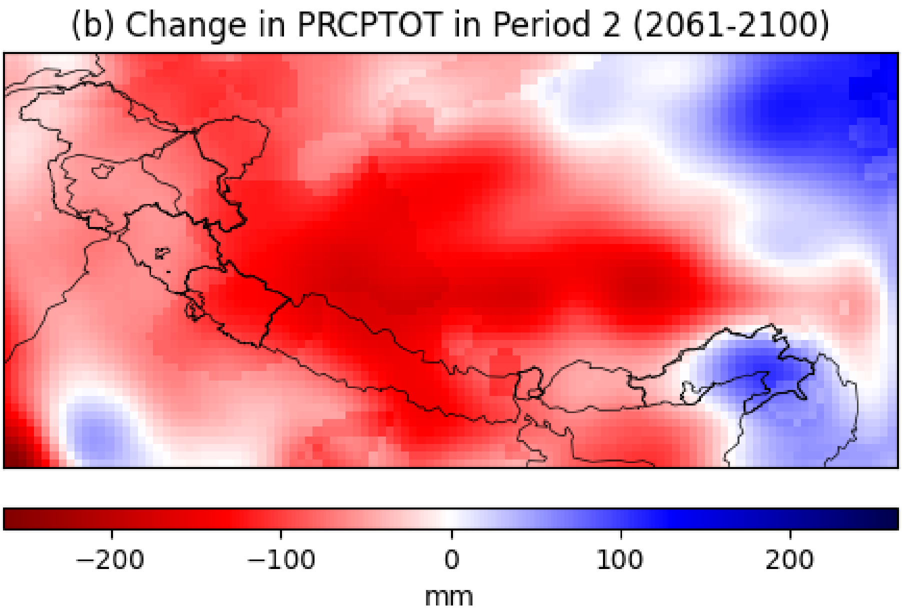


Figure 6: Time series and trend plots of CWD in 10 different cities

In the trend plots for cities, we notice that most of the cities do not have any trend as calculated by the M-K test. Only Gangtok shows a positive slope and Srinagar a negative slope. Rest all other cities are likely to have similar CWD values per year in future.

3. PRCPTOT





The above two plots represent the changes in PRCPTOT in Period 1 (2021-2060) and Period 2 (2061-2100) with respect to the historical period (1981-2020).

In Period 1, a slight decrease in total precipitation is observed, majorly in the Western Himalayas in the states J & K, Himachal Pradesh and Uttarakhand. We can see the decrease from J & K in the West to Bhutan in the Eastern Himalayas. The decrease is even more evident and high in Period 2, where we notice the highest decrease in the middle Himalayas along with Tibet. PRCPTOT is likely to decrease more in the state of Uttarakhand and Ladakh in Period 2 than in J&K and Sikkim.

The scenario changes when we move towards northeast India. In Period 1, we notice that PRCPTOT has slightly increased in the state of Arunachal Pradesh. We notice in Period 2 that PRCPTOT is likely to increase even more and form a coldspot in the eastern part of Arunachal Pradesh.

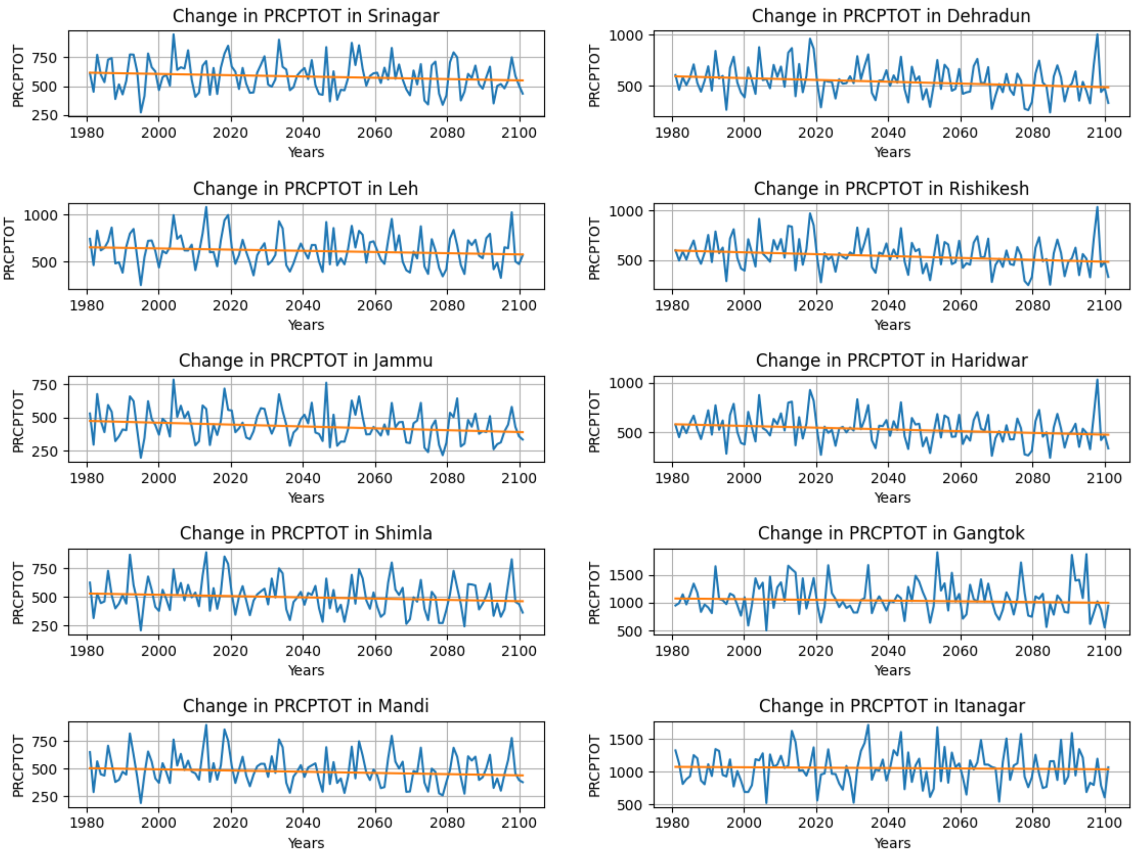


Figure 7: Time series and trend plots of PRCPTOT in 10 different cities

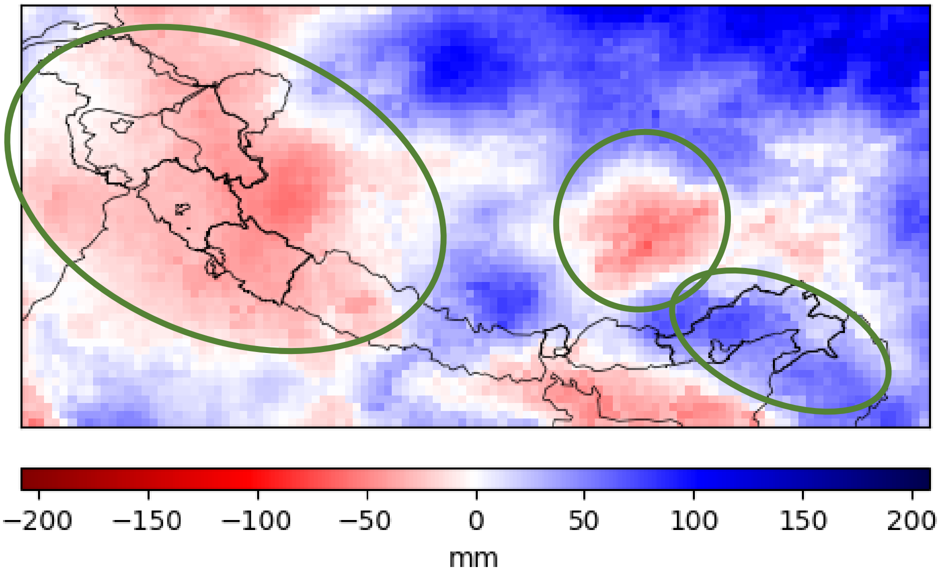
City	Trend	z value	Mann Kendall score	Sen's slope	Intercept
Srinagar	decreasing	-4.867414657	-592	-0.5606054562	616.2509125
Leh	decreasing	-5.248378222	-588	-0.6355642518	652.7280072
Jammu	decreasing	-9.060359717	-982	-0.7070135549	474.5776223
Shimla	decreasing	-5.119414204	-638	-0.5613918266	528.1870486
Mandi	decreasing	-5.456007715	-654	-0.5437268508	503.9684023
Dehradun	decreasing	-8.204088521	-1026	-0.8945621489	593.5911249
Rishikesh	decreasing	-8.841026816	-1080	-0.9611966301	595.8892689
Haridwar	decreasing	-8.78074068	-1024	-0.8823442471	581.3966707
Gangtok	decreasing	-2.704517682	-368	-0.6423890521	1076.21192
Itanagar	no trend	-1.133926806	-176	-0.3130417106	1072.434056

Table 4: Yue and Wang Modified MK Test Results for PRCPTOT

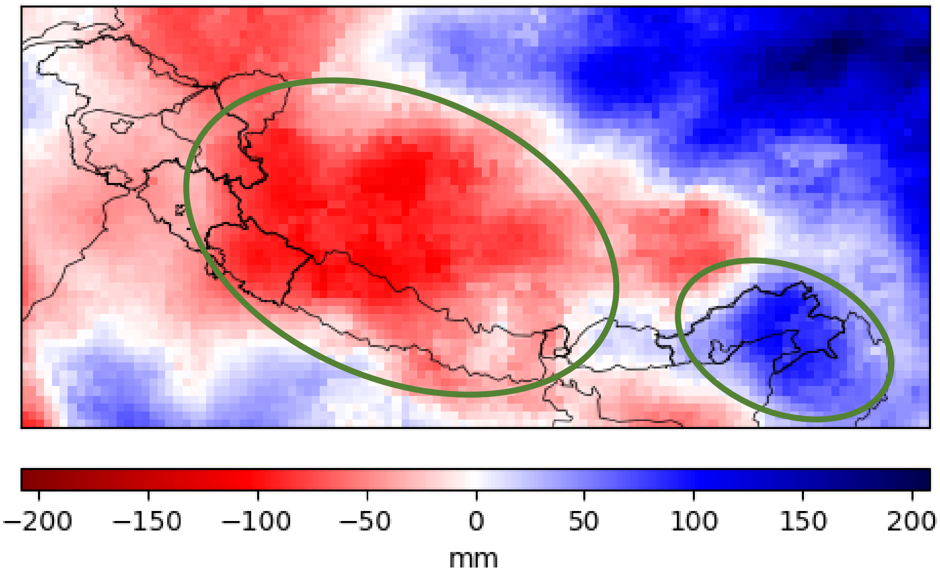
In the trend plots and M-K test, we observe that PRCPTOT is decreasing for all of the cities except Itanagar, as is evident from the map. Although we do see an increase in precipitation in Arunachal Pradesh, the same is mostly present in the eastern part of Arunachal Pradesh. Itanagar lies on the white boundary line of no change in both Period 1 and 2. The highest decrease can be identified by looking at the Sen's slope values which shows Rishikesh to have a major fall in overall precipitation, along with Dehradun and Haridwar.

4. R95PTOT

(a) Change in R95PTOT in Period 1 (2021-2060)



(b) Change in R95PTOT in Period 2 (2061-2100)



The above two plots represent the changes in R95PTOT in Period 1 (2021-2060) and Period 2 (2061-2100) with respect to the historical period (1981-2020).

In Period 1, a large area of decrease is visible in the western Himalayas, covering J&K, Ladakh, Himachal Pradesh and Uttrakhand. The East Sikkim and Arunachal Pradesh see a slight increase in R95PTOT. Also, we see another hotspot being formed just north of Bhutan in Tibet.

In Period 2, the large hotspot has further expanded, and a major decrease can be seen in Uttarakhand and north of Uttrakhand. The hotspot joins the hotspot that was formed in the north of Bhutan. Arunachal Pradesh, on the other hand, has seen a more intensive increase in R95PTOT concentrated in the east.

City	Trend	z value	Mann Kendall score	Sen's slope	Intercept
Srinagar	decreasing	-3.047836565	-390	-0.2656208697	261.3489933
Leh	decreasing	-3.076191703	-510	-0.4272162709	324.5872783
Jammu	decreasing	-7.416842813	-782	-0.4371410146	226.6327196
Shimla	no trend	-1.906661251	-286	-0.1574711265	257.3788846
Mandi	decreasing	-2.394939479	-360	-0.2588346000	256.7359178
Dehradun	decreasing	-3.944640974	-702	-0.4698649074	312.6715256
Rishikesh	decreasing	-4.825818757	-810	-0.5795871167	330.6619253
Haridwar	decreasing	-4.707296263	-756	-0.5269356139	319.2642168
Gangtok	no trend	0.170452471	30	0.0388182659	542.8091176
Itanagar	no trend	1.545452089	276	0.4112306349	524.1218798

Table 5: Yue and Wang Modified MK Test Results for R95PTOT

In the trend plots, we observe that there are mostly decreasing trends in R95PTOT In all the cities. Shimla does not show a trend in the M-K test even while being near the hotspot zone. Itanagar again does not show any trend, which shows the increase is mostly concentrated towards the east of Arunachal Pradesh. Even though the slope for Itanagar is comparable to Dehradun, Leh or Jammu, the z-value, which is very near to 1, shows the data to be in a normal distribution, and that is why the test does not detect a trend.

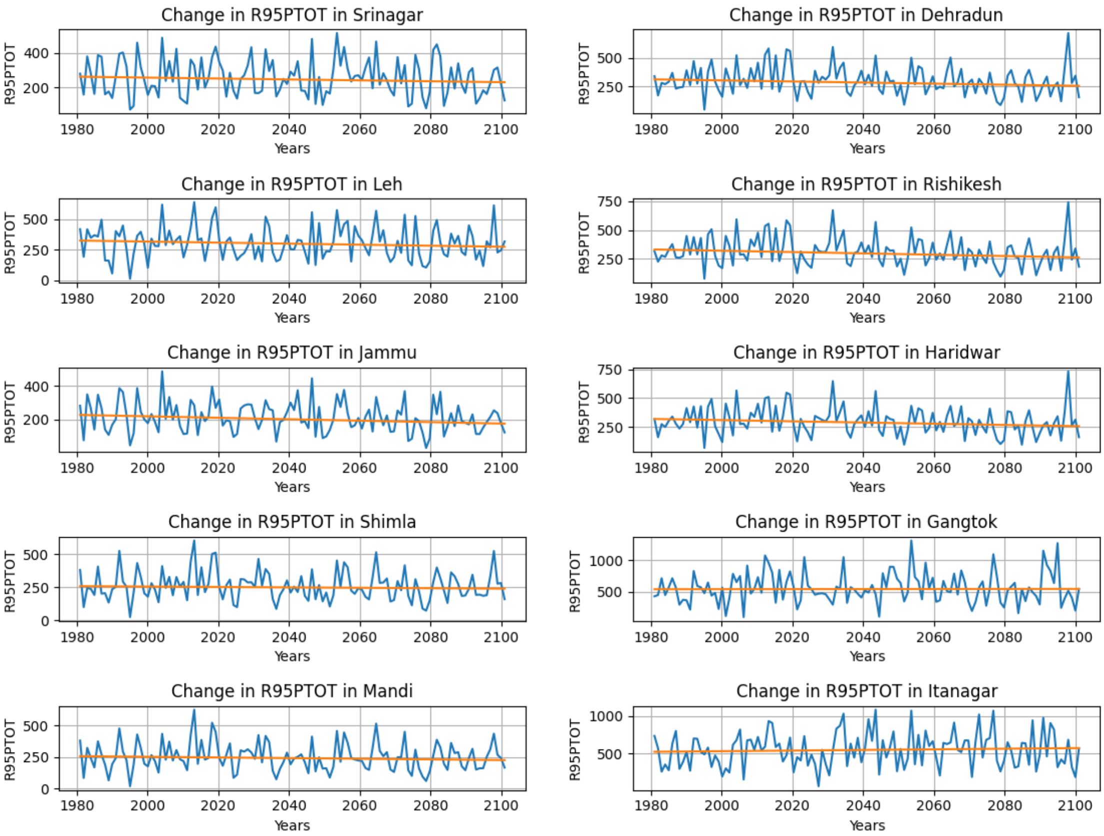
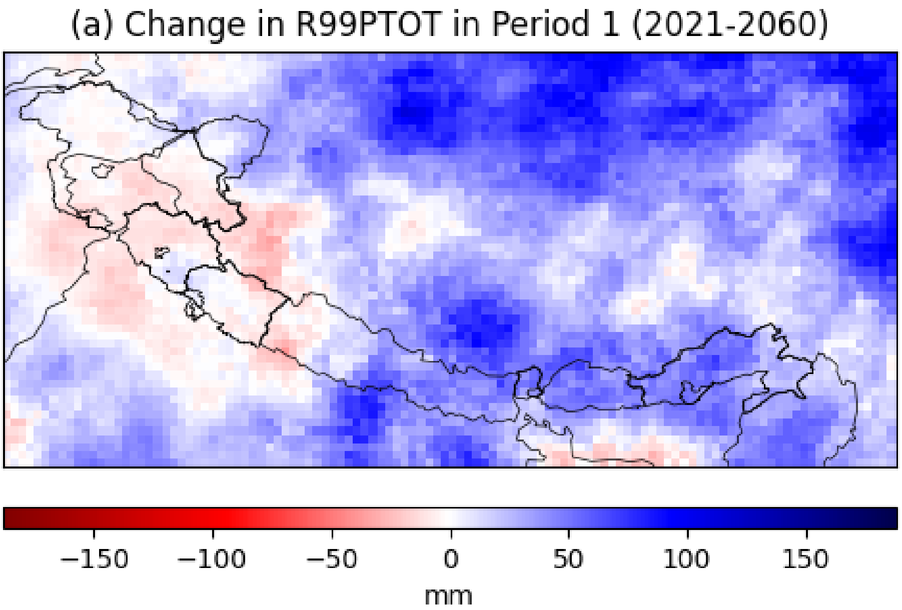
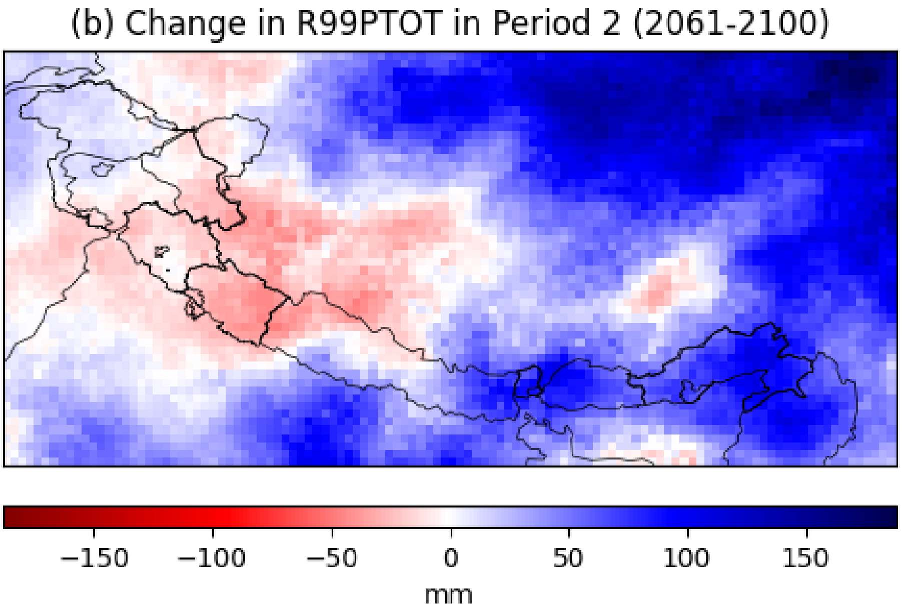


Figure 8: Time series and trend plots of R95PTOT in 10 different cities

5. R99PTOT





The above two plots represent the changes in R99PTOT in Period 1 (2021-2060) and Period 2 (2061-2100) with respect to the historical period (1981-2020).

In Period 1, similar to R95PTOT, an area of decrease is visible in the western Himalayas, covering J&K, Ladakh, Himachal Pradesh and Uttrakhand, although the intensity is less. In the Eastern half of the Himalayas, starting from Nepal all through Arunachal Pradesh, we observe an increase in extreme precipitation events. Although we see an overall decrease of precipitation in the east, the quantity of precipitation from extreme events is going to increase, which may lead to chances of a flash flood.

In Period 2, we clearly see a hotspot in the West and more extreme events in the east to increase further. Especially in Sikkim and Eastern Arunachal Pradesh, we see a maximum amount of R99PTOT.

City	Trend	z value	Mann Kendall score	Sen's slope	Intercept
Srinagar	increasing	2.258844109	382	0.1456550393	79.61407696
Leh	no trend	0.79990318	111	0.0487206143	109.8802269
Jammu	decreasing	-5.891906515	-499	-0.1822875301	84.73297931
Shimla	no trend	0.608760242	143	0.0515212325	89.18009623
Mandi	no trend	-0.772290698	-167	-0.0688383801	94.93450373
Dehradun	no trend	-0.623073078	-130	-0.0634284097	116.6862237
Rishikesh	no trend	-0.989115615	-211	-0.0946703417	127.4132144
Haridwar	no trend	-1.783670694	-304	-0.1373533201	127.7664477
Gangtok	increasing	6.459885295	1063	0.9374458723	153.4101871
Itanagar	increasing	3.166161177	825	0.7222260690	163.1675486

Table 6: Yue and Wang Modified MK Test Results for R99PTOT

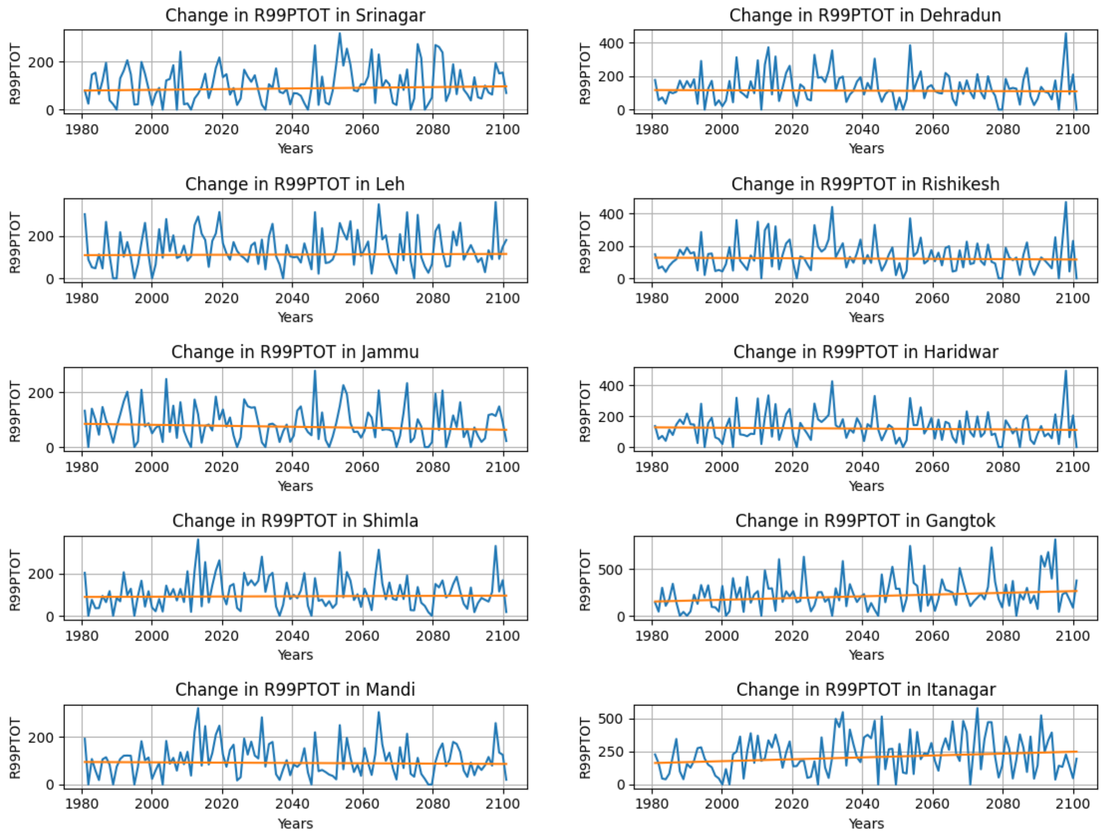
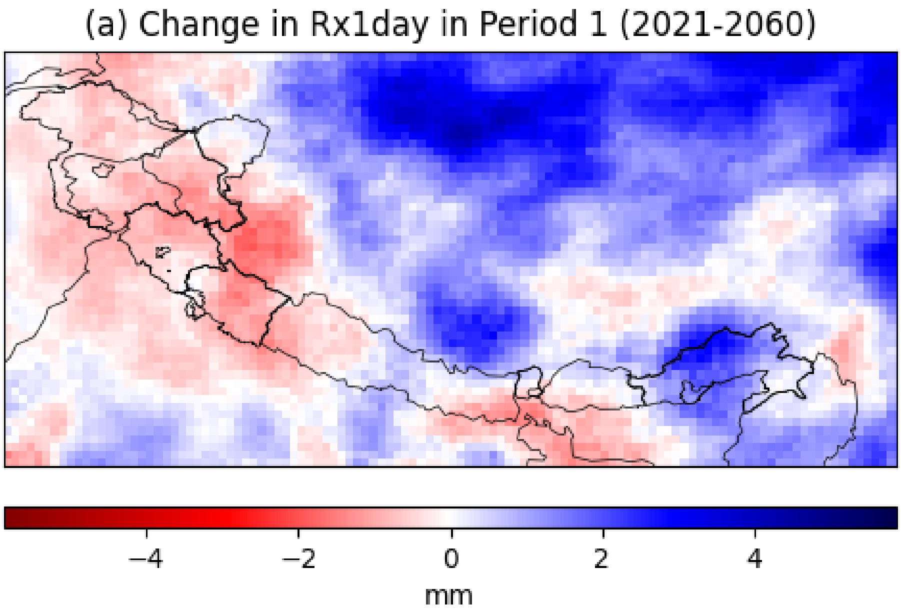
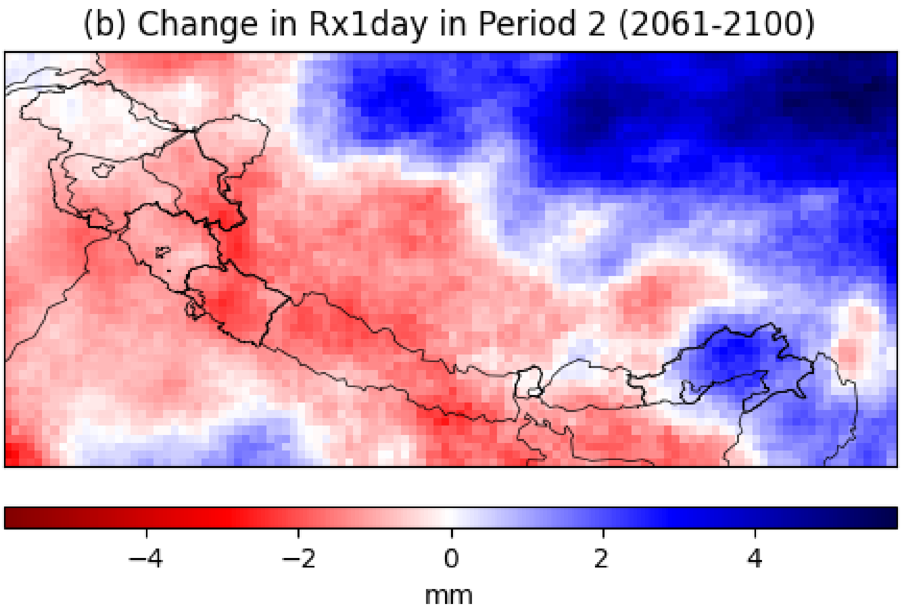


Figure 9: Time series and trend plots of R99PTOT in 10 different cities

In the trend plots, most cities do not have a monotonous trend, as can be seen from the M-K test. Only Itanagar and Gangtok shows significant slope values and can be affirmed from the map. All other cities have wither no trend or a very weak trend.

6. Rx1day





The above two plots represent the changes in Rx1day in Period 1 (2021-2060) and Period 2 (2061-2100) with respect to the historical period (1981-2020).

In Period 1, we again observe a decrease in the western Himalayas covering J&K, Ladakh, Himachal and Uttarakhand. Sikkim doesn't have many changes, but Northern Arunachal Pradesh sees a prominent increase in Rx1day value.

In Period 2, we again see the expansion of hotspot created in the West. Uttarakhand has seen the maximum decrease in Rx1day values, which is a piece of evidence that the flash flood events are likely to decrease in Uttarakhand in future. Arunachal Pradesh still sees an increase, but concentration shifted towards the centre of the state. Sikkim has the least change of all.

City	Trend	z value	Mann Kendall score	Sen's slope	Intercept
Srinagar	decreasing	-2.190696973	-31520	-0.0008152388	10.83438165
Leh	decreasing	-2.866897856	-23916	-0.0007460924	12.45472217
Jammu	decreasing	-7.01210993	-59538	-0.0013219466	9.685729873
Shimla	decreasing	-3.014318226	-27242	-0.0007062061	10.70425083
Mandi	decreasing	-3.858562625	-32902	-0.0008428940	10.44352448
Dehradun	decreasing	-5.616905504	-48996	-0.0014219808	12.12381768
Rishikesh	decreasing	-7.258825092	-56762	-0.0017044069	12.66728192
Haridwar	decreasing	-7.014568653	-50902	-0.0014642933	11.97289131
Gangtok	no trend	-1.051209282	-15688	-0.0008923743	21.26429966
Itanagar	no trend	-0.449346163	-6172	-0.0003275155	20.79189126

Table 7: Yue and Wang Modified MK Test Results for Rx1day

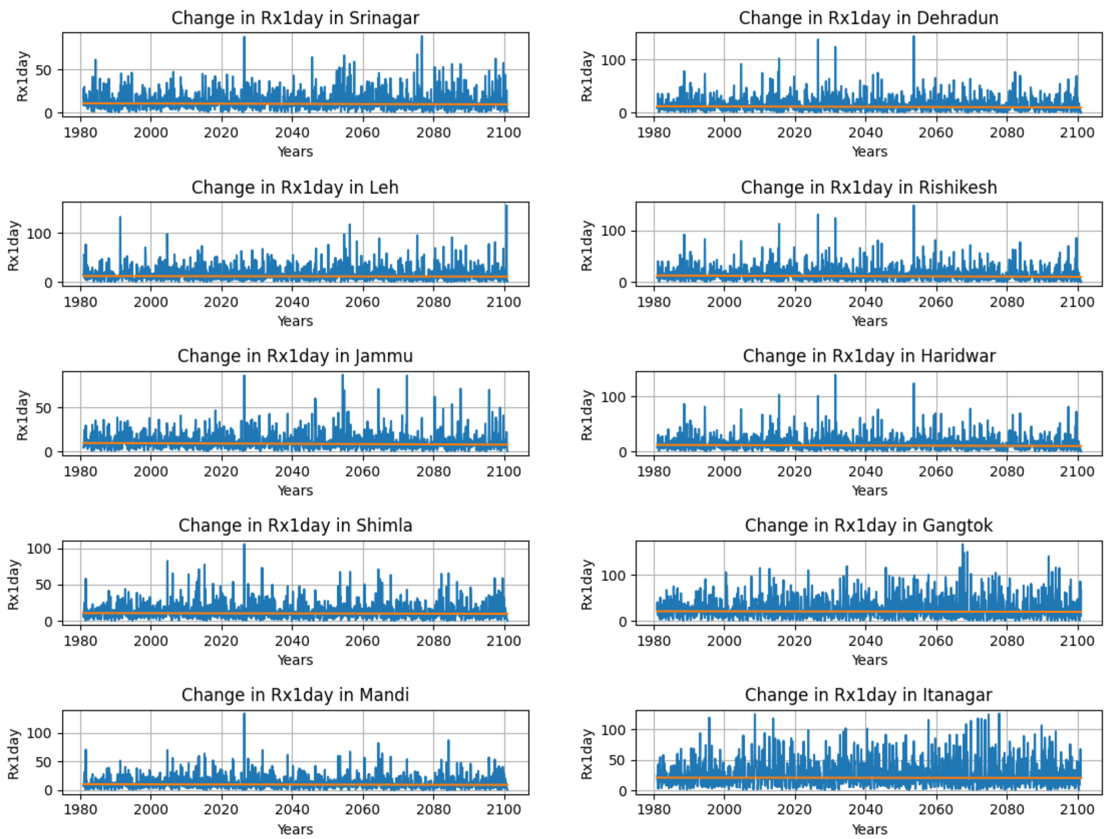
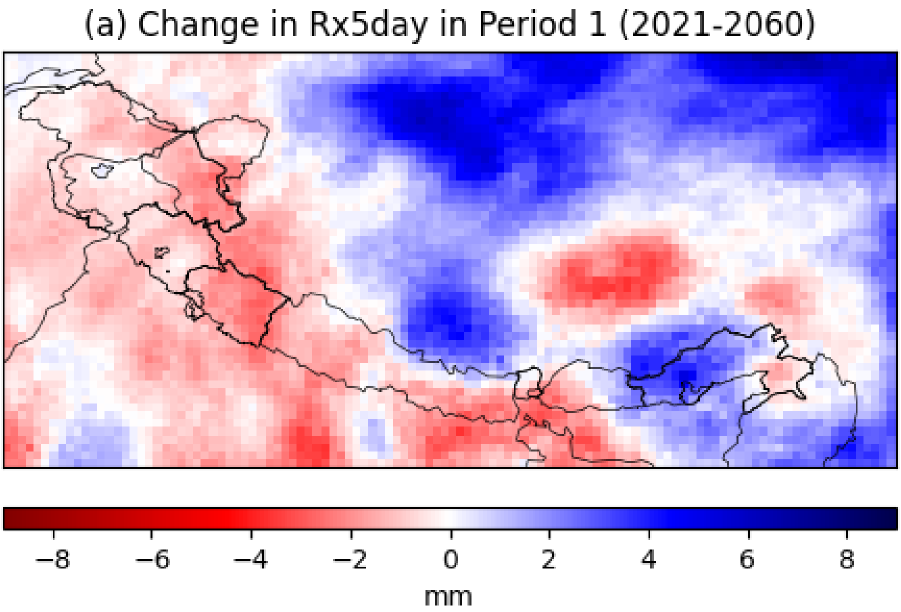
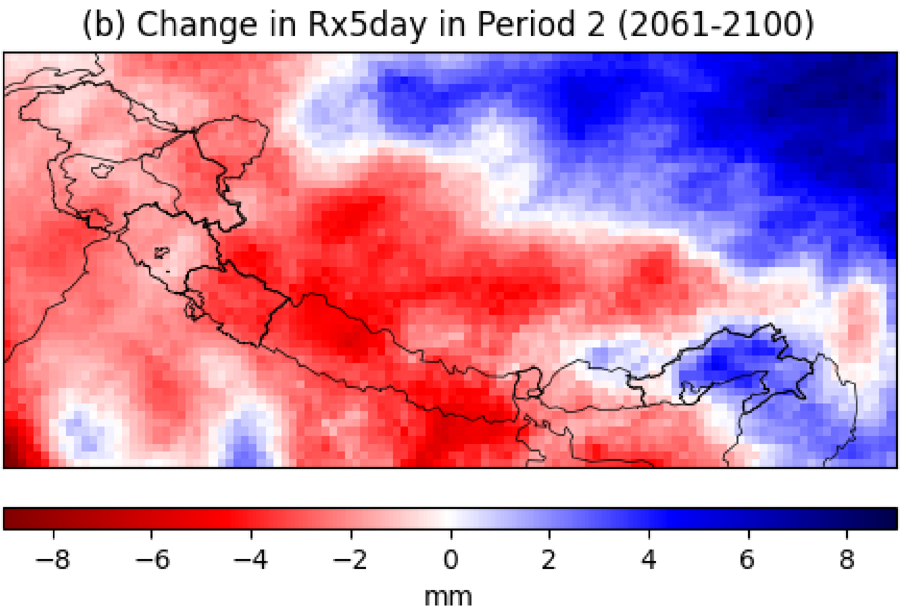


Figure 10: Time series and trend plots of Rx1day in 10 different cities

In the trend plots, most of the cities have a decreasing trend but with a very low value of the slope. That means the decrease is not very steep. Gangtok and Itanagar show no trend, which is also evident from the map.

7. Rx5day





The above two plots represent the changes in Rx1day in Period 1 (2021-2060) and Period 2 (2061-2100) with respect to the historical period (1981-2020).

In Period 1, Rx5day is similar to Rx1day in the fact that it shows decreasing areas in the western Himalayas. In addition to this, it also shows an area of decrease above Bhutan, as was earlier seen in R95PTOT. The values are consistent in showing a rainfall increase in the eastern part of the Himalayas.

In Period 2, the area of decrease further expands, and the two separate hotspot joins to form one large hotspot. The maximum decrease can be seen in the middle Himalayas around Uttarakhand and Nepal. An increase in Rx5day values in Arunachal Pradesh can be seen.

City	Trend	z value	Mann Kendall score	Sen's slope	Intercept
Srinagar	decreasing	-3.173546046	-28760	-0.0015438270	22.04289242
Leh	decreasing	-3.587756428	-25382	-0.0015217962	24.00634678
Jammu	decreasing	-8.827766124	-60100	-0.0026614064	18.98831068
Shimla	decreasing	-3.609728837	-26140	-0.0013797693	20.39796783
Mandi	decreasing	-3.883192512	-26842	-0.0013632708	20.23528546
Dehradun	decreasing	-7.38798084	-45276	-0.0025582566	23.11391135
Rishikesh	decreasing	-8.330460361	-49172	-0.0028392701	24.21861505
Haridwar	decreasing	-7.276699464	-43880	-0.0024669947	23.04282779
Gangtok	decreasing	-2.076202236	-28588	-0.0029746423	40.62915977
Itanagar	no trend	-0.827810322	-11160	-0.0011145563	38.3860357

Table 8: Yue and Wang Modified MK Test Results for Rx5day

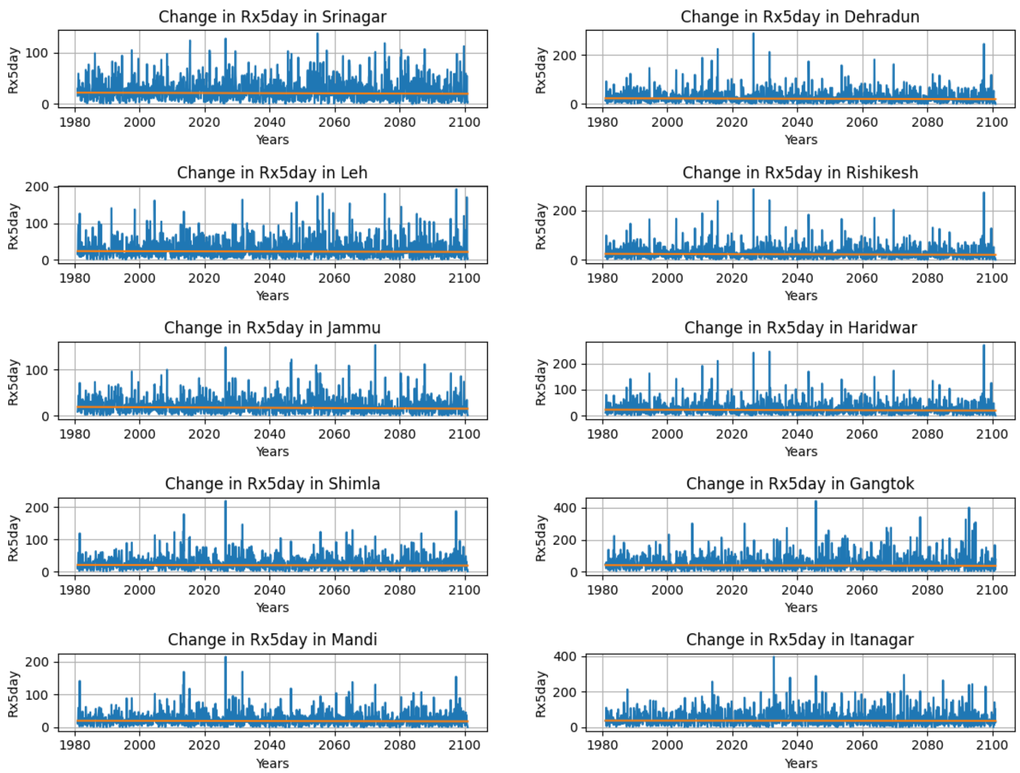
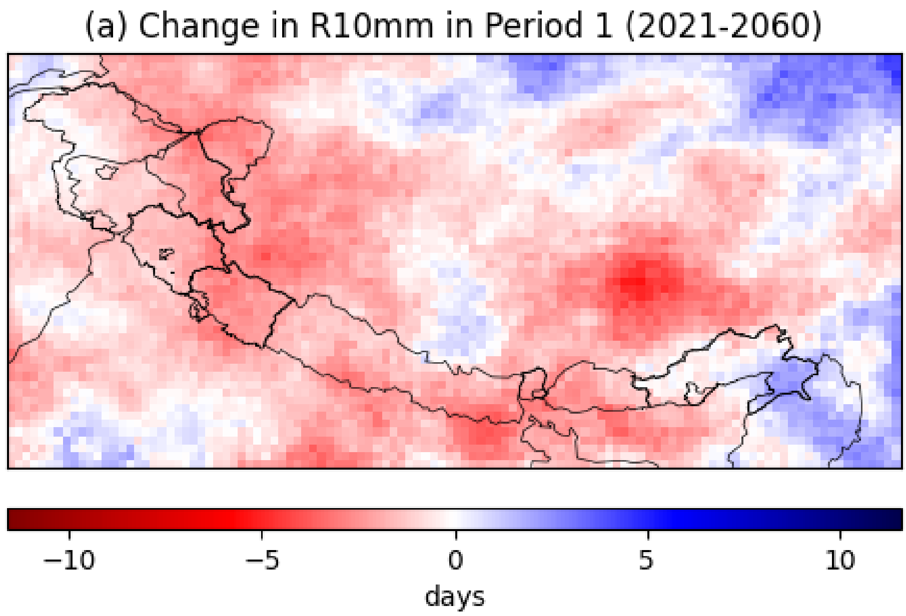
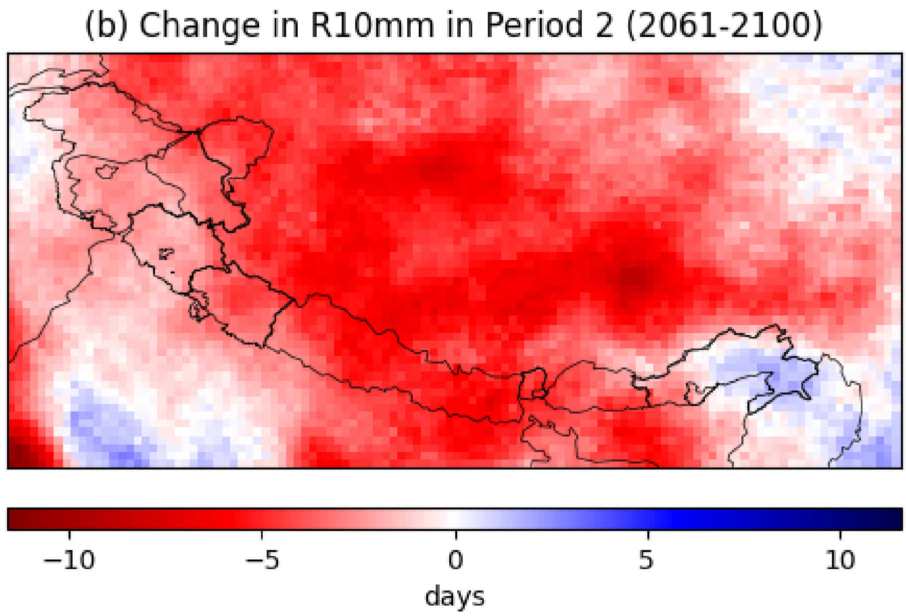


Figure 11: Time series and trend plots of Rx5day in 10 different cities

The trend plots show values very similar to Rx1day, with most of the cities showing a decreasing trend except Itanagar, which shows no trend. Having a z-value between -1 and 0 shows a normal distribution of data points. All the other cities have a very gradual decrease in Rx5day values.

8. R10mm





The above two plots represent the changes in R10mm in Period 1 (2021-2060) and Period 2 (2061-2100) with respect to the historical period (1981-2020).

In Period 1, A mostly uniform decrease in R10mm has been observed all throughout the Himalayan range except the most eastern part in Arunachal Pradesh and a small patch in the north of Nepal. The most western part of J&K remains unchanged.

In Period 2, The uniformity stays the same in the middle part of the Himalayas, but the magnitude of negative change is much more. The western and eastern part remains almost the same as Period 1.

City	Trend	z value	Mann Kendall score	Sen's slope	Intercept
Srinagar	decreasing	-3.721754495	-662	-0.0212765957	13.26595745
Leh	decreasing	-5.748847994	-735	-0.0259740260	15.04545455
Jammu	decreasing	-7.942637573	-1024	-0.0259180475	9.542123824
Shimla	no trend	-1.525369835	-367	0.0000000000	10
Mandi	decreasing	-5.270736729	-679	-0.0189577718	11.12798742
Dehradun	decreasing	-7.074662886	-853	-0.0238095238	14.41666667
Rishikesh	decreasing	-6.008907033	-941	-0.0259740260	14.54545455
Haridwar	decreasing	-6.43147771	-1007	-0.0270270270	14.60810811
Gangtok	decreasing	-5.816187103	-939	-0.0486620886	32.89539427
Itanagar	decreasing	-3.827665167	-511	-0.0258075258	30.53554779

Table 9:Yue and Wang Modified MK Test Results for R10mm

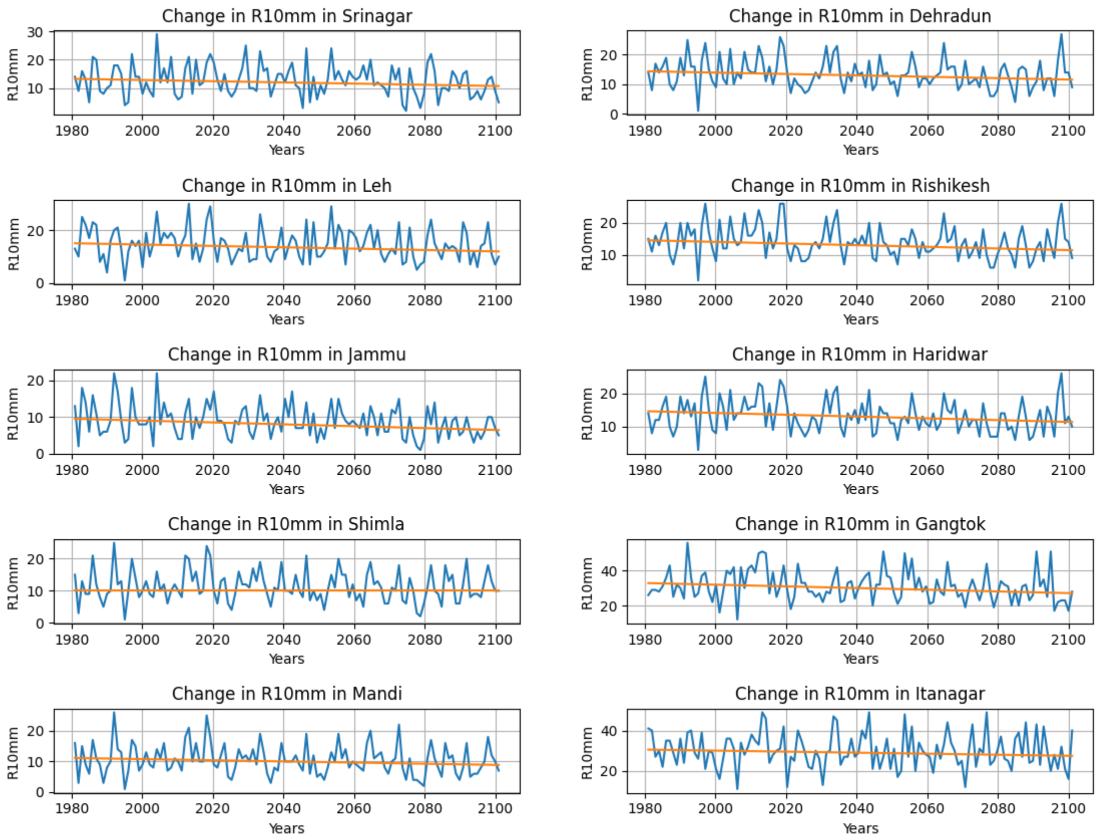
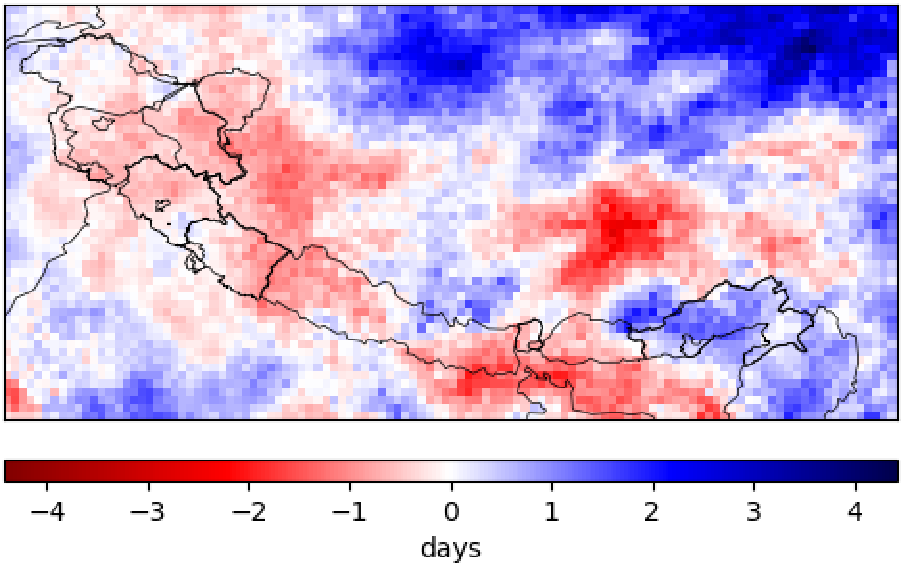


Figure 12: Time series and trend plots of R10mm in 10 different cities

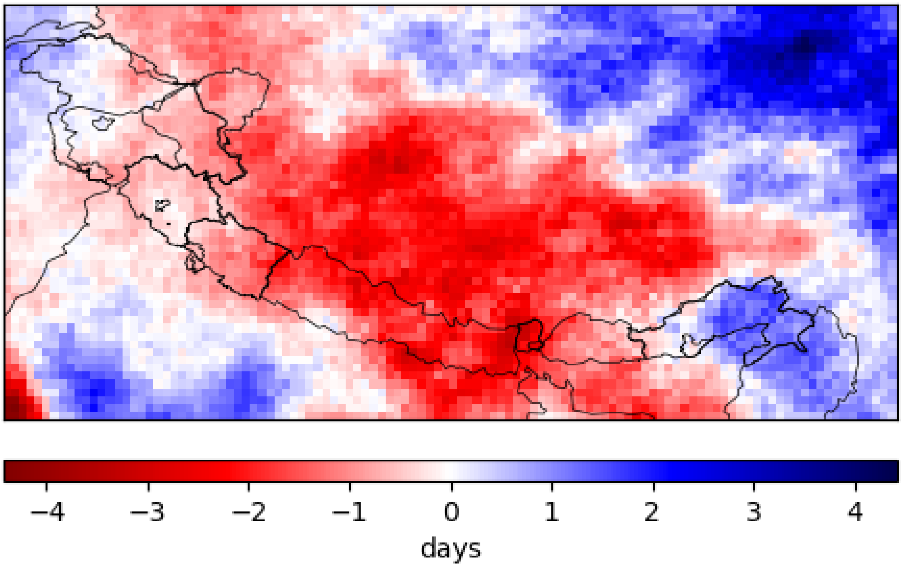
In the trend plots, all the cities except Shimla show a decreasing trend in R10mm values, but with a low value for Sen's slope hence the magnitude of the trend being less. The highest magnitude of the decrease can be seen in Gangtok, but a more consistent decrease is likely in Dehradun and Jammu.

9. R20mm

(a) Change in R20mm in Period 1 (2021-2060)



(b) Change in R20mm in Period 2 (2061-2100)



The above two plots represent the changes in R20mm in Period 1 (2021-2060) and Period 2 (2061-2100) with respect to the historical period (1981-2020).

In Period 1, Change in R20mm is more distributed in patches throughout the Himalayas. Red patches, which denote decrease, can be seen near the western part, around Ladakh and Uttarakhand. Another big red spot is visible north of Bhutan and around Sikkim. The middle of the Himalayas has a very small blue patch showing an increase and a large blue area in the east in Arunachal Pradesh.

In Period 2, we observe a very large red hotspot with a higher magnitude being formed in the middle Himalayas and in the north of Tibet. East and West part remains more or less the same.

City	Trend	z value	Mann Kendall score	Sen's slope	Intercept
Srinagar	no trend	0.050710039	8	0.0000000000	3
Leh	no trend	-1.758146521	-341	0.0000000000	4
Jammu	no trend	-1.877949012	-670	0.0000000000	2
Shimla	no trend	-0.414805061	-94	0.0000000000	2
Mandi	no trend	0.1054594	26	0.0000000000	2
Dehradun	no trend	-1.387066779	-259	0.0000000000	3
Rishikesh	no trend	-1.036964687	-263	0.0000000000	4
Haridwar	decreasing	-2.312990631	-492	0.0000000000	3
Gangtok	decreasing	-4.781872671	-907	-0.0270270270	14.60810811
Itanagar	no trend	0.064745155	9	0.0000000000	12

Table 10: Yue and Wang Modified MK Test Results for R20mm

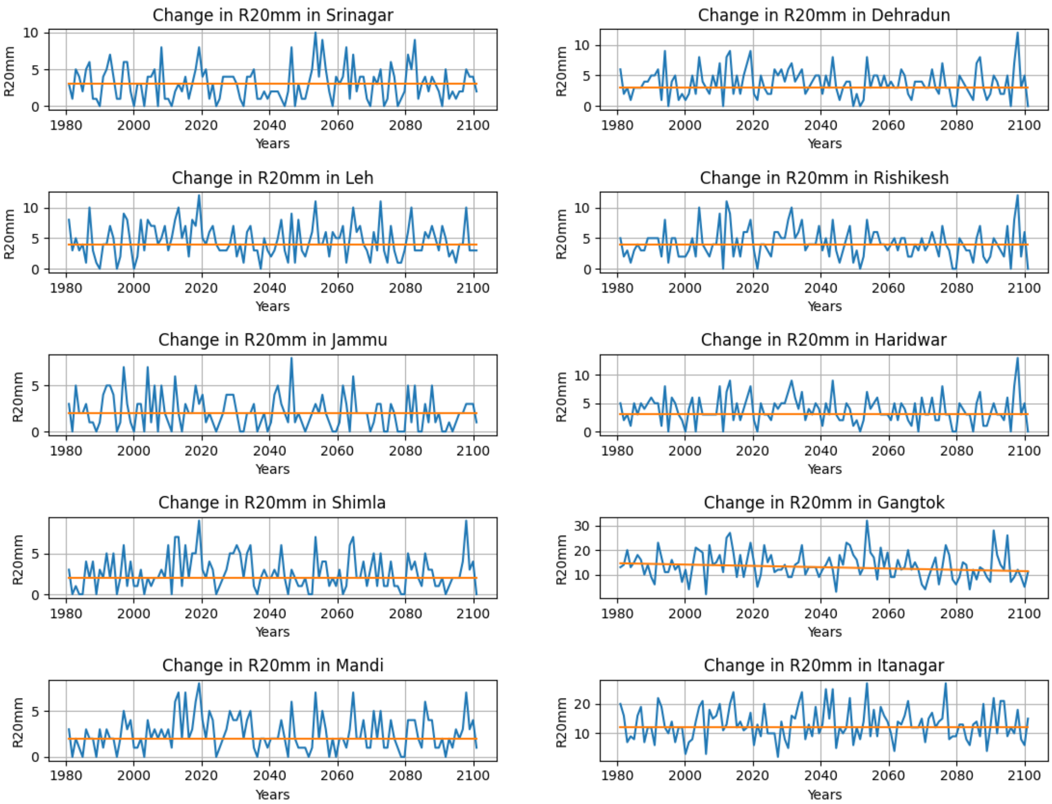
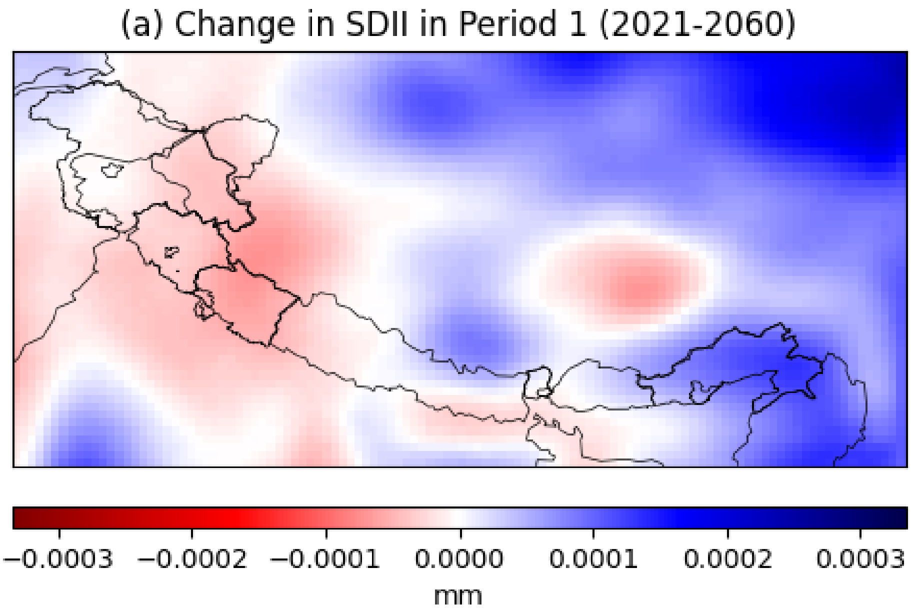
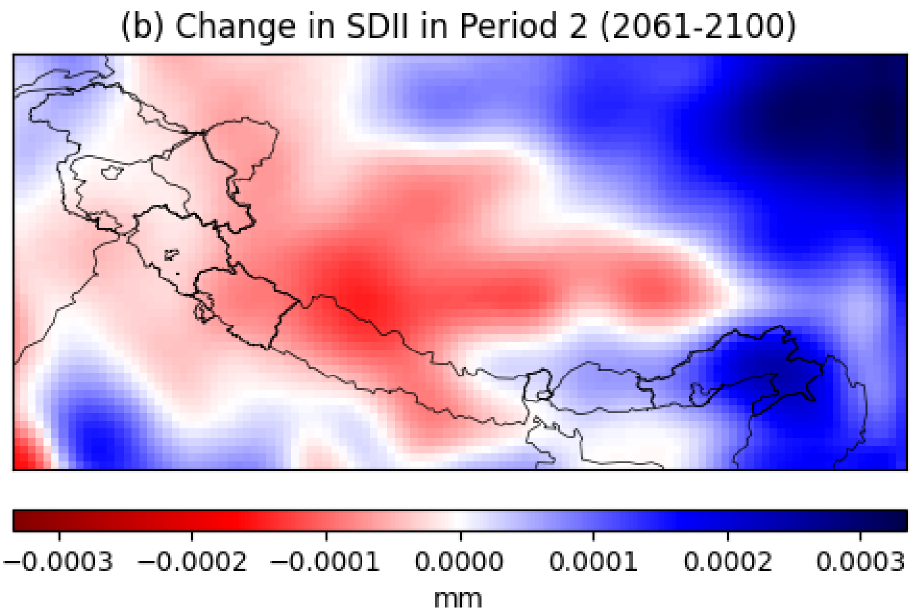


Figure 13: Time series and trend plots of R20mm in 10 different cities

In the trend plots and M-K test, we see that most of the cities do not show any trend. Only Haridwar and Gangtok show a decrease in R20mm values over time, with Gangtok having a significantly higher magnitude. This is because the 10 cities considered in the analysis does not lie in any of the red or blue patches visible on the map except for Gangtok.

10. SDII





The above two plots represent the changes in SDII in Period 1 (2021-2060) and Period 2 (2061-2100) with respect to the historical period (1981-2020).

In Period 1, SDII is known to slightly decrease in the western part of the Himalayas. The change, though, is very light, as can be inferred by the strength of the red patch. On the other hand, SDII is likely to increase in the eastern Himalayas over Arunachal Pradesh. This result is consistent with the results from other climate indices.

In Period 2, We observe a higher magnitude change in the middle Himalayas, just the north of Nepal. Western Himalayas remain more or less the same. The magnitude of increase in the eastern part is likely to increase, as is evident from a darker blue patch.

City	Trend	z value	Mann Kendall score	Sen's slope	Intercept
Srinagar	no trend	-0.257008759	-28	-0.0000000348	0.000746811
Leh	no trend	-0.498857183	-56	-0.0000000666	0.000787111
Jammu	decreasing	-4.89753349	-490	-0.0000004112	0.000583789
Shimla	no trend	-1.370418747	-184	-0.0000001834	0.000626545
Mandi	no trend	-1.575674918	-202	-0.0000001945	0.00060953
Dehradun	decreasing	-3.922321473	-528	-0.0000004941	0.00070655
Rishikesh	decreasing	-4.737437931	-606	-0.0000006111	0.000717223
Haridwar	decreasing	-4.089529799	-512	-0.0000005075	0.000704239
Gangtok	no trend	-0.109415667	-22	-0.0000000255	0.001314207
Itanagar	increasing	3.138095549	452	0.0000008639	0.001261796

Table 11: Yue and Wang Modified MK Test Results for SDII

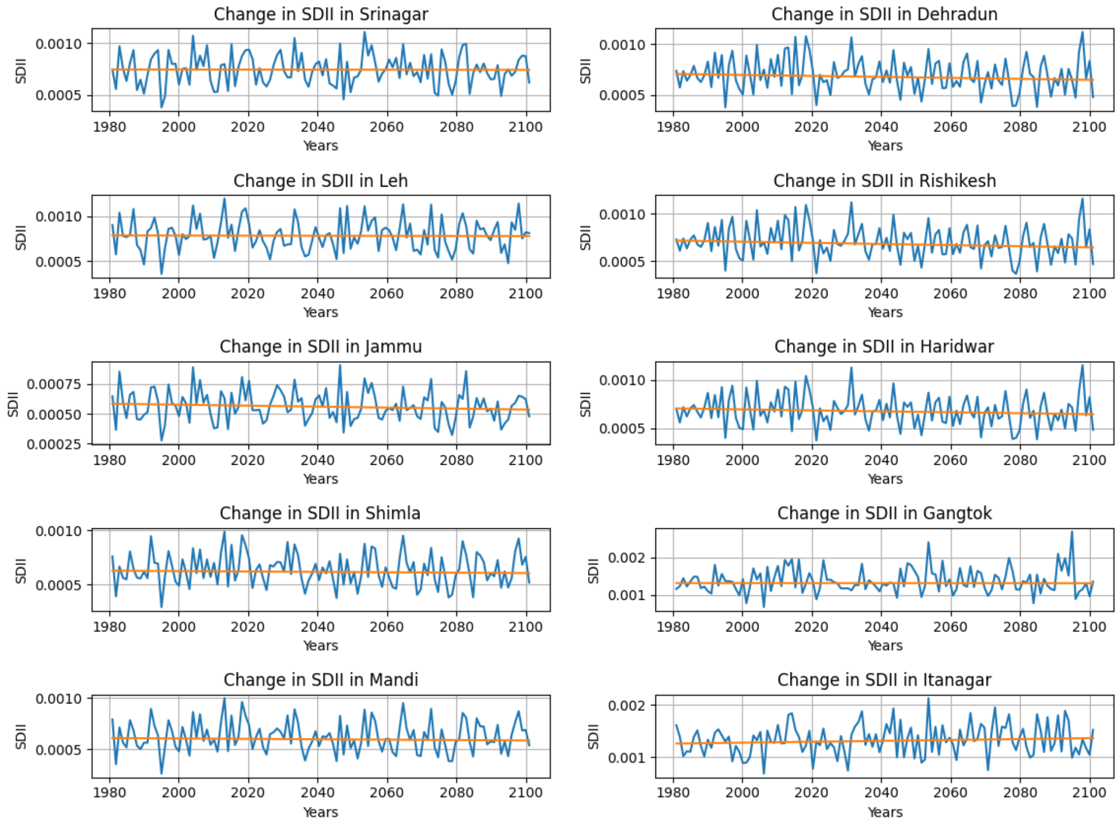


Figure 14: Time series and trend plots of SDII in 10 different cities

In the trend plots and M-K test results, we can observe that there are a varied set of results from the West to the east. Srinagar and Leh show no trend whatsoever, but Jammu shows a decreasing trend. Shimla and Mandi from Himachal Pradesh again show no trend. Whereas Dehradun, Rishikesh and Haridwar all have a decreasing trend. Gangtok again shows no trend. But Itanagar distinctively shows a positive trend with a higher value of slope than others.

Conclusion

- The above study shows that there will be a decrease in overall rainfall in the Himalayas in the next 80 year.
- The number of consecutive dry days are likely to increase with almost no change in consecutive wet days.
- Other extreme precipitation indices like R95PTOT, R99PTOT, R20mm and R10mm all show a formation of hotspot from the western Himalayas in the first period and then have the maximum decrease in the middle Himalayas towards the end of the second period.
- Extreme events are likely to decrease more in the middle Himalayas than in the western or eastern Himalayas.
- Single-day and five-day max precipitation are likely to consistently decrease in the western and middle Himalayas.
- Eastern Himalayas show an opposite trend to the remaining Himalayan range. Northeast India already sees the highest amount of annual rainfall, which is likely to increase in future too.
- Almost all of the precipitation indices show an increase in the eastern part of the Himalayas, inferring that extreme events like flood are likely to increase.
- Eastern Himalayas also show the highest increase in very extreme precipitation events shown by R99PTOT.
- Further, this study assumes that global climate models are not the actual values of precipitation but just the simulated value considering some physical, chemical and biochemical scenarios. Hence the models may not be completely accurate.
- Himalayan terrain is the most uneven terrain to study precipitation. Hence the model may contain some biases with plain landforms.
- Still, a similar study can be carried out on different GCMs, and an average of all the GCMs can help in reducing the errors and biases.

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