ASSESSMENT OF CHANGE IN DTR OVER THE KRISHNA RIVER BASIN FOR FUTURE SCENARIOS USING R PROGRAMMING



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By

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CERTIFICATE

Certified that this thesis titled 'Assessment of change in DTR over the Krishna River Basin for future scenarios using R Programming' is a bonafide work done by Miss Sreejoni Banerjee at Symbiosis Institute of Geoinformatics, under our supervision.

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INDEX

SERIAL	TOPIC	PAGE
NUMBER		NUMBER
1.	Certificate	2
2.	Acknowledgement	3
3.	List of Figures	6
4.	List of Tables	7
5.	Preface	8
6.	Introduction	9
7.	Literature Review	13
8.	Study Area	17
9.	Methodology	22
	i. Data Collection	23
	ii. Software and Packages	23
	iii. Data Pre-processing and Analysis	24
	iv. Time Series Forecasting	25
	v. Climate Models	28
10.	Results and Discussion	29
	i. Comparing DTR for data collected from ssp245 and	30
	ssp585 (2015-2100) with historical data (1951-2014)	
	ii. Simple Moving Average	33
	iii. Maximum, Minimum temperatures and DTR for the	36
	various seasons throughout the years	
	iv. Maps showing rainfall from 1991-2100	39
	v. Maps showing maximum temperature from 1991-	41
	2100	
	vi. Maps showing minimum temperature from 1991-	43
	2100	

	vii.	Relationship between DTR and Rainfall	45
	viii.	Relationship between maximum temperature and	47
		rainfall	
	ix.	Relationship between minimum temperature and	48
		rainfall	
	X.	ARIMA Forecasts	50
11.	Conclusion	n	52
12.	Reference		53

LIST OF FIGURES

FIGURES	PAGE NUMBER
Figure 1: Map showing position of Krishna River Basin in India	19
Figure 2: Krishna River Basin showing major and minor cities	20
Figure 3: Map of the Krishna River Basin showing all the rivers and tributaries	21
Figure 4: Graphs showing DTR for ssp245 for all climate models (2015-2100)	20
Figure 5: Graphs showing DTR for ssp245 for all climate models (2015-2100)	31
Figure 6: Graphs showing DTR from 1951-2014 for all climate models	31
Figure 7: Graph showing the original data points in black and the 10-year moving	33
average value in red for ssp245	
Figure 8: Graph showing the original data points in black and the 10-year moving	34
average value in red for ssp585	
Figure 9: Graph showing the original data points in black and the 10-year moving	34
average value in red for historical data	
Figure 10: Graphs showing Maximum, Minimum Temperature with DTR for	36
Pre-Monsoon Season	
Figure 11: Graphs showing Maximum, Minimum Temperature with DTR for	37
Monsoon Season	
Figure 12: Graphs showing Maximum, Minimum Temperature with DTR for	37
Post-Monsoon Season	
Figure 13: Graphs showing Maximum, Minimum Temperature with DTR for	38
Winter Season	
Figure 14: Map showing rainfall from 1991-2020	39
Figure 15: Map showing rainfall from 2021-2040	39
Figure 16: Map showing rainfall from 2041-2070	39
Figure 17: Map showing rainfall from 2071-2100	39
Figure 18: Map showing maximum temperature from 1991-2020	41
Figure 19: Map showing maximum temperature from 2021-2040	41
Figure 20: Map showing maximum temperature from 2041-2070	41

Figure 21: Map showing maximum temperature from 2071-2100	41
Figure 22: Map showing minimum temperature from 1991-2020	43
Figure 23: Map showing minimum temperature from 2021-2040	43
Figure 24: Map showing minimum temperature from 2041-2070	43
Figure 25: Map showing minimum temperature from 2071-2100	43
Figure 26: Scatterplot between DTR and Rainfall with linear trend line from	45
2021-2100	
Figure 27: Scatterplot between DTR and Rainfall with linear trend line from	45
1991-2020	
Figure 28: Scatterplot between mean maximum temperature and rainfall with	47
linear trend line	
Figure 29: Scatterplot between mean minimum temperature and rainfall with	48
linear trend line	
Figure 30: Graph showing forecasts for ssp245 data for ARIMA (0,1,1)	50
Figure 31: Graph showing forecasts for ssp585 data for ARIMA (0,1,1)	50

LIST OF TABLES

TABLES	PAGE NUMBER
Table 1: Salient Features of the Krishna River Basin	18
Table 2: Table showing correlation statistics for all measures vs Rainfall	49

PREFACE

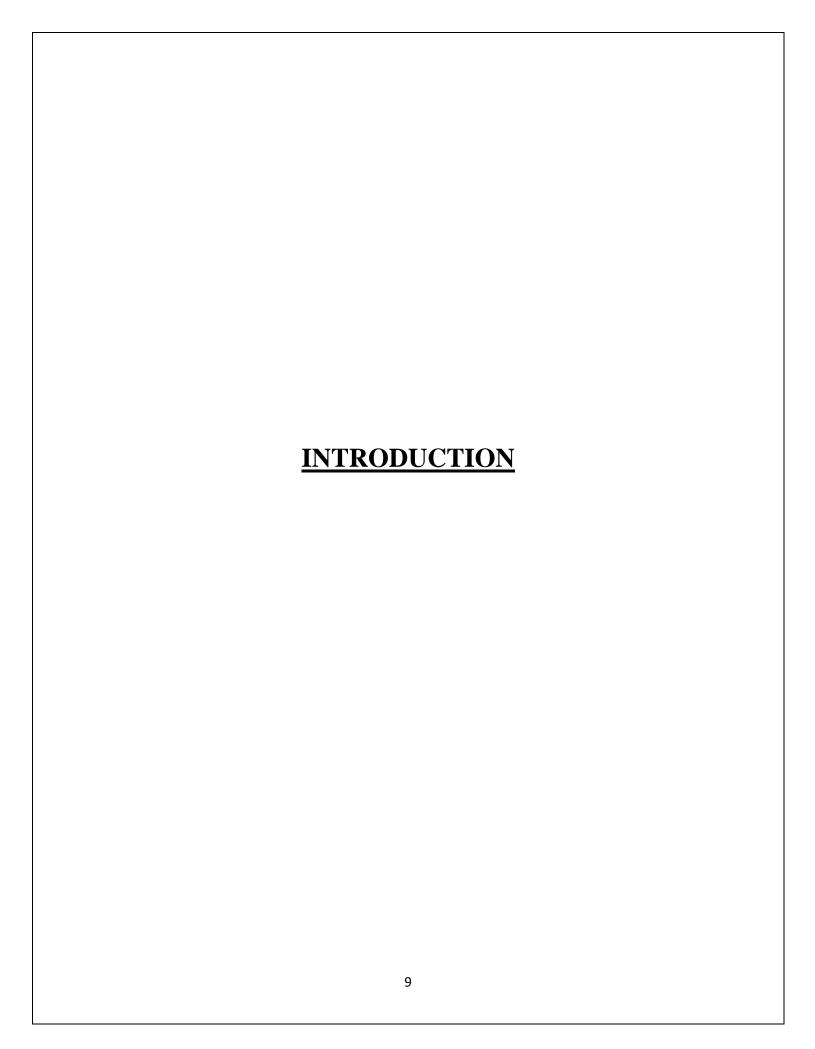
While variations in global mean surface temperature is an important indication of climate change and variability, variations in day-to-day maximum and minimum temperatures give additional information than the mean. This is owing to the fact that changes in mean temperature can be caused by variations in maximum or minimum temperature, or by comparative variations in both. Over the last 70 years, temperature increase has been observed and associated with substantially greater increases in daily minimum temperatures than in daily maximum temperatures, despite the fact that both exhibit considerable increases. As a result, the observed diurnal temperature range (DTR) across land has decreased during the past 70 years.

Observations and climate model simulations reflecting natural climate variability and anthropogenic climate variation are used to assess the global diurnal temperature range (DTR) as a measure of climate change and variability. On decadal timeframes, the observed and modelled variability of DTR link favourably and are unaffected by changes in global mean temperature. The observed drop in DTR during the previous 70 years or so has been significant, but the drop in predicted DTR over the next 80 years is much greater.

This study has been conducted to find how the DTR and Precipitation will vary in the future over the Krishna River Basin as compared to the past observed data. The past data for about 70 years is the observed data which is to be compared to the future data which has been collected from climate model simulations for the next 80 or so years. Maximum and Minimum temperatures were analysed to find DTR for the time period of 1951-2100. Time Series Analysis was carried out on the data collected.

It was also found that precipitation will become more intense all over the basin as time passes, mostly due to the increases in temperature that will lead to more evaporation of the water and more moisture in the atmosphere.

From the results obtained we can come to the conclusion that the climatic abnormalities such as global warming is going to affect the area over time and hence the decreasing trend in DTR. We also found a non-proportional relationship between DTR and Precipitation/Rainfall, i.e. with decreasing DTR, rainfall/precipitation increases manifold.



INTRODUCTION

Due to various land cover characteristics at the basin level, variations in climatic variables are critical for planning, development, and design of hydrological infrastructure in the context of climate change. Monitoring climate change in a river basin is critical for sustainable management and water resource infrastructure development since it needs extra considerations in the context of climate change. Climate change is expected to have a substantial influence and will pose a serious risk to a basin's water supplies in the future. Temperature, as one of the most significant climatological factors, influences hydrological processes within a basin and is often used to identify climatic changes. (*Iqbal*, et al., 2017)

The Mean temperature is a very commonly used indicator of total climate variability and change. Changes in the diurnal cycle, as given by the daily maximum and minimum temperatures, can be equally significant since they govern numerous physical processes in the Earth's climate system. The diurnal temperature range has fallen throughout the twentieth century as the minimum temperature has warmed faster than the maximum temperature. (*Qu, M., et al., 2014*)

The Diurnal Temperature Range (DTR) is a significant thermal metric for assessing the impact of climate change on agricultural and human health. This important meteorological measure can be calculated by finding the difference between the maximum and minimum temperatures of a given area within one day. The DTR is a significant dynamic component in most climatic methods and an important key for diurnal fluctuations. Due to the greater rate of increase in minimum temperatures than maximum temperatures, the frequency, intensity and duration of precipitation are rising with a reduction in DTR. Additionally, any shift in DTR increases the risks related with heat stress, drought, human health, mortality, and agricultural failure.

DTR is one of the many climate variables that has an impact on people's health, agriculture, and society. It's vital to understand how DTR changes as an outcome of global warming. Because the different physical climate change variables, namely aerosols and greenhouse gases, have

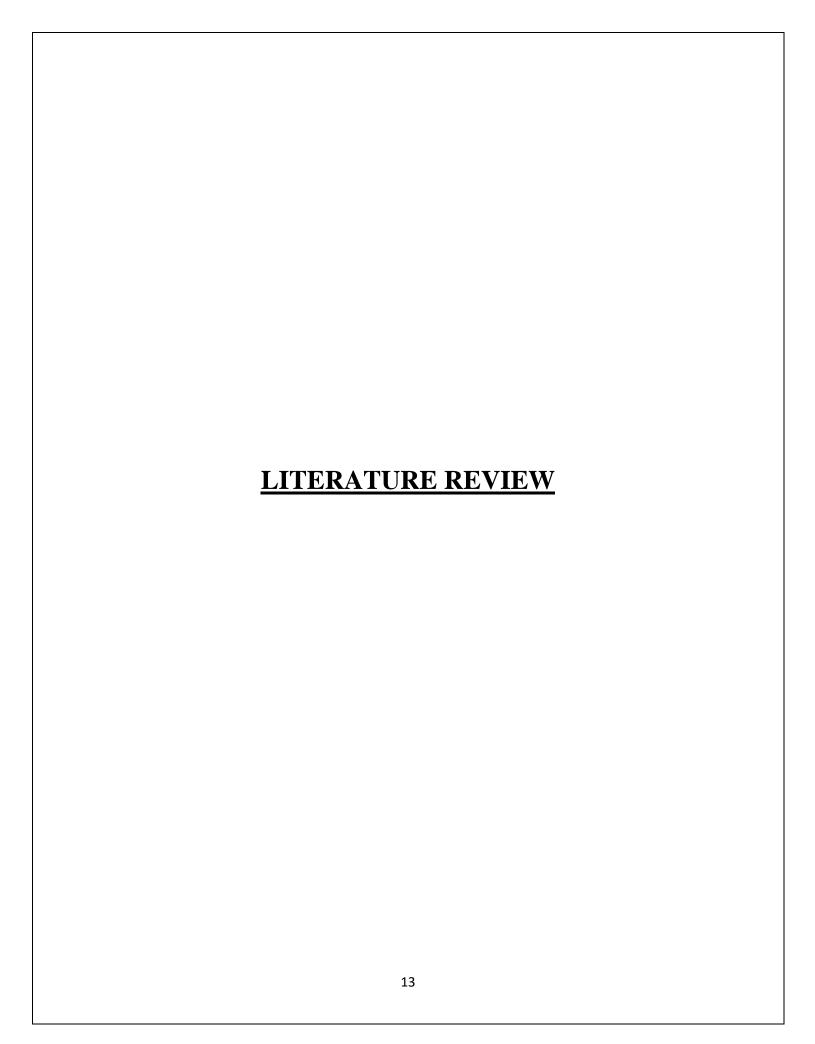
different effects on regional and global climate, forecasting the future development of DTR needs understanding of the effects of the future emissions mix and the individual climate forcers as well.

We have analysed CMIP historical simulations and two scenarios from the Scenario Model Intercomparison Project. The protocol for the historical simulations (experiment name: "historical") has 63-year simulations (from 1951 to 2014). The scenario simulations are run for 85 years, from 2015 to 2100. ScenarioMIP recommends four tier-1 simulation protocols, reflecting different Shared Socioeconomic Pathways (SSPs) that result in various radiative forcing magnitudes by 2100. These experiments represent low-end (SSP1-2.6: "ssp126"), medium-end (SSP2-4.5: "ssp245"), and high-end (SSP3-7.0: "ssp370"; SSP5-8.5: "ssp585") forcing scenarios. (Weijer, et al., 2020)

In this study, I have used "ssp245" and "ssp585". I have worked on output from 13 different climate models, as listed below:

- ACCESS-CM2
- ACCESS-ESM1-5
- BCC-CSM2-MR
- CanESM5
- EC-Earth3
- EC-Earth-Veg
- INM-CM4-8
- INM-CM5-0
- MPI-ESM1-2-HR
- MPI-ESM1-2-LR
- MRI-ESM2-0
- NorESM2-LM
- NorESM2-MM

Here, I have attempted to use Time Series Analysis in RStudio for assessing the change in the value of DTR over the Krishna River Basin. Time Series Forecasting is a method used by Data Scientists for forecasting events over an interval of time. The methods can predict future events by exploratory analysis of historical trends and under the assumption that future trends will follow in the footsteps of prior trends.



LITERATURE REVIEW

Previous studies conducted on DTR have given us several insights as to what to expect during the study and what to look out for.

Studies have shown that there is a strong evidence indicating widespread decline in the DTR during the last few decades in various parts of the world. There are several environmental factors that might influence the DTR, but reports indicate that cloud cover, especially low clouds, has increased in many locations where the DTR has decreased. Cloud cover increases might be attributed to observable global warming and increases in greenhouse gases, to the indirect impacts of increased aerosols, to simply a representation of natural climatic variability, or to a mix of all three. A concerted worldwide effort is needed to create meaningful and homogenous time series of maximum and minimum temperature, as well as information on changes in meteorological factors that impact the DTR, such as cloudiness, stability, humidity, thermal advection, and snow cover.

A study conducted in the Source Region of Yellow River and Its Sub-Basins in China, it was found that temperatures warmed during the time period 1965-2014. The value of annual DTR in the area was found to decrease steadily from 1975 to 2004 as compared to the time period 1965-1974, and increased swiftly in the decade from 2005 to 2014 with approximately the same magnitude during 1975-1984. (*Iqbal, et al., 2017*)

Another study conducted in the continental United States show there to be a steady decrease in the trend of DTR over the past 100 years and with a higher rate during recent decades. It also showed that the DTR trend also has spatial and temporal variations. (Qu, M., et al., 2014)

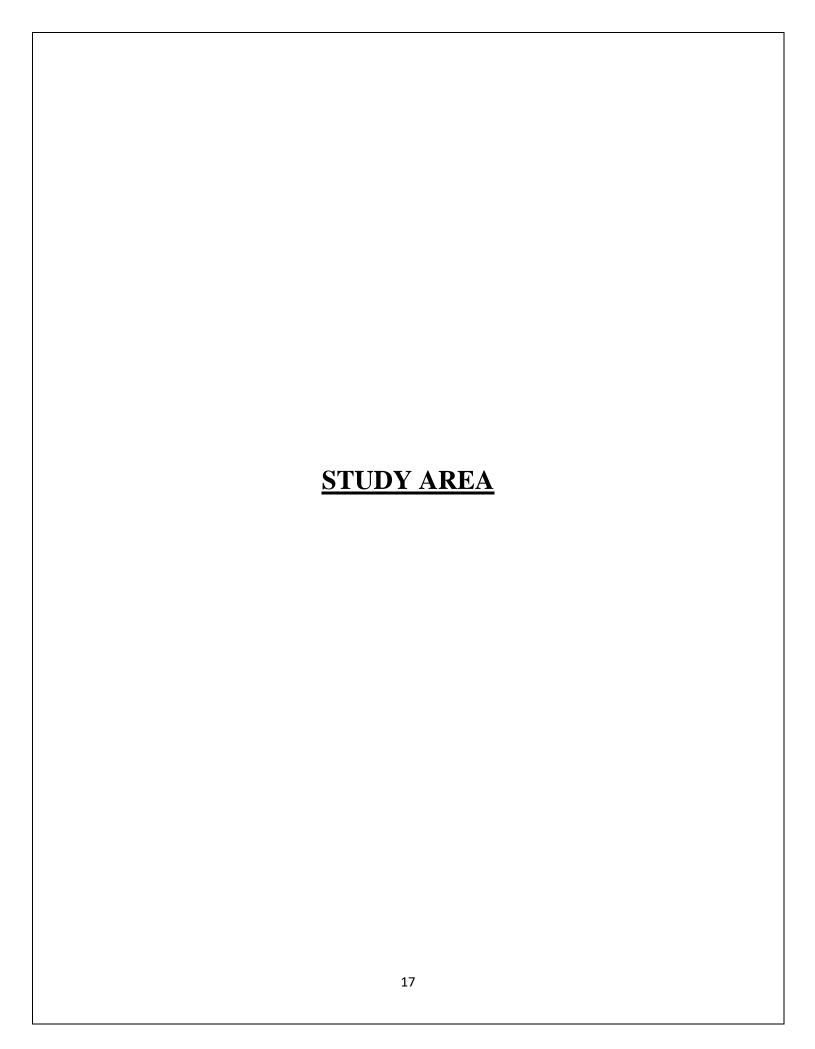
Upon investigation it was found that some studies indicate that the all India mean DTR shows a unique spatial peculiarity in trends for the last 50 years. The DTR in the northern parts of India is decreasing, whereas the DTR in the southern part is increasing. The annual and seasonal DTR averaged across India shows mixed patterns. Winter and post-monsoon DTRs are dropping,

whereas monsoon DTRs are growing, and yearly and summer DTRs are stable. However, both the mean maximum temperature and the mean minimum temperature are increasing during the monsoon season. Increases in anthropogenic aerosols and urbanization, as well as increased cloud cover and rainy days, may be to blame for the Indo-Gangetic plains' ongoing decline in annual and seasonal DTR. Mean minimum and maximum temperatures are growing across India, with the maximum at a higher rate in South India and minimum at a higher rate in North India. Variability of DTR in relation to relevant meteorological parameters like the number of rainy days low cloud covers are physically consistent. (*Jaswal, et al., 2016*)

A study conducted on the north-eastern region of India, showed decreasing trends in DTR observed at certain locations for the annual, seasonal and monthly time scales. In certain areas, there was significant increase in DTR trends during months of October and during the monsoon and the post-monsoon seasons. There was no trend found in the temperatures during winter and pre-monsoons seasons. Mean temperatures were observed to have increasing trends in such areas. Upon further analysis, it was found that different meteorological constraints affect the DTR in different seasons at different places. (*Jhajhariaa and Singh, 2010*)

A study conducted by have shown that total cloud cover and other ancillary factors such as moisture present in the soil and precipitation appeared to be the apparent reason for the increase in DTR all over India from 1948 to 2003. The variation in DTR was found to be highly negatively correlated with the variations in precipitation and total cloud cover, forecasting the two climatic variables as major influences for the increase in DTR. It was found that the minimum temperature had increased significantly (95% significant) during the period of 1901–2003. (*Rai, et al., 2012*)

A study was conducted by implementing a non-stationary and non-linear approach known as Multi-dimensional Ensemble Empirical Mode Decomposition (MEEMD) method to analyse DTR across India from 1951 to 2010. It was found that due to the rate of increase in maximum temperature being lower than that of the minimum temperature, areas that are arid, semi-arid and such, show negative trends in DTR when they should be showing the opposite. There is no positive trend in DTR in the southern and western regions that contain equatorial grassland and sub-tropical



STUDY AREA:

The Krishna river basin is Peninsular India's second largest eastward draining interstate river basin. It is located in the Deccan Plateau, covering major parts of Maharashtra (69,425 km²), Karnataka (113,271 km²), and Andhra Pradesh (76,252km²).

The Krishna River begins in Mahabaleshwar, Maharashtra extending over an area of 258,948 km² which is almost 8% of the entire topographical area of India. The details of the basin are as follows:

Table 1: Salient Features of the Krishna River Basin

Basin Extent	
Longitude	73° 21' to 81° 09' E
Latitude	13° 07' to 19° 25' N
Length of Krishna River (Km)	1400
Catchment Area (Sq.km.)	258948
Average Water Resource Potential(MCM)	78120
Utilizable Surface Water Resource (MCM)	58000
Live Storage Capacity of Completed Projects (MCM)	50117
Live Storage Capacity of Projects Under Construction (MCM)	4287
Total Live Storage Capacity of Projects (MCM)	54404

Source: MITRA, 2014

The Krishna River is one of the longest rivers in India, which flows for about 1300km and meets the Bay of Bengal. Elevated at 1337m and north of Mahabaleshwar, it starts in the Western Ghats, around 64km from the Arabian Sea. The principal tributaries joining the Krishna are Koyna, Bhima, Mallaprabha, Ghataprabha, Yerla, Warana, Dindi, Musi, Panchaganga, Dudhganga, etc.

Other than the western boundary that is made by an uninterrupted stretch of the Western Ghats, the majority of this basin is made up of rolling and undulating territory. Black soils, alluvium, red soils, laterite and lateritic soils, mixed soils, and alkaline and salty soils are all prominent soil types present in the basin.

This basin has a 78.1 km³ average annual surface water potential, according to estimates. There is 58.0km³ of water that can be used. The basin's cultivable area is approximately 203,000km², accounting for 10.4% of the country's total cultivable area. (*MITRA*, 2014)

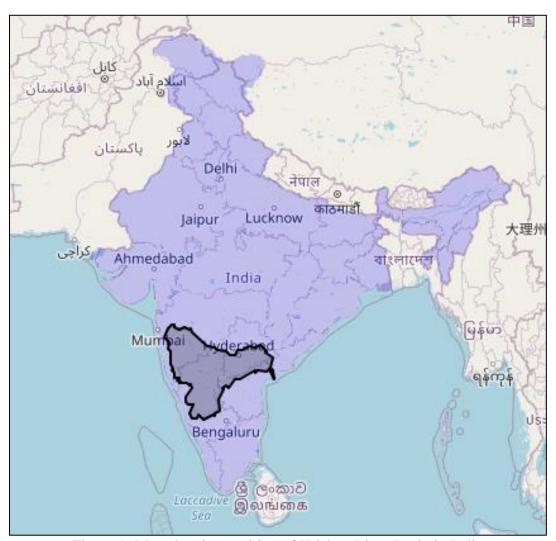


Figure 1: Map showing position of Krishna River Basin in India

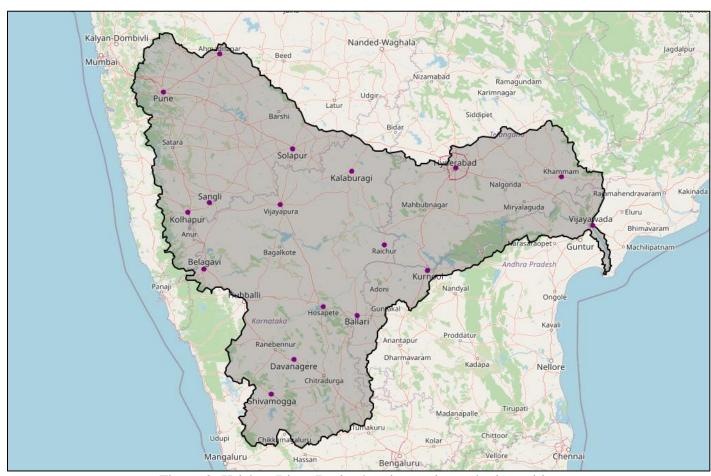
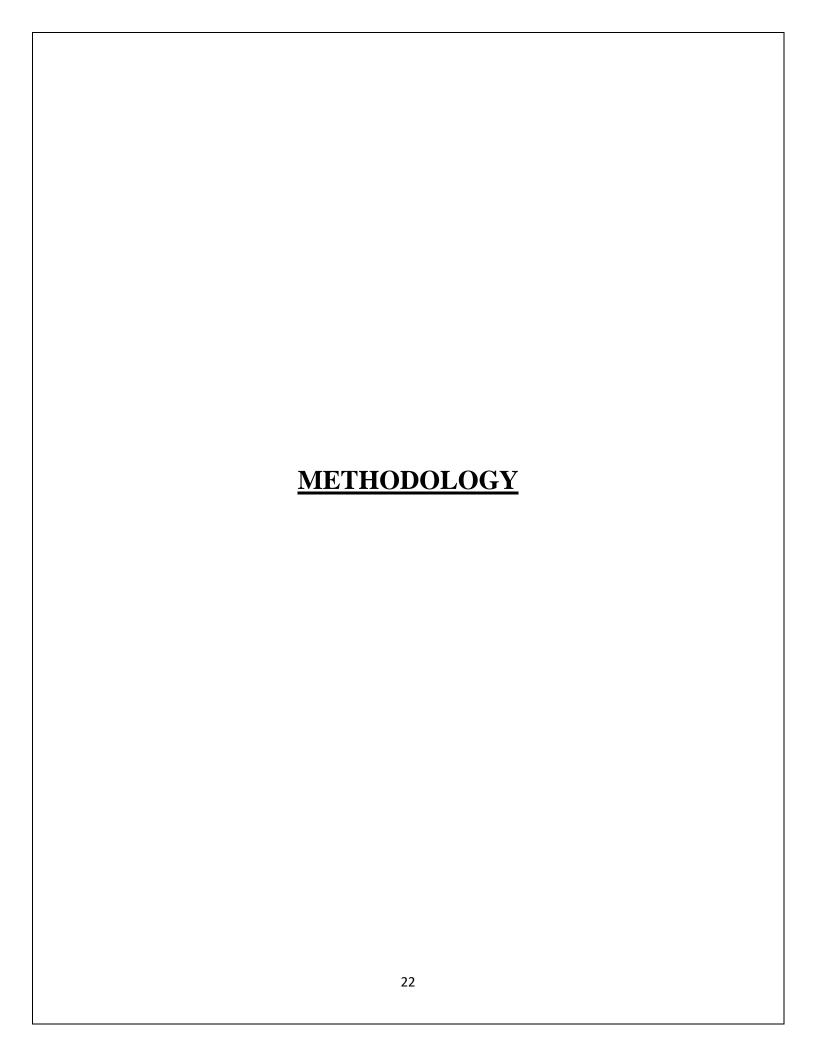


Figure 2: Krishna River Basin showing major and minor cities



Figure 3: Map of the Krishna River Basin showing all the rivers and tributaries

Source: Data from GTOPO30, HYDRO1k, and Natural Earth



METHODOLOGY:

Data Collection:

I have obtained data with the help of my guide from the National Data Centre (NDC) of India Meteorological Department (IMD). A sequence of high quality control methods at data inputting centres and NDC are employed prior to archiving all climatological data at NDC. On the IMD website, rainfall is available for a period of 1901 to 2020 and temperature data is available from 1951 to 2020. Daily gridded rainfall data is of new high spatial resolution (0.25x0.25 degree). Data is arranged in 135x129 grid points. For temperature, gridded daily data is in high resolution form 1 by 1 degree.

Data has also been obtained from the above mentioned climate models for 85 years, from 2015 to 2100 to help understand the future scenario of DTR.

All data was in the form of daily Maximum Temperature, Minimum Temperature and Precipitation over the Krishna River Basin during the mentioned time periods.

Software and Packages:

The RStudio software is used for the duration of the project to perform time series analysis and plot graphs. RStudio provides various packages having functionalities to perform the analysis required.

<u>Packages and Libraries used:</u>

- tidyverse: It is a collection of packages intended to make it simple to install and load multiple packages. It loads the tidyr, ggplot2, readr, tibble, dplyr and purrr packages. These are the core of the tidyverse.
- ggplot2: It is a package used for making complex plots easily from data in any data frame.

- dplyr: This package contains numerous functions that perform data manipulation processes such as selecting specific columns, applying filter, sorting data, aggregating data and adding or deleting columns.
- xts: This package allows uniform handling of many R time series classes by providing an extensible time series class. It is also known as eXtensible Time Series.
- forecast: It provides techniques and tools to display and analyse univariate time series forecasts that include exponential smoothing through automatic ARIMA modelling.
- stats: It contains functions for statistical calculations and random number generation, and also the arima() function.
- TTR: This package contains many of the most popular technical analysis functions that help in time series analysis. The SMA() function in this package is made to smooth time series data by using the simple moving average method.
- tidyquant: It includes charting tools to assist users in developing quick visualizations in ggplot2.

(RDocumentation: https://www.rdocumentation.org/)

Data Pre-processing:

After the process of data collection, it was found that the data contained some unnecessary columns of information which was then removed before starting the analysis. The data was available in a daily format, i.e., data for each day was recorded from 1951-2100.

Hence, the dataset was extremely extensive and had to be divided into various factions during the analysis,

- Data was divided according to years into historical (1951-2014) and current (2015-2100)
- Data was divided according to years into historical (1991-2020), the 20s (2021-2040), the
 50s (2041-2070) and the 80s (2071-2100)
- Data was divided according to seasons into Pre-Monsoon (March, April, and May),
 Monsoon (June, July, August, and September), Post-Monsoon (October, November) and
 Winter (December, January, February).

The data was available in the form of Maximum Temperature and Minimum Temperature. Hence, DTR was calculated as,

DTR = Maximum Temperature – Minimum Temperature

After calculation of DTR, annual rainfall of each year was found by finding sum of rainfall of each year.

Graphs and maps were plotted to find comparison, understand the data better, and analysis.

The time series was decomposed using Simple Moving Average (SMA) and exponential smoothing was carried out by performing AutoRegressive Integrated Moving Average (ARIMA).

Correlation coefficient between rainfall and DTR was also calculated and plotted in a scatter plot showing us the relationship between these two variables.

Time Series Forecasting:

In the fields of Machine Learning and Data Science, Time Series Forecasting is one of the most challenging problems. It involves forecasting a set of continuous variables over a series of time intervals. Traditional procedures need the calculation of regression components analytically to fit the curve to the time series and make projections.

Recent advancements within the fields of Big Data have resulted in an increase in a rise data that may be evaluated to assist us make better decisions. The time series data is one such kind of data that is plentiful. One of the foremost difficulties facing today's data scientists and academics is analyzing and forecasting Time Series data. The essential goal of time series forecasting is to spot patterns in data and model them appropriately. After that, the model will be used to extrapolate and generate accurate forecasts for any application. A good model attempts to fit the data as accurately as possible with the smallest amount of error while maintaining generality.

A time series data set maybe a collection of data points that indicate metrics that change over time. It is defined as a set of vectors X(t), where t = 0, 1, 2,...n. If the number of parameters

changing with reference to time is one, the time series is said to be univariate. Multivariate time series data is known as a set of data with more than one parameter.

The following four elements are present in any Time Series:

- 1. Trend: The general movement of the average of the data across the series is influenced by this component. Variations in housing rents over time are an example.
- 2. Cyclic: This component describes the cyclic changes in data over a standard period of time. Economic and financial statistics are two examples.
- 3. Seasonal: When a pattern emerges throughout the series at a fixed period, this component is present. Temperature variations throughout the course of a year are an example.
- 4. Irregular: This component contributes to time series data unpredictability. Wars, strikes, and natural disasters are cases of real-life events.

Two major models, Multiplicative and Additive, is determined based on the fluctuation of the four components. They are mathematically represented as follows:

Additive Model:
$$Y(t) = T(t) + S(t) + C(t) + I(t)$$

Multiplicative Model:
$$Y(t) = T(t) \times S(t) \times C(t) \times I(t)$$

T, S, C, and I show Trend, Seasonal, Cyclic, and Irregular components. The assumption is that they are independent in the multiplication model.

If the statistical process does not adjust with time, the series is thought to be stationary. It is always easier to study a stationary process. The series is assumed to be stationary in some forecasting models, like ARIMA. The series is non-stationary because of the presence of trend and seasonality.

ARIMA and exponential smoothening techniques are two instances of conventional procedures. As an input, the ARIMA model requires a stationary series. Non-stationary series are converted to stationary series by removing non-stationary components like trends and seasonality

(which are removed by differencing Time Series). Analyzing ACF and PACF plots is additionally required to compute the auto regressive and moving average components. The downside of this model is that these parameters must be determined for every series, making the procedure tedious, time-consuming, and error-prone.

ARIMA's Auto Regressive (AR) component can be represented mathematically as:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + ... + \beta_p Y_{t-p} + \epsilon_1$$

The moving average represents the complete trend of the time series. It is given as:

$$Y_t = \alpha + \epsilon_t + \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + \dots + \phi_q \epsilon_{t-q}$$

The complete ARIMA model is given by sum of AR and MA components. It is represented as: $Y^{t} = AR + MA$

Although the exponential smoothening process can operate with non-stationary data, its drawbacks, like the forecast lagging behind the trends because the data grows. It also ignores the dynamic changes that occur in the real world. The approaches stated above are a number of the traditional methods for obtaining forecasts. Every day, the amount of time series data created increases tremendously. This analysis aids various organizations in maintaining control over their operations by allowing them to create better judgments. (*Yatish and Swamy*, 2020)

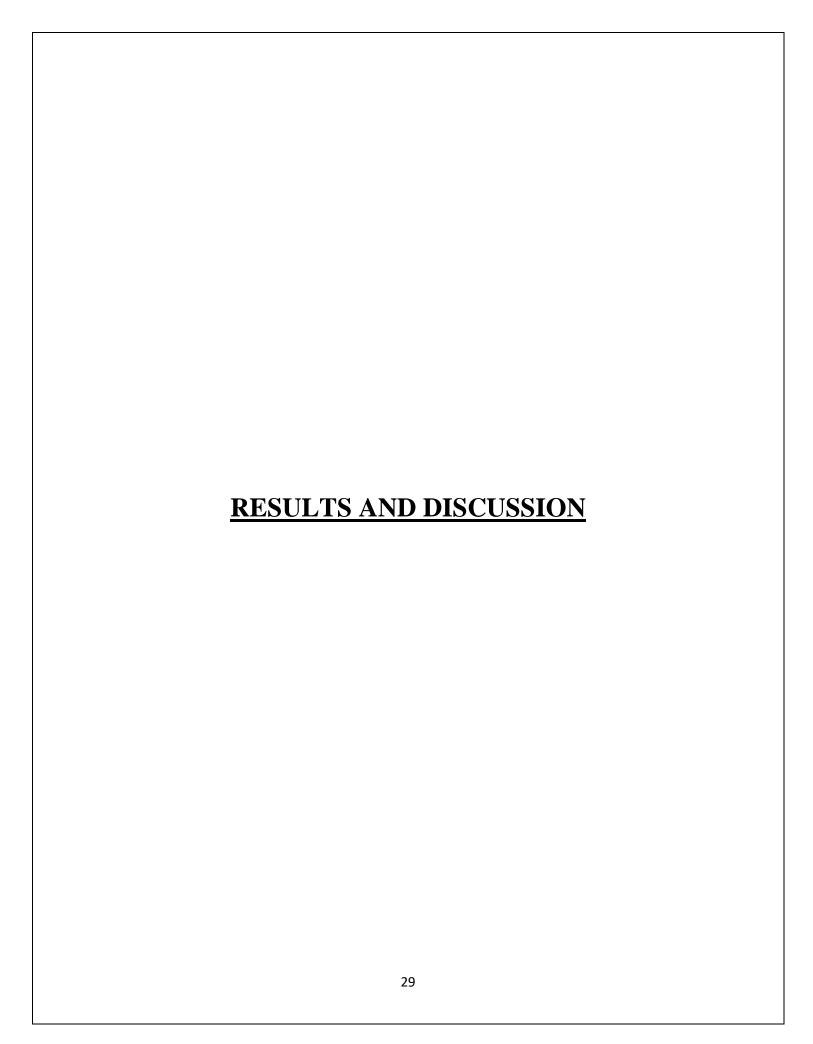
Climate Models:

Climate models have become the most important tools for studying the reaction of the climate system to various forcings, making climatic predictions on seasonal to decadal time periods, along with producing climate projections for the next century and beyond. As a result, evaluating the performance of these models, both collective and individual, is critical. Model findings are being acquired as part of the Coupled Model Intercomparison Projects (CMPI3 and CMPI5), which again are a set of coordinated and consistent climate model experiments that are becoming increasingly well-documented. Other methods are also used, like those involving Regional Climate Models (RCMs) and Earth System Models (ESMs) of Intermediate Complexity.

It is worth noting that the CMIP3 model archive has been thoroughly assessed, with a large part of that examination occurring after the AR4. The CMIP5 models, on the other hand, are only now being reviewed, hence there is less published material. (*Flato*, et al., 2013)

Simple energy balance models to large Earth System Models (ESMs) needing advanced high-performance computers are employed in climate research. The model used is directly related to the scientific subject being addressed. Simulating historical climate, process studies for attribution and sensitivity and predicting near-term climate variability, physical understanding, and variation on seasonal to decadal time scales, creating projections of future climate change over the next century or more, and scale back these projections to get more information at the local and regional scale are few examples of applications. Because computational cost is a consideration in all of them, simpler models (with lower complexity or spatial resolution) are being utilized whenever bigger ensembles or longer integrations are needed. Climate change simulations on a millennial or longer time period or exploration of parameter sensitivity are two examples.

The Coupled Model Intercomparison Project (CMIP) is a shared framework in climatology that aims to enhance climate change understanding. It is analogous to the Atmospheric Model Intercomparison Project (AMIP) for global coupled ocean-atmosphere general circulation models (GCMs). It had been held in 1995 by the World Climate Research Programme's Working Group on Coupled Modelling (WGCM) (WCRP). It is being built in stages to help enhance climate models as well as support national and international climate change assessments. (*Flato*, *et al.*, 2013)



Comparing DTR for data collected from ssp245 and ssp585 (2015-2100) with historical data (1951-2014):

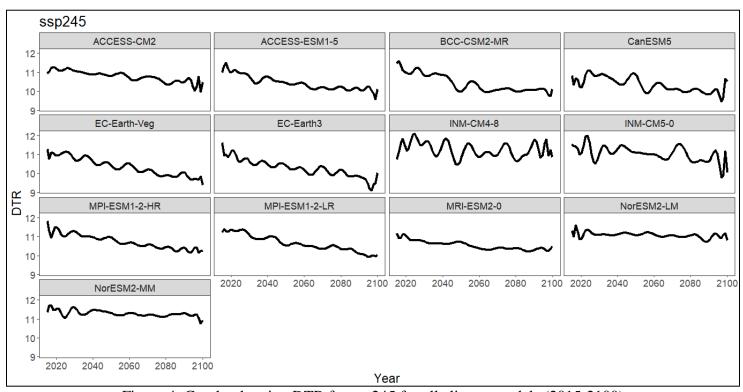


Figure 4: Graphs showing DTR for ssp245 for all climate models (2015-2100)

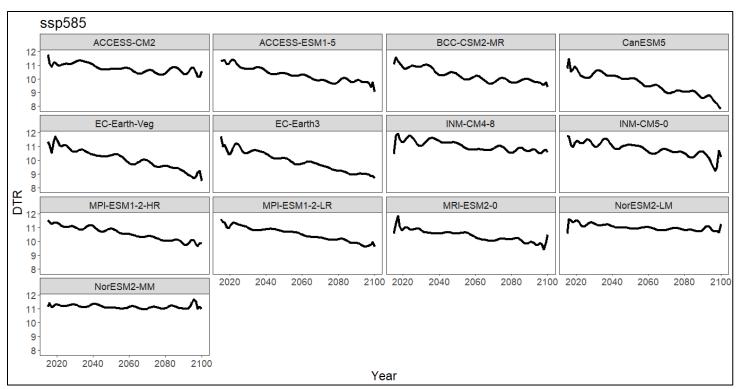


Figure 5: Graphs showing DTR for ssp585 for all climate models (2015-2100)

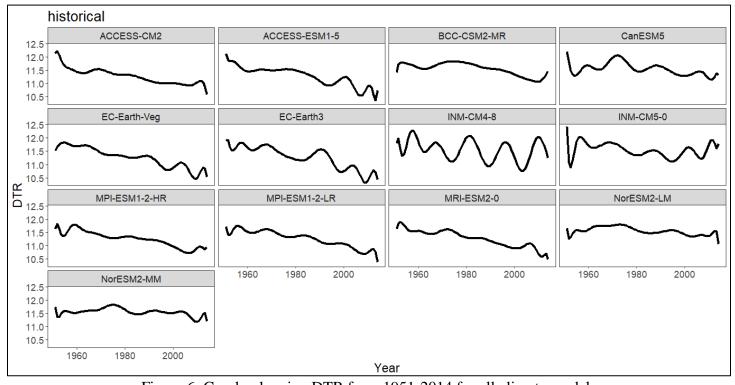
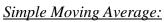


Figure 6: Graphs showing DTR from 1951-2014 for all climate models

From the above Figure 4, we can see that over the same period of time, it has been predicted by not all but most of the climate models in ssp245 that DTR falls at a steady rate, although some models show a fairly constant trend in DTR. Whereas in all the climate models in ssp585, Figure 5 show a decreasing rate in DTR over the time period, except NorESM2-LM and NorESM2-MM.

In Figure 6, which shows a time period before global warming, we see a constant DTR that slowing starts decreasing over time as we enter the global warming stages.

Decreasing DTR would mean that the difference between the Maximum and the Minimum temperatures is reducing, which can be better understood by the following graphs.



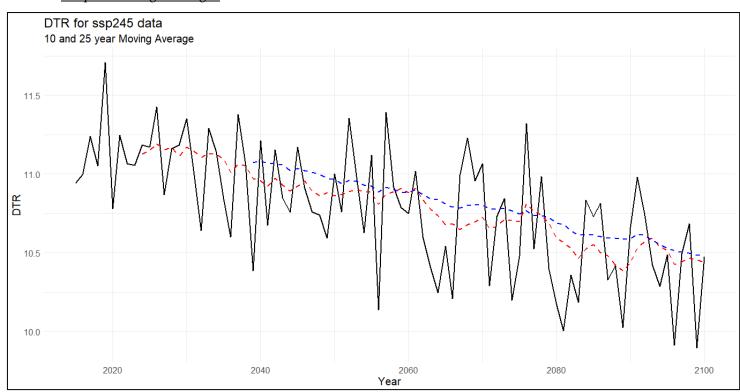


Figure 7: Graph showing the original data points in black and the 10 (in red) and 25 (in blue) year moving average value in red for ssp245

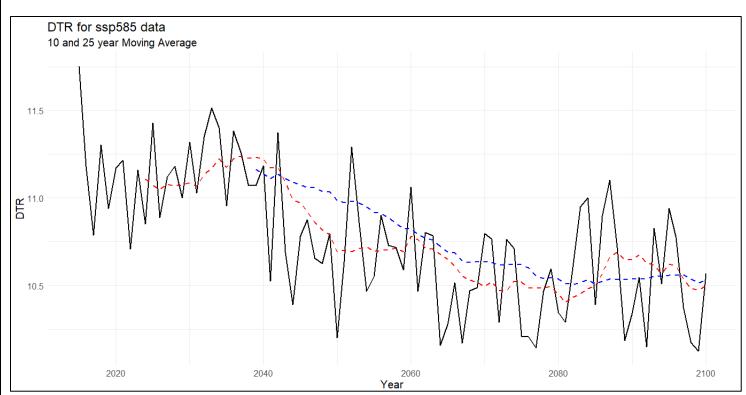


Figure 8: Graph showing the original data points in black and the 10 (in red) and 25 (in blue) year moving average value in red for ssp585

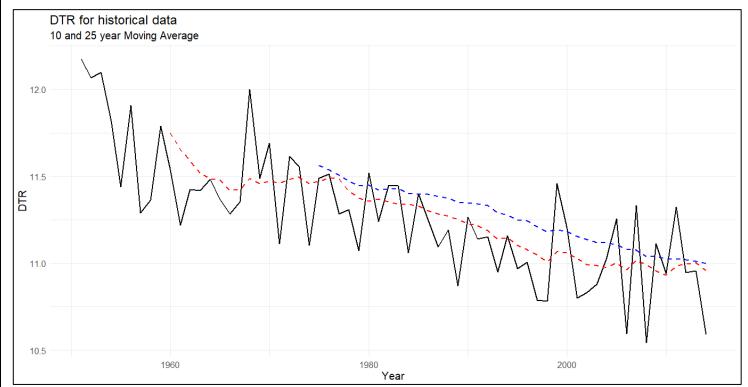


Figure 9: Graph showing the original data points in black and the 10 (in red) and 25 (in blue) year moving average value for historical data

From the above graphs, we can see the decomposed time series values in red and blue, which shows us a very rapid decrease in DTR over the years.

The historical data shows a steep decrease from around 1975 to 1995, and continues to decrease in the years to come.

Ssp585 data shows a sharp decreasing trend in the beginning but a somewhat steady but still decreasing trend at a far lower rate after 2050. Whereas ssp245 shows a steady rate of decrease in DTR throughout.

Maximum, Minimum temperatures and DTR for the various seasons throughout the years:

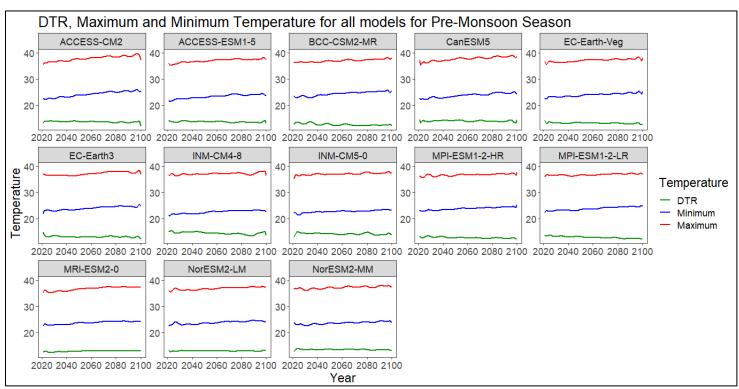


Figure 10: Graphs showing Maximum, Minimum Temperature with DTR for Pre-Monsoon Season

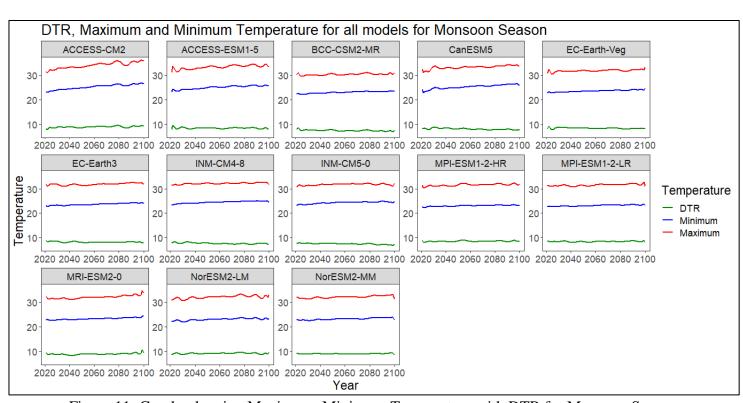


Figure 11: Graphs showing Maximum, Minimum Temperature with DTR for Monsoon Season

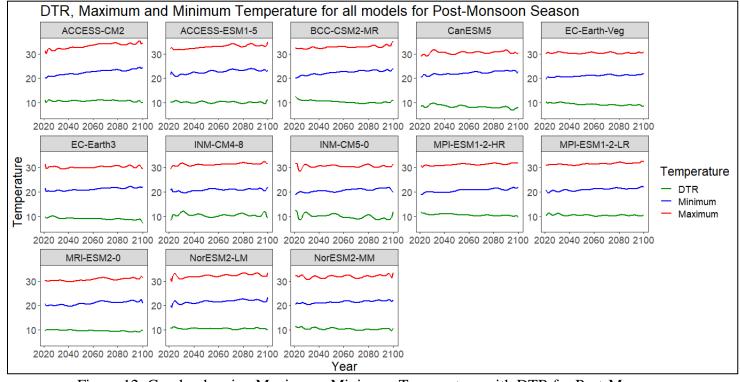


Figure 12: Graphs showing Maximum, Minimum Temperature with DTR for Post-Monsoon Season

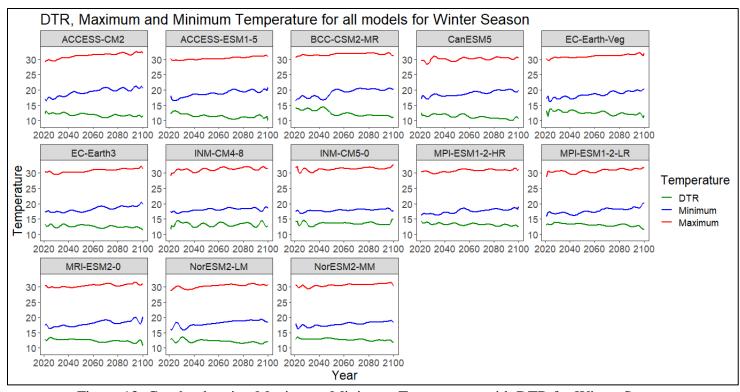


Figure 13: Graphs showing Maximum, Minimum Temperature with DTR for Winter Season

From the above graphs, it can be seen that during the Pre-Monsoon Season, temperatures are mostly constant throughout the years but with a slight rate of increase. Temperatures in the Monsoon season seem to be extremely constant, any increase is negligible to the naked eye. The Post-Monsoon season sees a steady increase in both maximum and minimum temperatures. And the Winter season has increasing temperatures throughout, with the gap between the maximum and minimum temperatures closing in. In all of the above scenarios, the rate of increase in the maximum temperature is lower than the rate of increase in the minimum temperature, which causes the decrease in DTR.

Maps showing rainfall from 1991-2100:

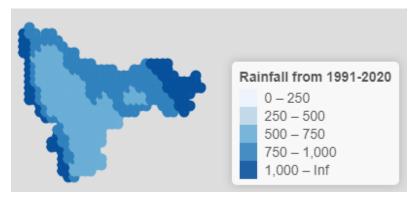


Figure 14: Map showing rainfall from 1991-2020

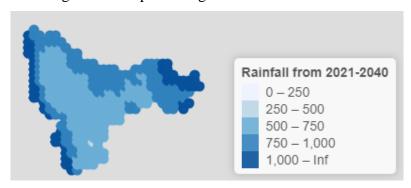


Figure 15: Map showing rainfall from 2021-2040

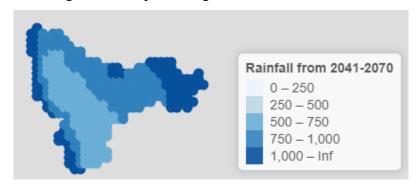


Figure 16: Map showing rainfall from 2041-2070

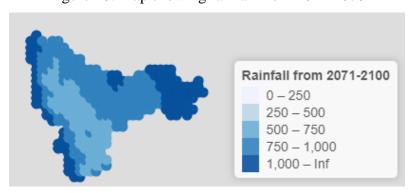


Figure 17: Map showing rainfall from 2071-2100

From the above maps showing the Krishna River Basin from 1991-2100, we see that rainfall increases over the years. Rainfall from 2021-2040 has been the minimum overall. Since the darker shades of blue indicate more rainfall, we can see that the map from years 2071-2100 is the darkest and hence can be concluded to receive the most rainfall compared to other time periods.

Also on the contrary, rainfall from 1991-2020 has not been minimum, but more than that of 2021-2040.

Maps showing maximum temperature from 1991-2100:

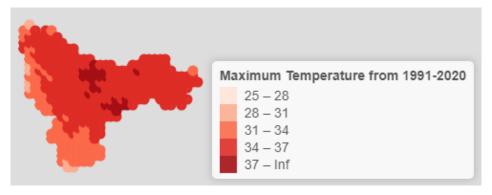


Figure 18: Map showing maximum temperature from 1991-2020

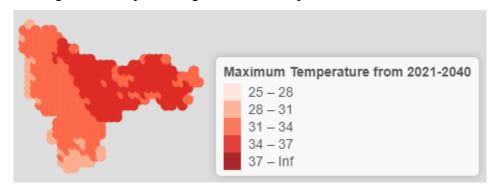


Figure 19: Map showing maximum temperature from 2021-2040

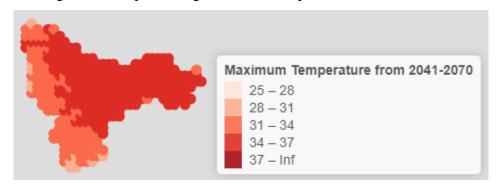


Figure 20: Map showing maximum temperature from 2041-2070

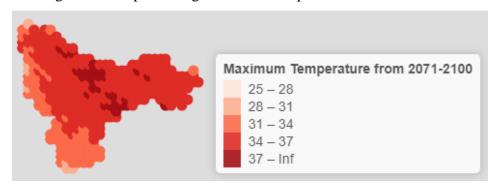


Figure 21: Map showing maximum temperature from 2071-2100

From the above maps showing the Krishna River Basin from 1991-2100, we see that maximum temperature increases over the years. Rainfall from 2021-2040 has been the minimum overall. Since the darker shades of blue indicate more rainfall, we can see that the map from years 2071-2100 is the darkest and hence can be concluded to receive the most rainfall compared to other time periods.

Also on the contrary, temperatures from 1991-2020 has not been minimum, but more than that of 2021-2040.

Maps showing minimum temperature from 1991-2100:

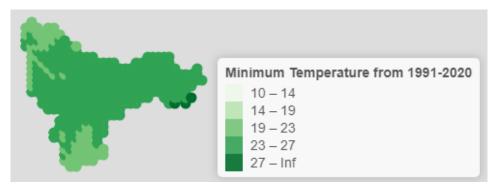


Figure 22: Map showing minimum temperature from 1991-2020

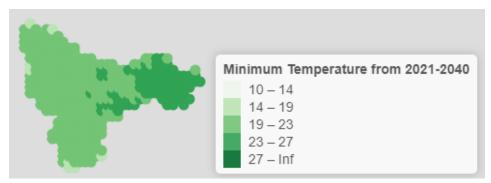


Figure 23: Map showing minimum temperature from 2021-2040

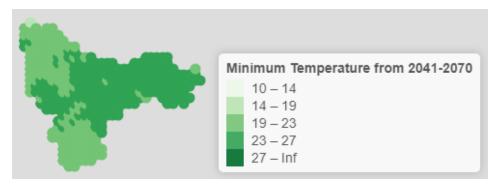


Figure 24: Map showing minimum temperature from 2041-2070

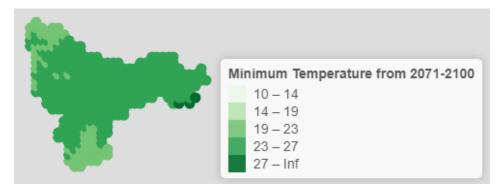


Figure 25: Map showing minimum temperature from 2071-2100

From the above maps showing the Krishna River Basin from 1991-2100, we see that minimum temperature increases over the years. Rainfall from 2021-2040 has been the minimum overall. Since the darker shades of blue indicate more rainfall, we can see that the map from years 2071-2100 is the darkest and hence can be concluded to receive the most rainfall compared to other time periods.

Also on the contrary, temperatures from 1991-2020 has not been minimum, but more than that of 2021-2040.

Relationship between DTR and Rainfall:

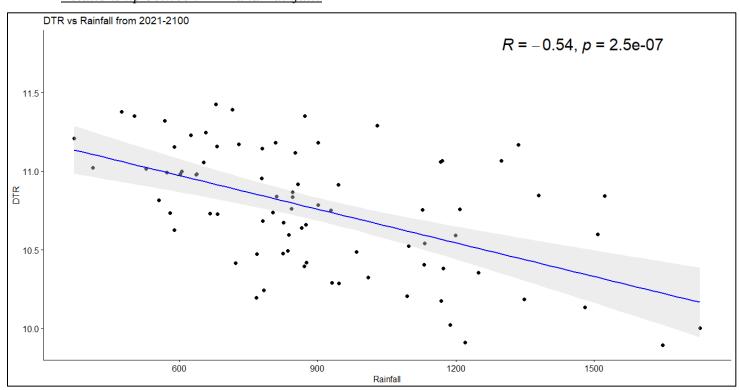


Figure 26: Scatterplot between DTR and Rainfall with linear trend line from 2021-2100 at 95% confidence interval

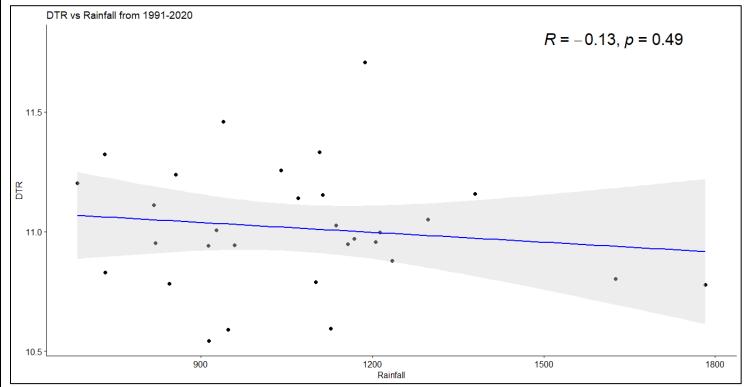


Figure 27: Scatterplot between DTR and Rainfall with linear trend line from 1991-2020 at 95% confidence interval

The correlation coefficient between DTR and Rainfall for both time periods is seen to be negative, i.e., as one increases the other decreases and vice-versa. The correlation coefficient between DTR and Rainfall was found to be -0.5389 for time period 2021-2100 which means it is highly negatively correlated and -0.1317 for time period 1991-2020 which means it is slightly negatively correlated. Both indicate that with increase in Rainfall, DTR decreases.

Relationship between Maximum Temperature and Rainfall:

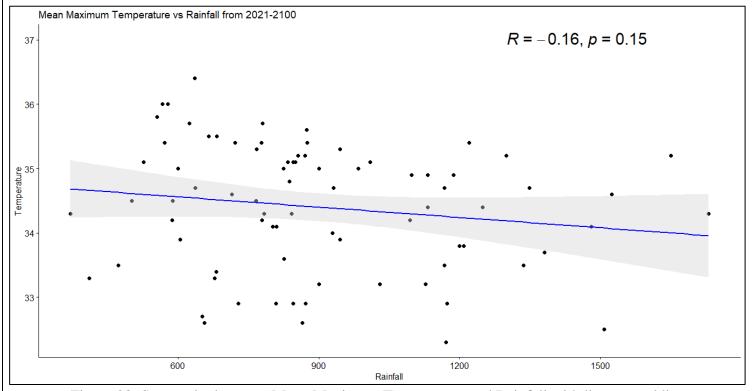


Figure 28: Scatterplot between Mean Maximum Temperature and Rainfall with linear trend line at 95% confidence interval

The correlation coefficient between Mean Maximum Temperature and Rainfall is seen to be negative, i.e., as one increases the other decreases and vice-versa. The correlation coefficient was found to be -0.1617, which says that it is slightly negatively correlated. This indicates that with rising temperatures, rainfall is decreasing at a very small rate.

Relationship between Minimum Temperature and Rainfall:

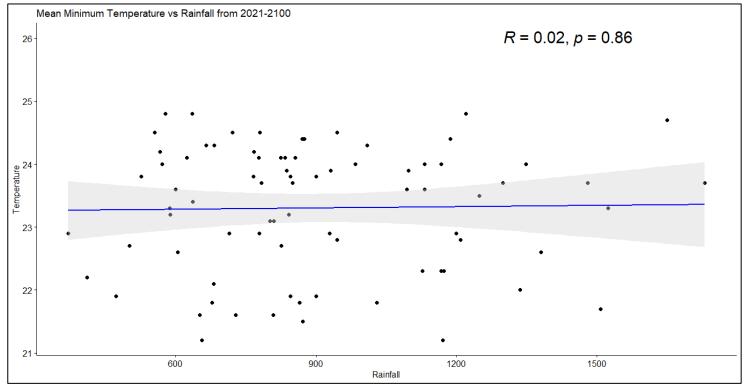


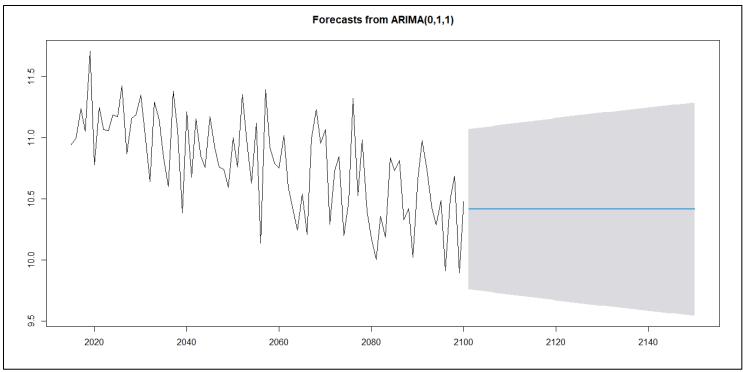
Figure 29: Scatterplot between Mean Minimum Temperature and Rainfall with linear trend line at 95% confidence interval

The correlation coefficient between Mean Minimum Temperature and Rainfall is seen to be positive, i.e., as one increases the other increases as well. The correlation coefficient was found to be 0.02, which says that it is slightly positively correlated. This indicates that with rising temperatures, rainfall is also increasing but at a very small rate.

Table 2: Table showing correlation statistics for all measures vs Rainfall

Measure	Correlation	t-	Degrees	p-value	Confidence Interval		
	Coefficient	statistic	of freedom				
					Lower limit	Upper limit	
DTR (1991-2020)	-0.1317	-0.703	28	0.4878	-0.4697	0.24	
DTR (2021-2100)	-0.5389	-5.6496	78	0.0000003	-0.6783	-0.362	
Mean Maximum Temperature	-0.1612	-1.4422	78	0.1532	-0.3679	0.0607	
Mean Minimum Temperature	0.02	0.1764	78	0.8604	-0.2007	2.2386	

ARIMA Forecasts for DTR for 10 years:



sssFigure 30: Graph showing forecasts for ssp245 data for ARIMA (0,1,1)

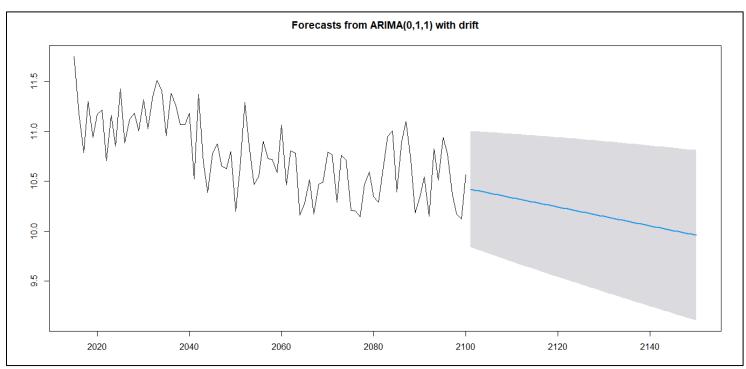


Figure 31: Graph showing forecasts for ssp585 data for ARIMA (0,1,1)

		now exponential					
		nd shows future			ars, i.e., tili 21:	50. From the 10	recasts
steau	decrease in D	ΓR values is see	ii to occui ii	i the future.			

CONCLUSION:

A gradual and steady decrease in DTR is observed over the entire time period, 1951-2100. Seasonal and annual time scales both show decreasing trend in DTR and increasing trend Maximum and Minimum temperatures, except in the Monsoon season, where all factors remain mostly constant.

Rainfall is seen to be increasing at a steady rate during the time period, 1991-2100. Warmer temperatures lead to higher precipitation.

Correlation analysis showed that rainfall or precipitation has negative effect on DTR, i.e., with increase in rainfall, DTR decreases, which proves the above conclusion that DTR is decreasing and rainfall is increasing at the same time period. Correlation analysis between maximum and minimum temperatures and rainfall showed a minimal negative and positive relationship, respectively.

It was found that the maximum temperature has seen a rise of approximately 1.8°C and the minimum temperature has seen a rise of approximately 1.7°C from 1991-2020.

Further, it was calculated that the maximum temperature will see a further rise of approximately 4.1°C and the minimum temperature will see a rise of approximately 3.6°C by 2100.

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