

**IMPACT OF CLIMATE CHANGE ON DROUGHTS IN
MADURU OYA RIVER BASIN IN SRI LANKA OVER THE
21st CENTURY**

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Degree of Master of Science

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Sri Lanka

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Sri Lanka

February 2022

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ABSTRACT

Impact of Climate Change on Droughts in Maduru Oya River Basin in Sri Lanka over the 21st Century

Drought is an creeping hazard that is least understood and the most complex of all-natural hazards. The drought study requires large historical climatological and meteorological datasets and their complex inter-relationships. Its impacts are prominently observed on a local scale only when the severity becomes high, and the coherent onset and persistence of mild droughts may go unnoticed. The current study investigates the existing drought conditions and future drought risk in the Maduru Oya River Basin over the 21st-century in terms of meteorological and hydrological drought indices (i.e., SPI, SPEI, RDI, EDI and SRI). The future hydrology over the basin is simulated for this research, using bias-corrected precipitation and potential evapotranspiration outputs under RCP 4.5 and 8.5 of the MPI-M-MPI-ESM-MR. The relevant drought-related indices were computed in monthly and seasonal timescales over the 1951-2099 period. The time series have been classified for drought characterization, including drought frequency, severity, trend, and probability computation. Further, to assess the impact of these droughts on the basin's response, a hydrological model (i.e., HEC-HMS) was developed to simulate the discharge at the Padiyathalawa outlet considering 2008-2012 as validation period.

The results of the monthly timescale for SPI (approximately similar drought frequency and severity by RDI and EDI) depicted that the severe and extreme droughts (45) occurred in March (8), August (5), September (4), October (6) and November (9) in the historical period. Severe and extreme droughts (110 under RCP 4.5, 104 under RCP 8.5) are projected in January (17), February (12), April (10), May (12) and December (13) under RCP 4.5 and January (12), February (10), April (13), June (13) and August (10) under RCP 8.5 over the 21st-century. The SPEI at monthly timescale identified highest number of severe and extreme drought (67) events in the historical period and projected highest severe and extreme drought (128 under RCP 4.5, 122 under RCP 8.5) events over the 21st-century in the study area. The hydrological drought index, SRI projected severe and extreme droughts under RCP 4.5 (65) and RCP 8.5 (62) over the 21st-century that is about 50 % frequency of the meteorological drought indices. The Northeast Monsoon season had the least drought episodes (~20) in the historical period, and on a seasonal time scale, high drought frequency (~30 using meteorological drought indices and ~20 using SRI under RCP 4.5 and RCP 8.5) and severity (severe and extreme droughts) are projected in the Northeast Monsoon. It is also observed that there is a consistent mild drought throughout the mid (~70) and end (~65) century for a maximum duration compared to the historical (~50) period. The accuracy of results obtained from the continuous HEC-HMS model (NSE, RMSE Std. Dev, and R^2 values of 0.59, 0.72, and 0.60 achieved in validation) highlights the efficient way to simulate a basin's hydrological parameters. The model can project the future variation of streamflow of the Maduru Oya River Basin under varied climatic conditions. The discharge is projected to have a decreasing trend (Sen's slope = -0.008) for future years, identified as droughts. It can be concluded that the impact of climate change on meteorological drought will affect the discharge of the basin. Moreover, due to time lag between meteorological and hydrological drought, about 50 % of meteorological droughts may lead to a severe and extreme hydrological drought in the Maduru Oya River Basin over the mid-century (14) under RCP 8.5 and end-century (13) under RCP 4.5 scenarios. This study will begin with quantitative investigations including streamflow variability and climatology over the basin incorporating the application of regional circulation models.

Keywords: Drought Indices, HEC-HMS, Trend Analysis

DEDICATION

This thesis is dedicated to my beloved parents, S. Mohan Singh and Mrs Amardeep Kour, for their encouragement, constant love and endless support.

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TABLE OF CONTENT

Declaration of the candidate and supervisor	V
Abstract.....	VII
Dedication	IX
Acknowledgement	XI
Table of content	XIII
List of figures.....	XIX
List of tables.....	XXV
List of abbreviations	XXVII
Chapter 1	1
1 Introduction	1
1.1 Drought	2
1.2 Impacts of Droughts.....	4
1.3 Sri Lanka's History of Droughts.....	5
1.4 Hydrological Modelling for Drought Prediction.....	6
1.5 Problem Identification and Problem Statement	6
1.5.1 Problem Identification.....	6
1.5.2 Problem Statement	7
1.6 Objectives	7
1.6.1 Main Objective.....	7
1.6.2 Specific Objectives.....	7
1.7 Research Gap	8
1.8 Research Scope	8
1.9 Outline of the Thesis	8
Chapter 2	11
2 Literature Review	11

Table of content

2.1	Climate Change and Drought	12
2.2	IPCC Climate Change Scenarios	13
2.3	Climate Models.....	14
2.4	Bias Correction	15
2.5	Drought Concept, Definition and Types	17
2.5.1	Drought Definition	17
2.5.2	Types of Droughts.....	18
2.6	Drought Indices	19
2.6.1	Standardized Precipitation Index (SPI)	20
2.6.2	Standardized Precipitation Evapotranspiration Index (SPEI).....	21
2.6.3	Reconnaissance Drought Index (RDI).....	23
2.6.4	Effective Drought Index (EDI).....	24
2.6.5	Standardized Runoff Index (SRI).....	26
2.7	Hydrological Modelling.....	27
2.7.1	Types of Hydrological Models.....	28
2.7.2	Application of Hydrological Modelling in Sri Lanka	29
2.7.3	Selection of Model and Objective Function.....	30
2.7.4	HEC-HMS for Continuous Hydrological Modelling	32
2.7.5	Calibration of Hydrological Model	34
2.7.6	Validation of Hydrological Model	35
2.8	Trend Analysis.....	35
2.8.1	Mann-Kendall Trend Test	36
2.8.2	Sen's Slope Estimator	37
Chapter 3		39
3 Materials and Methods		39
3.1	Overview of Study Area	39
3.1.1	Study Area for Calculation of Drought Indices.....	39
3.1.2	Study Area for Hydrological Modelling.....	40
3.2	Data and Data Sources.....	41
3.2.1	Land Use	43
3.2.2	Digital Elevation Model (DEM).....	44
3.2.3	Soil Map.....	45
3.2.4	Hydro-meteorological Datasets.....	45

3.3	Tools/Software Used.....	46
3.4	Data Checking.....	46
3.4.1	Details of Missing Data.....	48
3.4.2	Thiessen Average Rainfall	48
3.5	Filling of Missing Data	49
3.5.1	Aralaganwila Station	51
3.5.2	Ekiriyankumbura Station.....	53
3.5.3	Kudasigiriya Station.....	55
3.5.4	Passikuda Station.....	57
3.5.5	Valachchanai Station	59
3.5.6	Padiyathalawa Station	63
3.6	Research Methodology	65
3.7	Methodology Flowchart.....	66
3.8	Development of the Basin Model	66
3.8.1	Development of the Canopy Model	66
3.8.2	Development of the Precipitation Loss Model	67
3.8.3	Development of the Transform Model.....	68
3.8.4	Development of Baseflow Model.....	69
3.9	Development of Precipitation Model.....	69
3.10	Model Calibration	70
Chapter 4		71
4	Analysis and Results.....	71
4.1	Bias Correction	71
4.2	Standardized Precipitation Index (SPI).....	75
4.2.1	SPI for Monthly Timescale	76
4.2.2	SPI for Seasonal Timescale.....	80
4.3	Standardized Precipitation Evapotranspiration Index (SPEI)	85
4.3.1	SPEI for Monthly Timescale.....	85
4.3.2	SPEI for Seasonal Timescale.....	90
4.4	Reconnaissance Drought Index (RDI).....	95
4.4.1	RDI for Monthly Timescale	96
4.4.2	RDI for Seasonal Timescale.....	100

Table of content

4.5	Effective Drought Index (EDI).....	104
4.5.1	EDI for Monthly Timescale	105
4.6	Lumped HEC-HMS Model.....	109
4.6.1	Initial Parameters Statistical Goodness of Fit Measures	109
4.6.2	Optimization of Parameters.....	113
4.6.3	Optimum Parameters in Calibration Period for the Lumped Model	113
4.6.4	Lumped Model Result for Validation Period	117
4.6.5	Future Streamflow Variation in Padiyathalawa Watershed.....	120
4.7	Standardized Runoff Index (SRI)	121
4.7.1	SRI for Monthly Timescale.....	121
4.7.2	SRI for Seasonal Timescale	126
Chapter 5		131
5	Discussion	131
5.1	Data and Data Period.....	131
5.2	Meteorological Drought Indices	131
5.2.1	Standardized Precipitation Index (SPI)	131
5.2.2	Standardized Precipitation Evapotranspiration Index (SPEI).....	132
5.2.3	Reconnaissance Drought Index (RDI).....	133
5.2.4	Effective Drought Index (EDI).....	134
5.3	Model Development and Evaluation of Model Performance.....	135
5.4	Standardized Runoff Index (SRI)	136
5.5	Climate Change Impact on Drought in Maduru Oya River Basin	136
Chapter 6		139
6	Conclusion and Recommendations	139
6.1	Conclusion	139
6.2	Recommendations.....	140
Bibliography		143
Annexure 1		157
Bias Correction		157

Annexure 2	159
SPI	159
Annexure 3	175
SPEI.....	175
Annexure 4.....	191
RDI	191
Annexure 5.....	207
EDI	207
Annexure 6.....	219
HEC-HMS Model Outputs.....	219
Annexure 7.....	225
SRI.....	225
Annexure 8.....	241
Trend Analysis.....	241

LIST OF FIGURES

Figure 1-1: Understanding drought perspectives	4
Figure 2-1: Scheme representing different categories of drought and their development (Source: Van Loon (2015)).....	18
Figure 2-2: Hydrological model classification by Chow et al. (1988).....	28
Figure 3-1: Study area of the Maduru Oya River Basin	40
Figure 3-2: The Padiyathalawa sub-watershed area for hydrological modelling.....	41
Figure 3-3: Land use land cover map of the Padiyathalawa watershed area	43
Figure 3-4: Soil Map of the Padiyathalawa watershed	45
Figure 3-5: Region 6-South Asia	46
Figure 3-6: Time-period of Streamflow and Rainfall data availability.....	47
Figure 3-7: Thiessen polygons and assigned weights for the Maduru Oya Basin	49
Figure 3-8: Monthly variation of rainfall at the Aralaganwila station	51
Figure 3-9: Seasonal variation of rainfall at the Aralaganwila station.....	51
Figure 3-10: Annual variation of Rainfall at the Aralaganwila station.....	52
Figure 3-11: Daily Rainfall time series and single mass curve.....	52
Figure 3-12: Monthly variation of rainfall at the Ekiriyankumbura station.....	53
Figure 3-13: Seasonal variation of Rainfall at the Ekiriyankumbura station.....	53
Figure 3-14: Annual variation of Rainfall at the Ekiriyankumbura station	54
Figure 3-15: Daily Rainfall time series and single mass curve.....	54
Figure 3-16: Monthly variation of rainfall at the Kudasigiriya station.....	55
Figure 3-17: Seasonal variation of Rainfall at the Kudasigiriya station	55
Figure 3-18: Annual variation of Rainfall at the Kudasigiriya station.....	56
Figure 3-19: Daily Rainfall time series and single mass curve.....	56
Figure 3-20: Monthly variation of rainfall at the Pasikuda station	57
Figure 3-21: Seasonal variation of rainfall at the Pasikuda station.....	57
Figure 3-22: Annual variation of Rainfall at the Pasikuda station.....	58
Figure 3-23: Daily Rainfall time series and single mass curve.....	58
Figure 3-24: Monthly variation of rainfall at the Valachchanai station.....	59
Figure 3-25: Seasonal variation of rainfall at the Valachchanai station	59
Figure 3-26: Annual variation of Rainfall at the Valachchanai station.....	60

List of figures

Figure 3-27: Daily Rainfall time series and single mass curve	60
Figure 3-28: Double mass curve for Aralaganwila station.....	61
Figure 3-29: Double mass curve for Kudasigiriya station.....	62
Figure 3-30: Double mass curve for Pasikuda station.....	62
Figure 3-31: Monthly variation of Streamflow at the Padiyathalawa station.....	63
Figure 3-32: Seasonal variation of Streamflow at the Padiyathalawa station	63
Figure 3-33: Annual average variation of Streamflow at the Padiyathalawa station	64
Figure 3-34: Daily streamflow variation of Streamflow at the Padiyathalawa station.....	64
Figure 3-35: Methodology Flowchart	66
Figure 4-1: Bias correction of the historical period and RCP 4.5 scenario (1981-2018)	72
Figure 4-2: Bias correction of the historical period and RCP 8.5 scenario (1981-2018)	72
Figure 4-3: PDF plot for the historical period and RCP 4.5 scenario (1981-2018).....	72
Figure 4-4: PDF plot for the historical period and RCP 8.5 scenario (1981-2018).....	73
Figure 4-5: CDF plot for the historical period and RCP 4.5 scenario (1981-2018)	73
Figure 4-6: CDF plot for the historical period and RCP 8.5 scenario (1981-2018)	73
Figure 4-7: Monthly RMSE values in CORDEX data (1981-2018)	74
Figure 4-8: Monthly RMSE values in CORDEX data (1981-2018)	74
Figure 4-9: The SPI values at monthly timescale for the historical period and RCP 4.5 scenario.....	76
Figure 4-10: The SPI values at monthly timescale for the historical period and RCP 8.5 scenario.....	76
Figure 4-11: SPI values of the monthly timescale for the historical period and RCP 4.5 (January).....	77
Figure 4-12: SPI values of the monthly timescale for the historical period and RCP 8.5 (January).....	78
Figure 4-13: The projected monthly variation of SPI for RCP 4.5 (2022-2100)	78
Figure 4-14: The projected monthly variation of SPI for RCP 8.5 (2022-2100)	79
Figure 4-15: Projected frequency and severity of drought events (RCP 4.5) over 2022-2100 period.....	79
Figure 4-16: Comparison of the historical, mid-, and end-century period drought events under RCP 4.5	80
Figure 4-17: SPI for the historical period and Northeast Monsoonal period (Dec.-Mar.) under RCP 4.5.....	80

Figure 4-18: SPI for the historical and Northeast Monsoonal period (Dec-Mar) under RCP 8.5.....	81
Figure 4-19: The SPI for the historical Southwest Monsoonal period (May-Sep) for RCP 4.5	81
Figure 4-20: The SPI for the historical Southwest Monsoonal period (May-Sep) for RCP 8.5	82
Figure 4-21: Seasonal variation of SPI for RCP 4.5 (2022-2100)	82
Figure 4-22: Seasonal variation of SPI for RCP 8.5 (2022-2100)	82
Figure 4-23: Projected frequency and severity of seasonal drought events under RCP 4.5 for 2022-2100 period	83
Figure 4-24: Probability of occurrence of droughts during the mid-century (left) and end-century (right) periods under RCP 4.5	84
Figure 4-25: Probability of occurrence of droughts during the mid-century (left) and end-century (right) periods under RCP 8.5	84
Figure 4-26: SPEI values of the monthly timescale for the historical period and RCP 4.5 ...	85
Figure 4-27: SPEI values of monthly timescale for the historical and future periods under RCP 8.5	86
Figure 4-28: SPEI values of January for historical and future periods under RCP 4.5	87
Figure 4-29: SPEI values of January for the historical and future periods under RCP 8.5....	87
Figure 4-30: Monthly variation of SPEI for RCP 4.5 scenario over 2022-2100 period	88
Figure 4-31: Monthly variation of SPEI under RCP 8.5 over 2022-2100 period	88
Figure 4-32: Projected frequency and severity of drought events under RCP 4.5 over 2022-2100 period.....	89
Figure 4-33: Comparison of the historical, mid-century and end-century drought events under RCP 4.5	90
Figure 4-34: SPEI for the historical and Northeast Monsoonal period (Dec-Mar) under RCP 4.5	90
Figure 4-35: SPEI for the historical and Northeast Monsoonal period (Dec-Mar) under RCP 8.5	91
Figure 4-36: SPEI for the historical and Southwest Monsoonal period (May-Sep) under RCP 4.5	91
Figure 4-37: SPEI for the historical and Southwest Monsoonal period (May-Sep) under RCP 8.5	92
Figure 4-38: Seasonal variation of SPEI for RCP 4.5 (2022-2100).....	93
Figure 4-39: Seasonal variation of SPEI for RCP 8.5 (2022-2100).....	93

List of figures

Figure 4-40: Projected frequency and severity of seasonal drought events under RCP 4.5 for 2022-2100 period.....	94
Figure 4-41: Probability of occurrence of droughts during mid-century (left) and end-century (right) periods under RCP 4.5.....	94
Figure 4-42: Probability of occurrence of droughts during mid-century (left) and end-century (right) periods under RCP 8.5.....	95
Figure 4-43: RDI values of monthly timescale for the historical and future periods under RCP 4.5.....	96
Figure 4-44: RDI values of monthly timescale for the historical and future periods under RCP 8.5.....	96
Figure 4-45: RDI values of January for historical and future periods under RCP 4.5	97
Figure 4-46: RDI values of January for historical and future periods under RCP 8.5	97
Figure 4-47: Monthly variation of RDI for RCP 4.5 scenario over 2022-2100 period	98
Figure 4-48: Monthly variation of RDI for RCP 4.5 scenario over 2022-2100 period	98
Figure 4-49: Projected frequency and severity of drought events (RCP 4.5) over 2022-2100 period.....	99
Figure 4-50: Occurrence of mild (top-left), moderate (top-right), severe (bottom-left), and extreme (bottom-right) droughts over the historical period (1950-2021) and future period (2022-2100) under RCP 4.5	99
Figure 4-51: RDI for the historical Northeast Monsoonal period (Dec-Mar) for RCP 4.5 ..	100
Figure 4-52: RDI for the historical Northeast Monsoonal period (Dec-Mar) for RCP 8.5 ..	100
Figure 4-53: RDI for the historical Southwest Monsoonal period (May-Sep) for RCP 4.5.	101
Figure 4-54: RDI for the historical Southwest Monsoonal period (May-Sep) for RCP 4.5.	101
Figure 4-55: Seasonal variation of RDI for RCP 4.5 (2022-2100)	102
Figure 4-56: Seasonal variation of RDI for RCP 8.5 (2022-2100)	102
Figure 4-57: Projected frequency and severity of seasonal drought events under RCP 4.5 for 2022-2100 period.....	103
Figure 4-58: Probability of occurrence of droughts during the mid-century (left) and end-century (right) periods under RCP 4.5.....	103
Figure 4-59: Probability of occurrence of droughts during the mid-century (left) and end-century (right) periods under RCP 8.5.....	104
Figure 4-60: EDI values of monthly timescale for historical period and future periods under RCP 4.5.....	105
Figure 4-61: EDI values of monthly timescale for historical period and future periods under RCP 8.5.....	105

Figure 4-62: Monthly variation of EDI for RCP 4.5 scenario over 2022-2100	106
Figure 4-63: Monthly variation of EDI for RCP 8.5 scenario over 2022-2100	106
Figure 4-64: Projected frequency and severity of drought events under RCP 4.5 over 2022-2100 period.....	107
Figure 4-65: Occurrence of mild (top-left), moderate (top-right), severe (bottom-left), and extreme (bottom-right) droughts over the historical period (1950-2021) and future period (2022-2100) under RCP 4.5	107
Figure 4-66: Probability of drought occurrence during mid and end-century (RCP 4.5)	108
Figure 4-67: Probability of drought occurrence during mid and end-century (RCP 8.5)	108
Figure 4-68: Flow duration curve for initial parameters	109
Figure 4-69: Hydrograph for the simulation run over four continuous years (2004-2008) .	110
Figure 4-70: Flow duration curves of the simulations with initial parameters of the calibration period	111
Figure 4-71: Hydrographs resulting from the initial parameters for the calibration period.	112
Figure 4-72: Flow duration curve for the calibration period for Padiyathalawa watershed.	114
Figure 4-73: Hydrograph resulting from the optimised simulation of four continuous years	114
Figure 4-74: Flow duration curve for each year in the calibration period	115
Figure 4-75: Hydrograph of optimized parameters in the calibration period	116
Figure 4-76: Flow duration curve of the lumped model for validation period	117
Figure 4-77: Flow duration curve for each year of the validation period	118
Figure 4-78: Simulated hydrograph for the validation period (2008-2012).....	119
Figure 4-79: Projected streamflow trend over the 21 st century under RCP 4.5	120
Figure 4-80: Projected streamflow trend over the 21 st century under RCP 8.5	120
Figure 4-81: SRI values of monthly timescale for historical and future periods under RCP 4.5	121
Figure 4-82: SRI values of monthly timescale for historical and future periods under RCP 8.5	122
Figure 4-83: SRI values of January for the recent period (2005-2021) and future period (2022-2100) under RCP 4.5	123
Figure 4-84: SRI values of January for the recent period (2005-2021) and future period (2022-2100) under RCP 8.5	123
Figure 4-85: Monthly variation of SRI for RCP 4.5 scenario over 2022-2100 period	124
Figure 4-86: Monthly variation of SRI for RCP 8.5 scenario over 2022-2100 period	124

List of figures

Figure 4-87: Projected frequency and severity of drought events under RCP 4.5 for 2022-2100 period.....	125
Figure 4-88: Occurrence of mild (top-left), moderate (top-right), severe (bottom-left), and extreme (bottom-right) droughts over the historical (1986-2005) and future periods (2022-2100) under RCP 4.5.....	125
Figure 4-89: SRI for the recent and Northeast Monsoonal period (Dec-Mar) under RCP 4.5	126
Figure 4-90: SRI for the recent and Northeast Monsoonal period (Dec-Mar) under RCP 8.5	126
Figure 4-91: SRI for the recent and Southwest Monsoonal period (Dec-Mar) under RCP 4.5	127
Figure 4-92: SRI for the recent and Southwest Monsoonal period (Dec-Mar) under RCP 8.5	127
Figure 4-93: Seasonal variation of SRI for RCP 4.5 (2022-2100)	128
Figure 4-94: Seasonal variation of SRI for RCP 8.5 (2022-2100)	128
Figure 4-95: Projected frequency and severity of the projected seasonal drought events under RCP 4.5 for the 2022-2100 period.....	129
Figure 4-96: Probability of occurrence of droughts during the mid-century (left) and end-century (right) periods under RCP 4.5.....	129
Figure 4-97: Probability of occurrence of droughts during the mid-century (left) and end-century (right) periods under RCP 8.5.....	130

LIST OF TABLES

Table 2-1: Set of major regional coordinated RCM projects	15
Table 2-2: Moisture categories for the indices.....	20
Table 2-3: HEC-HMS model performance evaluation	32
Table 3-1: Coordinates of Meteorological stations.....	42
Table 3-2: Data sources and Resolution	42
Table 3-3: Land Use classification of the Padiyathalawa watershed	44
Table 3-4: Description of Missing data.....	48
Table 3-5: Application of interpolation methods	50
Table 3-6: Maximum canopy storage calculation.....	67
Table 3-7: Weighted Curve Number Calculation	68
Table 3-8: Thiessen weight of rainfall stations	70
Table 4-1: Monthly RMSE values in CORDEX data before and after bias correction	75
Table 4-2: HEC-HMS model performance for simulation run	110
Table 4-3: Optimization results of HEC-HMS parameters.....	113
Table 4-4: HEC-HMS model performance after parameter optimization.....	114
Table 4-5: HEC-HMS model performance for validation run	117
Table 5-1: HEC-HMS Model Performance for 4-year continuous modelling.....	135

LIST OF ABBREVIATIONS

CMIP	Coupled Model Intercomparison Project
CORDEX	Coordinated Regional Climate Downscaling Experiment
DMC	Disaster Management Center
DSD	Divisional Secretariat Division
EDI	Effective Drought Index
EP	Effective Precipitation
ERA	ECMWF Re-Analysis
GCM	General Circulation Model
GDP	Gross Domestic Product
GHG	Greenhouse Gas
HEC-HMS	Hydrologic Engineering Centre - Hydrologic Modeling System
IAM	Integrated Assessment Models
IDW	Inverse Distance Weightage Method
IPCC	Inter-governmental Panel for Climate Change
NSE	Nash Sutcliffe Efficiency
PBIAS	Percent Bias
PET	Potential Evapotranspiration
R ²	Coefficient of Determination
RCM	Regional Climate Model
RCP	Representative Concentration Pathways
RDI	Reconnaissance Drought Index
RMSE	Root Mean Square Error
SPEI	Standardized Precipitation Evapotranspiration Index
SPI	Standardized Precipitation Index
SRI	Standardized Runoff Index
SWAT	Soil and Water Analysis Tool
UNFAO	Food and Agriculture Organization of the United Nations
VIC	Variable Infiltration Capacity
WMO	World Meteorological Organization

CHAPTER 1

1 INTRODUCTION

With the recent global trends of changing precipitation and temperature, climate change has raised severe issues about environmental sustainability, water security, and socio-economic development. Climate change is now widely acknowledged as one of the most severe challenges facing the world in the 21st-century, and it is expected to have a wide-ranging threat to socio-economic and environmental sectors, specifically to water and agricultural sectors (Deb & Babel, 2016).

The observations of temperatures over the past 157 years demonstrate that the surface temperatures have risen globally, with considerable regional variability, according to the Intergovernmental Panel on Climate Change (IPCC) report. The overall increase in extreme events, not the change in averages, is the consequence of global warming (Mishra & Singh, 2010). On a number of fronts, studies on how climate change may affect certain ecosystems have been done as part of an international effort. The majority of such research look at the impact of changing precipitation and temperature on discharge, with the consequences varied substantially depending on the scenarios utilized and the catchment type (Gleick (1987), Karl and Riebsame, (1989), He et al. (2013), Panagoulia (1992)).

Water is a critical resource for socioeconomic growth and environmental conservation, but scarcity, deteriorating quality of water, droughts, and floods are present issues that may worsen due to changing climate. Climate change will increase the issue of water stress in some parts of the world and increase runoff in others, specifically in South and East Asia. However, these increases may occur during the rainy season, the excess water may not be available during the dry season, when it is most required (Estrela et al., 2012).

Recent studies have indicated that the current trends may increase the frequency, duration and severity of droughts (e.g., Zarch et al. (2015), Johnson and Sharma

(2010), Burke et al. (2010), Hidalgo et al. (2013)). A significant drawback concerning drought identification is that it has an elliptic profile. With the slow initiation period and the drought being a insidious phenomenon, the drought event's start and end is difficult to determine (Vicente-Serrano et al., 2010). Thus, the characterization and analysis of drought is a complicated procedure (Shah et al., 2015).

Several drought indices for drought monitoring purposes have been developed and its relevant applications in the past. The meteorological data required as one of the inputs in estimating drought indices are widely extracted from ground meteorological stations. However, the density of meteorological stations in most regions of the world are insufficient to collect reliable spatial and temporal information (Brown et al., 2008). The time and cost required for data preparation, as well as the possibility of errors, raises concerns about the data's reliability.

Drought monitoring using satellite data has been increasingly used recently due to its relatively low cost, spatio-temporal data availability, and reliability (Dutta et al., 2015). Satellite-based meteorological datasets are available for time periods well before 1980 with finer resolution (e.g., ERA5, ERA-Interim) as well as for future climatic conditions (e.g., CORDEX). The availability of long-term data makes it suitable for drought indices computation and time-series analysis. Future drought extremes can also be predicted using such approaches as shown in works by Cancelliere et al. (2007), Li et al. (2019), Morid et al. (2007) and Modarres (2007).

To identify and quantify the influence of climate change on the study area's streamflow during drought circumstances, a suitable indicator, i.e. drought index is required. Therefore, this research study aims to calculate drought indices for the Maduru Oya basin using satellite-derived and model reanalysis data to evaluate the impact of the current change in the climate.

1.1 Drought

Drought is defined as a period of excessively dry weather with precipitation deficiency causing a severe hydrological imbalance, and it has connotations of a moisture deficiency concerning water usage (McMahon & Arenas, 1982). Drought occurs whenever and wherever the links in the hydrological cycle are broken or destabilised.

Drought occurs when the hydrological cycle's linkages are disrupted. Droughts are usually comprised of extensive spatial and temporal dimensions and thus it can have a severe impact on a region's socioeconomic stability. Nevertheless, possible adverse impacts of droughts can be managed or mitigated via preparedness. The success of such mitigation strategies is determined, among other things, by how accurately droughts are characterized, anticipated, and quantified (V. Smakhtin et al., 2004).

Drought begins with a deficiency in precipitation but may affect streamflow, soil moisture, groundwater, ecosystems and human beings. There is no precise definition of drought as definitions vary due to perception and the task for which it is defined (e.g., for academic study or a drought-relief plan). This enables the identification and classification of drought (meteorological, hydrological, agricultural, socio-economic, ecological), reflecting the perspectives. Figure 1-1 illustrates such commonly used drought classification perspectives concisely. Droughts are classified into three categories: meteorological, hydrological, and agricultural droughts. A fourth type of drought, known as socio-economic drought, could develop from any of these types, or their combinations. Droughts of any kind are said to start with a lack of precipitation, which leads to meteorological drought. When there is a shortage of water from meteorological or hydrological sources, irrigation water for crop production is reduced. This water is expected to be kept as soil moisture in the soil, which is also affected. As a result of the scarcity of soil moisture, agricultural drought occurs due to severe crop stress, lowering crop productivity (Mishra & Singh, 2010). The hydrological drought occurrence is noticed from the decreased streamflow, reduced inflow to lakes, reservoirs and ponds.

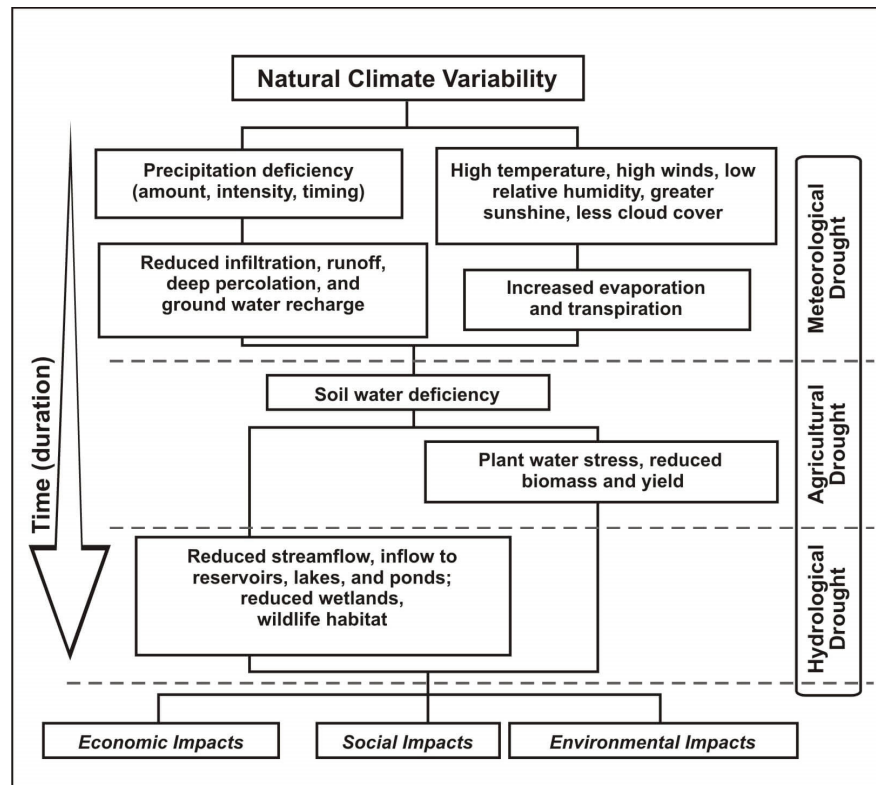


Figure 1-1: Understanding drought perspectives

(Source: Adapted from Obasi (1994))

1.2 Impacts of Droughts

- 1. Impact on economy:** Drought's influence on agriculture, forestry, and fisheries can have a negative impact on the country's economy. These industries rely on surface and ground water supplies to meet their fundamental needs. Droughts can result in agriculture and livestock output yield losses. As a result, a country's GDP, and thus its economy, eventually declines. The extended drought of 2001–02 resulted in a 1% decline in the country's GDP growth rate, primarily due to its impact on hydropower generation and agriculture (Lyon et al., 2009).
- 2. Impact on environment:** Drought damages flora and fauna, degrades landscape, biodiversity loss, and soil erosion, among other things. In the case of short-term impacts, normal conditions can be returned. However, if these effects last for a long time, the consequences may be permanent. Increased soil

erosion as a result of poor landscape quality, for example, could result in a long-term loss of biological production.

- 3. Impact on society:** Drought has a social influence because of how long it lasts and how severe it is. It can also result in human deaths as a result of food shortages, causing fear in society. Drought increases poverty directly or indirectly, which is a major concern in developing countries like Sri Lanka. According to UN-FAO estimates, rice production in Sri Lanka was 2.7 million tons in 2017, over 40% lower than in 2016, and 35% lower than the five-year average.

1.3 Sri Lanka's History of Droughts

Drought is the most common natural disaster in Sri Lanka, according to the Disaster Management Act No. 13 of 2005, describing 21 natural and man-made disasters. There were many major droughts in Sri Lanka between the years 1935-1937, 1947-1949, 1953-1956, 1965, 1974-1977, 1981-1983, 1985, 1991, 1995-1996, 2000-2001, and 2003-2004 (DMC,2005). The major droughts of 1953-1956, 1974-1977, 1981-1983, and 1995-1996 have all resulted in considerable economic losses. In 2001, Sri Lanka witnessed the worst drought in its history, followed by another severe drought in 2004 (DMC, 2005). According to Disaster Management Centre Annual Report (2014), drought in Sri Lanka demonstrated a cyclic trend creating peaks at three to four-year intervals (e.g., 1976, 1979, 1983, 1986, 1989, 1991, 1997, 2001, 2004, 2007, 2012 and 2013).

According to the Disaster Management Center Annual Report (2015), Polonnaruwa, Badulla, Ampara and Batticaloa districts are identified as the most prone areas to droughts. The report by International Labour Organization (2018) describes Batticaloa as the worst drought-affected district in Sri Lanka in 2016. In 2017, 2,440,290 persons in 667,939 families in 21 districts were affected due to drought (*Annual Report*, 2017).

When disasters occurred in 2015, the amount of money allocated to the disaster mitigation projects for floods was Rs. 247 million and Rs. 155 million for droughts. In 2017, Rs. 351 million and Rs. 84 million were the financial losses, respectively (*Annual Report*, 2017). Therefore, drought is one of the major concerns to Sri Lanka,

considering its impacts on society, environment and economy. Moreover, a limited number of studies undertaken for Sri Lankan river basins.

1.4 Hydrological Modelling for Drought Prediction

One of the major impacts on the hydrology of a basin due to droughts is related to discharge (Deshpande et al., 2019). Climate change's effects on water resources can be increased when they occur in areas where water supplies are already scarce and droughts are common, as well as when there are water demand-supply imbalances. However, due to the aforementioned fluctuation of the water cycle and the effects of water abstractions on flow discharges, detecting these effects is difficult, making it difficult to develop identifiable patterns. As a result, employing hydrological simulation models to better the assessment of climate change implications is necessary (Estrela et al., 2012). This can be assessed using hydrological models such as the Variable Infiltration Capacity (VIC) model (Wang et al., 2018), Soil and Water Assessment Tool (SWAT) (Ahn et al., 2016), and HEC-HMS (Meenu et al., 2013).

1.5 Problem Identification and Problem Statement

1.5.1 Problem Identification

Sri Lanka is extremely vulnerable to the effects of climate change. Drought has been the most significant hazard in Sri Lanka in terms of people affected and aid offered (Abeysingha & Rajapaksha, 2020). Batticaloa district in the Eastern province was worst affected by drought in 2020. The Nine DS Divisions with a population of 66,866 suffered from March 2020 to September 2020 (Drought situation report DMC, 2020). According to the Annual Report of the Disaster Management Centre (2017), the drought has affected 625,000 people by October 2016. The provinces of the north-central and eastern regions accounted for 45 percent of the total. Drought affected around 130,000 people (30 percent of the district's population) in Polonnaruwa, as well as considerable numbers in Batticaloa and Ampara.

1.5.2 Problem Statement

The rainfall distribution is inconsistent throughout any region, and drought on a basin level can occur in different stages of the basin on a local scale rather than on an overall basin scale. Therefore, understanding and characterizing drought on a basin level is a much-needed process that will help create awareness and to take appropriate mitigation measures accordingly.

1.6 Objectives

1.6.1 Main Objective

To assess the existing and future drought conditions of the Maduru Oya river basin using drought indices and investigate the effect of drought over the mid and end century periods to provide suitable drought-related impact mitigatory measures to the basin managers/planners.

1.6.2 Specific Objectives

1. To investigate the existing drought condition of the Maduru Oya basin in terms of meteorological and hydrological drought indices (i.e., SPI, SPEI, RDI, EDI and SRI) based time-series at monthly and seasonal time scales for the Maduru Oya River Basin.
2. To set up and calibrate a suitable hydrological model (i.e., HEC-HMS) to project the future variation of streamflow of the Maduru Oya River Basin under varied climatic scenarios.
3. To prepare future drought risk time series of the Maduru Oya River Basin by deriving the meteorological and hydrological indices using the projected precipitation from MPI and streamflow values obtained above (2) for the mid-and end-century periods.
4. To provide suitable drought mitigation measures/recommendations for Maduru Oya River Basin planners/managers to minimize future drought-related impacts.

1.7 Research Gap

Based on a review of the literature, it was found that just a few research have looked into the response to drought in Sri Lanka, a country where severe droughts occur often. Drought trend analysis is comparatively rare in Sri Lanka. It's important to look into the country's drought trend, especially for drought mitigation and agricultural planning. The assessment of drought as a disaster is insufficient if the factors that it impacts have not been assessed. Meteorological drought has majorly been responsible for the drought of the other types. Hence to assess the impact, further studies are to be undertaken using hydrological modelling.

1.8 Research Scope

1. *Real-time decision support system*: The model can be used for real-time applications such as flood and drought monitoring for policy-makers to mitigate the disasters more congruently.
2. *Drought assessment of the study area*: The present drought condition of the study area is assessed using five indices which will provide an insight into the factors causing the drought conditions.
3. *Actions at the grass-root level*: The results generated from the research will enable the dissemination of information at the basin level for mitigation strategies.

1.9 Outline of the Thesis

Chapter 1: This chapter covers the problem statement, research objective, and research scope, as well as the fundamentals of drought and hydrological modeling.

Chapter 2: This chapter discusses the drought concept, indices for drought assessment and explains hydrological modelling and trend analysis.

Chapter 3: This chapter offers a comprehensive overview of the research area and its significance. It highlights the methods utilized to attain the research objective and describes the various datasets used in the study.

Chapter 4: This chapter is the result part of the thesis, which critically observes different drought indices and their relationships. This chapter provides a comprehensive analysis of various drought indices, their relationships and the hydrological modelling results.

Chapter 5: This chapter consists of a brief overview of the findings and analysis.

Chapter 6: Conclusions and recommendations draw some conclusions from the study results obtained and propose some recommendations and opportunities for further research.

CHAPTER 2

2 LITERATURE REVIEW

Drought is a creeping phenomenon that begins, progresses, and ends slowly. The frequency and severity of climate change are expected to increase worldwide (Cook et al., 2014), especially in regions already facing water scarcity (Seager et al., 2014). Decision-makers always have a challenge to monitor drought onset, evolution and end. Generally, a rainfall deficit is considered an indicator of drought. The use of rainfall deficit alone as an indicator is insufficient to assess the severity and consequences of droughts. To monitor drought's severity and potential consequences, a comprehensive drought assessment system must accurately include indicators such as temperature, streamflow, groundwater level, soil moisture and evapotranspiration.

A study of existing literature for climate change and its impact was carried out around the globe and observed climate variations and data requirements for the study area. For future climate change studies, a literature review was undertaken concerning climate change scenarios, Regional Climate Models (RCMs), verification of the climate datasets (RCMs), and bias correction. Five indices were chosen based on the literature to study the frequency, intensity, and persistence of drought. A detailed study was carried out regarding the drought concept and application of the selected five drought indices over the study area. A review of Hydrological modelling, including hydrological model calibration and validation and trend analysis, was also carried out in this research.

This section presents the review of previous work related to the research topic climate change impacts on drought. The prime subjects reviewed comprises different drought indices, satellite data products, bias correction and trend analysis.

2.1 Climate Change and Drought

The distribution of water resources has been altered due to global warming in various regions of the world (Brutsaert & Parlange, 1998; Scanlon et al., 2007). Regional and global observations indicate significant shifts in the hydrological cycle in the past century. The dependency of Asian countries economies on agriculture and water resources are adversely impacted due to the implications of climate change (Deb & Babel, 2016; Shrestha et al., 2016). The Intergovernmental Panel on Climate Change (IPCC) has reported that due to climate change an increase in temperature and local precipitation is the cause of aggravated floods and droughts.

Under the global warming scenario considered in the IPCC reports, the impact of drought is expected to aggravate in future (Dai, 2011; Trenberth et al., 2014). Droughts have always occurred, but anomalies in sea surface temperature can cause global droughts (Seager et al., 2008). Processes like slow-moving anticyclones alter the regional climatology by hindering the synoptic weather systems progress, and it can cause enhancement of land-atmosphere feedback processes (Trenberth & Shea, 2005; Seneviratne et al., 2010). This process increases atmosphere temperatures and creates a moisture deficit within, leading to an increase in demand for moisture by the atmosphere. Another effect of the process is the increased heating and drying of land surfaces, often leading to disasters (such as wildfires) (Westerling et al., 2006). Thus, such mechanisms behind drought processes need to be thoroughly assessed to formulate and select relevant drought indices. The drought indices should be such that it includes factors like human contributions influencing drought characteristics, socioeconomic conditions (Cai et al., 2017), and non-stationary (Milly et al., 2008) future climate leading to uncertainties in drought quantification (Burke et al., 2010). Therefore, drought assessment needs robust and revised that comprises non-stationary climate information.

The future drought assessment depends on simulations of climate models over the 21st-century using different scenarios of anthropogenic forcing (e.g., Representative Concentration Pathways, RCPs, in the AR5). Drought trends have been consistent with model projections in recent time (e.g., (Marlier et al., 2017; Hoerling et al., 2012)).

However, some studies concerning the climate change impact on drought have arrived at different conclusions (e.g., (Trenberth et al., 2014; Deb & Babel, 2016; Marlier et al., 2017; Chandrasekara et al., 2021; Kumar et al., 2021)).

2.2 IPCC Climate Change Scenarios

The IPCC started the development of emission scenarios in 1996. Future greenhouse gas and sulphur emissions will be driven by a variety of demographic, economic, and technical variables, according to these scenarios. For the scenario quantification, four possible narrative stories were generated by evaluating the linkages between the forces generating emissions, their evolutions, and the surroundings. Each scenario represented one of the four storylines (IPCC, 2007). According to the narratives, the RCPs describe four possible scenarios for greenhouse gas (GHG) emissions in 21st-century.

The RCPs were developed by incorporating Integrated Assessment Models (IAMs) into a number of climate model simulations to estimate their influence on the climate system. These climate projections are then used to assess impacts and response. The RCPs are congruent with the vast range of mitigation strategies examined in the literature. The scenarios evaluate the costs of emission reductions in accordance with specific concentration pathways. The following are the RCPs Scenarios of the Special Report on AR5, IPCC.

RCP2.6 (low emission): The Netherlands Environmental Assessment Agency created this scenario. By 2100, the radiative force has increased to 3.1 W/m² before decreasing to 2.6 W/m². To achieve such forcing levels in the future, ambitious greenhouse gas emission reductions will be required.

RCP4.5 (intermediate emission): The Pacific Northwest National Laboratory in the United States created this scenario. Radiative forcing stabilizes shortly after 2100, which is in line with future predictions.

RCP6.0 (stabilizing emission): This scenario uses a high rate of GHG emissions and is a stabilization scenario in which total radiative forcing is stabilized after 2100 by a

range of technologies and approaches for GHG emission reduction. The radiative force will have reached 6.0 W/m^2 by 2100.

RCP 8.5 (high emission): This scenario is consistent with a future in which no emission-reduction strategies are implemented. It is defined by rising GHG emissions that result in high GHG concentrations over time, according to the International Institute for Applied System Analysis in Austria.

2.3 Climate Models

The most frequent tool for assessing climate change impacts is Global Climate Models (GCMs). The GCM is a type of climate model that reflects the general circulation of a planet's atmosphere or ocean mathematically (Li et al., 2017). GCMs lack detailed regional information due to low spatial resolution (approximately 100-250 km grid-cell resolution). Hence, downscaling procedures are required to obtain information at fine-resolution for climate change impact assessment at regional/basin scales (e.g., hydrological modelling). The two possible approaches for downscaling methods are statistical and dynamic downscaling (Teutschbein & Seibert, 2010a). The downscaling method serves as a link between the two various scales of climate projections, from coarse to fine (Hidalgo et al., 2013).

Statistical downscaling is based on statistical correlations between regional parameters and climatic data at a larger scale (Hewitson & Crane, 1996; Wilby et al., 2004). Dynamic downscaling implies RCM application based on GCM simulations with boundary conditions for limited regions (Teutschbein & Seibert, 2010a).

RCMs produce climate information with high spatial and temporal resolution, also called Limited-Area Models (LAMs) (Mearns et al., 2003). RCMs generally have a resolution of 25-50 km. Representations of Hydrological components surface and subsurface runoff (Teutschbein & Seibert, 2010a) are included in RCMs, but these components are restrictedly applicable at watershed scale. Hydrological variables are rarely directly used for the same reason. Climate data, such as temperature and precipitation, is frequently used to force hydrological models to simulate streamflow. Some major RCM projects are described in Table 2-1.

Table 2-1: Set of major regional coordinated RCM projects

Acronym	Name	Region
PIRCS	Project to Intercompare Regional Climate Simulations	North America
NARCCAP	North America Regional Climate Change Assessment Program	North America
MERCURE	Modelling European Regional Climate, Understanding and reducing Errors	Europe
PRUDENCE	Prediction of Regional Scenarios and Uncertainties for Defining European Climate Change Risks and Effects	Europe
ENSEMBLES	Ensemble-based Predictions of Climate Changes and their Impacts	Europe
AMMA	African Monsoon Multidisciplinary Analysis	West Africa
RMIP	Regional Model Intercomparison Project	East Asia

(Source: (Giorgi and Gutowski (2016))

As a result, RCMs are created based on GCMs for regional investigations. The CORDEX CCCR South Asia, climate analysis model is one of the most reliable RCMs for the South Asian region (Hidalgo et al., 2013).

2.4 Bias Correction

The atmospheric circulation patterns are simulated using large-scale GCMs, which have approximately 100-250 km resolution. To generate simulations at finer resolutions of roughly 25-50 km, downscaling techniques are required. RCMs are the most used downscaling technique (Eden et al., 2014). The climate model projections (e.g., precipitation, temperature, and wind) may not always match with observations

in the same period. Hence, the RCM projections for the future period may be affected by such errors in the numerical methods used. Therefore, bias correction procedures improve the fitting of climate model outputs by eliminating systematic errors having a better agreement with the observed data (Teutschbein & Seibert, 2010).

Several bias correction methods exist to eliminate the systematic errors in projected climatic parameters (Schmidli et al., 2006). Some bias correction methods are simple, while others are complex. There are some empirical bias correction methods for a specific climatic parameter, such as the precipitation (Leander & Buishand, 2007). The bias correction methods are based on the assumption that the correction technique and parameters for present conditions are valid for future climate, i.e. that all bias correction methods are constant.

The mean-based method is applied in various studies (Shrestha et al., 2017; Teutschbein & Seibert, 2010; Ines & Hansen, 2006) and is considered the most straightforward bias correction technique. It adjusts the mean value of the projected climatic variable. Here, the difference between the monthly mean model and observed data is applied. The biases are addressed using future downscaled daily time series based on the months they correspond. The bias-corrected RCM data is applied on a monthly basis using the mean-based technique (Schmidli et al., 2006; Lenderink et al., 2007; Wang et al., 2016). The method for precipitation bias-correction is as follows:

$$X'_M(i) = X_M(i) * \frac{\mu_o}{\mu_M} \quad [2-1]$$

where, i is a day in the month, μ_o and μ_M are monthly means of observed and model (RCM) data for the baseline period, respectively. X_M is the raw daily model data and X'_M is the bias-corrected daily data. The study conducted by Sirisena et al. (2021) for future periods, monthly values of $\frac{\mu_o}{\mu_M}$ were taken from baseline period and applied in Equation [2-1] to correct the bias in the data.

2.5 Drought Concept, Definition and Types

The earth's climate changes continuously with naturally occurring phenomena such as varying temperature extremes, rainfall and air movement. Therefore, drought is a natural climatic condition marked by periods of severe dryness. Droughts are unusual since they don't happen all the time or only once in a while in some regions.. Droughts, on the other hand, are not uncommon. Understanding the spatiotemporal variability of drought hazards and studying its trends under future climate change scenarios is necessary for water resources planners and decision-makers for effective mitigation and adaptation strategies. Drought indices can be used to characterize several aspects of droughts, including their spatial extent and intensity.

In Sri Lanka drought has been identified as the most frequent disaster, and it is experienced annually, with periodic severe droughts (Disaster Management Center, 2016). According to the Disaster Management Center of Sri Lanka statistics, the country had extreme droughts in 2001, 2004, 2012, 2014, and 2016. Due to the weakening of the South Asian monsoon, Sri Lanka has experienced increasing drought occurrences during the South-West Monsoon since 2000. Because of the weakening, moisture transport from the northwest Indian Ocean to Sri Lanka is reduced, resulting in net moisture divergence anomalies (Lin & Shelton, 2020). Therefore, drought quantification through indices becomes essential for drought mitigation measures/recommendations for Maduru Oya River Basin planners/managers to minimize the future drought-related impacts. In order to understand and assess drought events, drought definitions, types of droughts and their impacts are explained in detail in the subsequent sub-sections.

2.5.1 Drought Definition

Drought is difficult phenomenon to characterize, involving a variety of concepts to explain diverse scenarios. Drought has numerous definitions, which may be mutually incompatible. Ideally, the definition should be explicitly set for each location, considering the characteristics of that location (Gerber & Mirzabaev, 2017). Although deviation from average rainfall over an extended period is mainly accepted as an indicator, there is no universally accepted definition of drought. Drought is frequently

defined as the difference between estimated water demand and a regular water supply in a region. Drought definitions can be defined as operational or conceptual, with conceptual definitions referring to those formulated in broad terms to define the notion of drought's boundaries. Drought operational definitions attempt to determine the severity, length, and frequency of droughts. Some operational definitions incorporate estimates of potential impacts.

Drought is defined as a moisture deficit that is abnormal when compared to a certain baseline, but it is classified more specifically based on moisture anomalies in the hydrologic cycle. Drought is defined as a prolonged period of water scarcity. It's a common phenomenon throughout the world, with spatiotemporal characteristics significantly varying from one region to another. Drought can occur in both high and low rainfall regions. It is a situation in which the long-term average balance of rainfall and evapotranspiration in a certain area is changed, a situation that is frequently misunderstood as normal (Wilhite & Glantz, 1985).

2.5.2 Types of Droughts

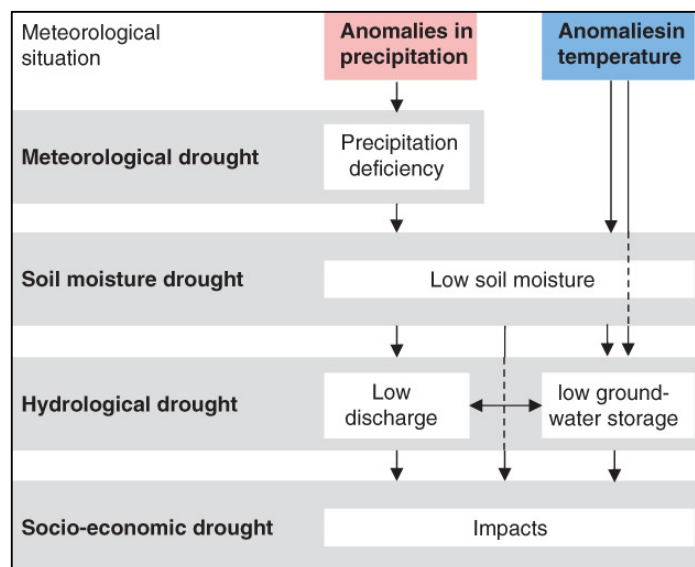


Figure 2-1: Scheme representing different categories of drought and their development
(Source: Van Loon (2015))

Willhite and Glantz (1985) analyzed more than 150 drought definitions and categorized them into four categories (Figure 2-1). The types of droughts are (a)

Meteorological drought, (b) Hydrological drought, (c) Agricultural/Soil moisture drought, (d) Socio-economic drought.

Meteorological drought is based on the precipitation deficit (Dracup et al., 1980). It simply means that precipitation in a certain area is reduced by more than 75% of the long-term climatological mean. Because precipitation deficiency varies greatly from one place to the next, these are region-specific..

Hydrological drought is linked to a water shortage on the surface or beneath the ground because of lack of precipitation. According to Hisdal and Tallaksen (2003), when compared to meteorological droughts, hydrological droughts are frequently delayed. Although they initiate from precipitation deficit, the main concern with hydrological droughts is how a lack of precipitation impacts components of the hydrological system such as groundwater, streamflow, soil moisture, and water level in reservoirs.

Agricultural/Soil moisture drought interconnects meteorological or hydrological drought features to agricultural impacts, with a focus on water shortages from meteorological or hydrological sources, reducing the amount of water used to irrigate crops. As a result, a lack of soil moisture causes agricultural drought, which causes severe stress on crops and lowers yield. Hence , agricultural drought is defined as a decrease in soil moisture content and, as a result, crop failure (Mishra & Singh, 2010).

Socio-economic drought is linked to the demand and supply of economic products, as well as factors of meteorological, hydrological, and agricultural drought. Due to a weather-related shortfall in water supply, this category of drought occurs when demand for an economic product exceeds supply.

2.6 Drought Indices

Indices of drought are defined to quantify intensity, duration and severity of droughts for planners/managers, supporting their decision making. It represents the severity of the drought and is used for real-time drought monitoring and determining the necessary drought adaptation/mitigation strategies. Drought indices combine the data on rainfall, snowfall, streamflow, and other water supply variables to create a clear picture.

Drought indices can be calculated using hydrological and meteorological data, as well as data from remote sensing. Table 2-2 provides an insight into the drought categories corresponding to a particular value of calculated drought indices at a specific time scale.

Table 2-2: Moisture categories for the indices

Values	Drought Categories
> 0	Wetness
0 to -0.99	Mild Drought
-1 to -1.49	Moderate Drought
-1.50 to -1.99	Severe Drought
<= -2.00	Extreme Drought

(Source: McKee et al., (1993))

2.6.1 Standardized Precipitation Index (SPI)

The SPI is the difference in precipitation from the mean for a certain period divided by the standard deviation, and the mean and standard deviation are calculated from historical data. Because the SPI has a normal distribution, it can be used to monitor wet and dry spells. The SPI is standardized to depict wetter and drier climates in the same way (McKee et al., 1993). SPI is an indicator representing the rainfall occurrence probability in a region at a certain period. It is simple to calculate, eliminates the spatial and temporal rainfall differences and applies to drought monitoring and assessment of climatic conditions above the monthly scale (Liu et al., 2021). A drought event can occur when the SPI is consistently negative and reaches an intensity of -1.0 or lower. The event is over when the SPI reaches positive. As a result, the start and end of each drought event, as well as the intensity for each month of occurrence, define the duration. The positive total of the SPI for all months within a drought period is used to calculate the magnitude of the drought.

The Cumulative Distribution Function (CDF) for a given month is obtained by :

$$G(x) = \frac{\int x^{\alpha-1} e^{-x/\beta} dx}{\beta^\alpha \Gamma(\alpha)} \quad [2-2]$$

where, α is a parameter about shape, β is a parameter about scale, x is the amount of precipitation, and $\Gamma(\alpha)$ is the gamma function. The CDF is recalculated with zero rainfall values as:

$$H(x) = q + (1 - q)G(x) \quad [2-3]$$

The SPI can be calculated as follows:

1. For $0 < H(x) \leq 0.5$

$$Z = \text{SPI} = - \left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3} \right) \quad [2-4]$$

$$t = \sqrt{\ln \left(\frac{1}{(H(x))^2} \right)} \quad [2-5]$$

2. For $0.5 < H(x) < 1$

$$Z = \text{SPI} = + \left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3} \right) \quad [2-6]$$

$$t = \sqrt{\ln \left(\frac{1}{(1.0 - H(x))^2} \right)} \quad [2-7]$$

2.6.2 Standardized Precipitation Evapotranspiration Index (SPEI)

SPEI is an improved and widely used drought index of SPI and was first proposed by Vicente-Serrano et al. (2010). It is based on the difference between precipitation and evapotranspiration, which is known as a hydro-climatic water balance. It is calculated by standardizing the difference between precipitation and evapotranspiration (Jia et al., 2018).

The calculation of SPEI involves the following briefly described steps is (Gao et al. (2017)):

1. The difference between the precipitation and the Potential Evapotranspiration (PET) monthly is to be calculated:

$$D_j = P_j - PET_j \quad [2-8]$$

where, P_j is the total precipitation of the $j - th$ month (mm); PET_j is the total PET of the $j - th$ month (mm).

2. The accumulated difference is calculated between the precipitation and the PET at different time scales (3-month, 6-month and 12-month). The accumulated difference ($X_{i,j}^k$) at the $k - month$ time scale in the $j - th$ month of the $i - th$ year is calculated using

$$\begin{cases} X_{i,j}^k = \sum_{l=13-k+j}^{12} D_{i-1,l} + \sum_{l=1}^j D_{i,l} & \text{if } j < k \\ X_{i,j}^k = \sum_{l=j-k+1}^j D_{i,l} & \text{if } j \geq k \end{cases} \quad [2-9]$$

where, $D_{i,l}$ is the monthly difference between the precipitation and the PET in the $l - th$ month of $i - th$ year.

3. Normalize the $X_{i,j}^k$ data series as there may be negative values in the original data series $X_{i,j}^k$. Vicente-Serrano et al. (2010) suggested the application of three-parameter log-logistic probability distribution. The accumulative function of the log-logistic probability distribution $F(X)$ for all timescales data series is as follows:

$$F(X) = \left[1 + \left(\frac{\alpha}{X-\gamma} \right)^\beta \right]^{-1} \quad [2-10]$$

where, α , β and γ are scale, shape and position parameters, respectively and Vicente-Serrano et al. (2010) proposed equations to calculate the parameters.

p is the probability of a definite $X_{i,j}^k$ value:

$$p = 1 - F(X) \quad [2-11]$$

If $p \leq 0.5$,

$$w = \sqrt{-2 \ln p} \quad [2-12]$$

$$SPEI = w - \frac{C_0 + C_1 w + C_2 w^2}{1 + d_1 w + d_2 w^2 + d_3 w^3} \quad [2-13]$$

If $p > 0.5$,

$$w = \sqrt{-2 \ln(1 - p)} \quad [2-14]$$

$$SPEI = \frac{C_0 + C_1 w + C_2 w^2}{1 + d_1 w + d_2 w^2 + d_3 w^3} - w \quad [2-15]$$

where, $C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$,

$d_2 = 0.189269$ and $d_3 = 0.001308$.

The SPEI value of less than -1.0 indicates a dry climate, whereas a SPEI value of more than 1.0 indicates that the climate is turning more humid (Gao et al., 2017).

2.6.3 Reconnaissance Drought Index (RDI)

The RDI index developed by Tsakiris and Vangelis (2005) allows a robust approach for drought indices classification as it incorporates the input and output of water in a system (Tigkas, 2015). There are three forms to express RDI: the initial, the normalised and the standardised. All of these types are based on precipitation aggregates and PET. The standardised RDI is directly comparable with SPI and it is more representative than SPI of the deficient water balance conditions (Tsakiris & Vangelis, 2005).

The initial value $a_k^{(i)}$ on a monthly time step in an aggregated form is presented and can be calculated on various time steps like an annual, seasonal or monthly basis.

Zarch et al. (2015b) calculated in a time basis of k (months) using the following equation [2-16]:

$$a_k^{(i)} = \frac{\sum_{j=1}^k P_{ij}}{\sum_{j=1}^k PET_{ij}}, i = 1 \text{ to } N \quad [2-16]$$

where P_{ij} and PET_{ij} are precipitation and PET of the $j - th$ month of the $i - th$ year and N is the total number of years of the available data.

The normalized RDI (RDI_n) is computed using:

$$RDI_{n(k)}^{(i)} = \frac{a_k^{(i)}}{\bar{a}_k} - 1 \quad [2-17]$$

where $\overline{a_k}$ is the arithmetic mean of a_k value. The formulation of the standardized RDI (RDI_{st}) used the assumption that a_k values follow the lognormal distribution, and thus:

$$RDI_{st(k)}^{(i)} = \frac{y_k^{(i)} - \overline{y_k}}{\widehat{\sigma_{y_k}}} \quad [2-18]$$

where y_k is $\ln(a_k^{(i)})$, $\overline{y_k}$ is the arithmetic mean of y_k and $\widehat{\sigma_{y_k}}$ is its standard deviation.

It should be noted that a_k follows both gamma and lognormal distributions. Nevertheless, Tsakiris et al. (2008) indicate that gamma distribution best fits most locations and timescales.

Therefore, RDI calculation can be similar to SPI and Equations [2-2] to [2-7] can be applied by replacing x by a_k values. The results from SPI and RDI_{st} can be interpreted similarly. Therefore, RDI_{st} values may be compared to the SPI and SPEI indices' similar threshold values, as shown in Table 2-2.

The study by Sobral et al. (2018) compared the performance of the SPI and RDI_{st} drought indexes spatially, using the annual scale in Rio de Janeiro State, Brazil. The results of the drought indices SPI and RDI_{st} indicated proximity of intense episodes of drought severity and frequency. Therefore, spatial and temporal comparisons of various drought indices can be incorporated in this study.

2.6.4 Effective Drought Index (EDI)

A new set of indexes was proposed by Byun and Wilhite (1999), to improve the drought monitoring process on daily time steps. The EDI tries to predict when a drought will start and how long it will last. However, its principles to calculate EDI on monthly time scale are similar to that of daily time scale as described in Smakhtin and Hughes (2004). Byun and Wilhite (1999) introduced Effective Precipitation (EP), a new concept as a basic tool for other processes. The EDI is a function of precipitation required to recover since the beginning of drought from the accumulated deficit (or to return to normal conditions (PRN)) and is related to EP. PRN is derived using effective monthly precipitation and the monthly deviation from the mean.

The study by Jain et al. (2015) described that drought index EDI and SPI use a similar type of classification for drought severity. To calculate EP, at least 30 years of data is

required to figure out the mean effective precipitation. More weight is given to the current month in the monthly EDI computation, with decreasing order weights to rainfall values for each preceding month.

The following steps are used by Jain et al. (2015) for EDI calculation:

1. Calculate Effective Precipitation (EP)

If P_i is rainfall in $m - 1$ months before the current month and N is the duration of the preceding period, then effective precipitation for the current month (EP_j) is given as

$$EP_j = \sum_{m=1}^N [(\sum_{i=1}^m P_i)/m] \quad [2-19]$$

For example if $N = 3$ then $EP = P_1 + (P_1 + P_2)/2 + (P_1 + P_2 + P_3)/3$, where P_1 , P_2 and P_3 are rainfall values during the current month (j), previous month and 2 months before respectively.

2. Calculation of deviations from the mean (DEP)

$$DEP_j = EP_j - \overline{EP_j} \quad [2-20]$$

The average and standard deviation of EP values for each month are calculated and the time series of EP values is converted to deviations from the mean (DEP).

3. The amount of precipitation required to return to normal (PRN_j) is calculated as:

$$PRN_j = \frac{EP_j - \overline{EP_j}}{\sum_{i=1}^N \left(\frac{1}{i}\right)} \quad [2-21]$$

The summation term in the denominator is the sum of the reciprocals of all the months in the duration N (i.e. for $N = 3$ months), this term will be equal to $\frac{1}{1} + \frac{1}{2} + \frac{1}{3}$.

4. EDI is calculated as follows:

$$EDI = \frac{PRN}{\sigma_{PRN}} \quad [2-22]$$

where, σ_{PRN} is the standard deviation of the corresponding month's PRN value.

Smakhtin and Hughes (2004) described in their study that EDI has not received much attention in South-West Asia. This is because EDI is computed based on daily precipitation data which is less readily available from agencies in the region.

2.6.5 Standardized Runoff Index (SRI)

The decrease in surface water (rivers, reservoirs, and lakes) and groundwater due to rainfall deficit indicates hydrological drought. A hydrological drought occurs when the water level in structures (e.g., dams and lakes) falls below the average condition. Water shortages are visible due to decreased natural river flows and groundwater levels. The groundwater storage can act as a reservoir during periods of surface water drought when there are sufficient volumes available. In other words, hydrological drought is not immediately reflected by decreased rainfall.

Numerous indices have been developed to monitor, evaluate and manage droughts. For example, SPI is a tool to determine meteorological droughts and Standardized Runoff Index (SRI) is an effective method to determine hydrological droughts. SRI values allow planners/managers to make rational water management related decisions (KatiPoğlu & Acar, 2019).

Many studies are carried out based on the SRI drought index Barker et al. (2016) studied SRI for drought monitoring and early warning based on climate and catchment properties. Sattar and Kim (2018) presented probabilistic relationships of weekly lag time between SRI, SPI and SPEI. Xu et al. (2019) conducted a comparative analysis of SPI and SRI over the Pearl River Basin, China. SPI and SRI are strongly correlated across the study area, according to this study, particularly at long-term scale. They also concluded that SPI could substitute for SRI for regions where streamflow data is unavailable.

Gao and Zhang (2016) evaluated spatio-temporal impact of climate change on hydrological drought, which is determined by SRI. Chen et al. (2019) assessed the probability of potential drought risk in a multivariate framework and characterized hydrological drought events in a three-dimensional framework. Shen et al. (2015) suggested to create twelve runoff series for each month in order to account for seasonal change in SRI, according to the ending month and fitted correspondingly.

The SRI is based upon SPI meteorological index. The calculation process of SRI is similar to SPI, except for the input data series required (precipitation time series for SPI has and streamflow time series for SRI calculation). Shukla and Wood (2008)

developed the SRI hydrological drought index which determines the influence of climate in the loss of streamflow.

The computation of SRI can be summarized in the following steps:

1. Streamflow series accumulation at a given time scale.
2. Fit the specific streamflow series to the probability distribution.
3. Estimation of the cumulative density function (CDF) for observed cumulative streamflow volume.
4. Conversion of the cumulative probability to a standard normal function with zero mean and unit variance, which can be calculated from a numerical approximation to the normal CDF.

The SRI values calculated using the above steps categorize drought similarly as SPI, SPEI, RDI and EDI (Table 2-2).

2.7 Hydrological Modelling

A comprehensive assessment strategy is required to establish timely and up to date information regarding the availability of water resources (Beven, 2012). Only a few basins have the continuous hydrologic measurements needed to conduct complete water resource analyses (Wale et al., 2009). The major challenge for researchers is the accurate prediction of the rainfall-runoff relationship. Because the rainfall-runoff transformation is highly nonlinear, time-varying, and spatially distributed, it is a complicated phenomenon. Several techniques are developed to evaluate the catchment response to rainfall events and quantify the water resources availability. Among these developed techniques, tools such as hydrologic models help researchers in decision-making concerning water management (Yener et al., 2007).

Hydrological models are simplified approximations of the actual hydrological cycle that are commonly utilized to develop long-term water resource planning and management strategies. In hydrological modeling, the quality of the data has a greater impact on the accuracy of the results than the model used (Todini, 1996). Therefore, modeling rainfall-runoff processes at river catchments with limited hydrological measurements poses several challenges.

2.7.1 Types of Hydrological Models

The capabilities and limitations can be the basis of hydrologic models classification. Chow et al. (1988) defined hydrological models (Figure 2-2) by categorizing them into two types: physical and abstract (mathematical). A physically-based model is an idealized depiction of a real event that includes the catchment's physical process (Devia et al., 2015). Physical models are of two types- scale models and analog models. A scale model is a physical approximation of a real system that keeps critical components of the system connected; analogue models are built on similar representations of the process under study.

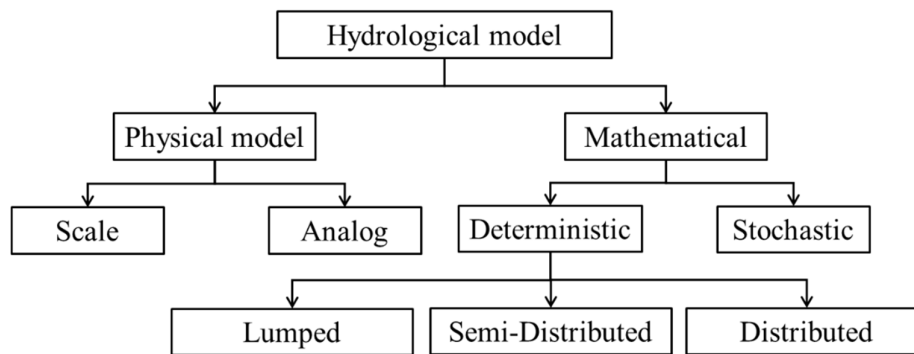


Figure 2-2: Hydrological model classification by Chow et al. (1988)

Abstract (mathematical) models are those that are created using logical computer languages and mathematical concepts to describe the land component of the hydrological cycle in time and space (Jajarmizadeh et al., 2012). Chow et al. (1988) described that the mathematical models can be characterized as deterministic or stochastic. In deterministic models, outputs are determined by established relationships between states and events, with random variation being neglected. To put it another way, a deterministic model produces the same outcome for a single input value and eliminates randomness. On the other hand, in a stochastic model, different output values can be produced for a range of inputs. The deterministic models can be classified into lumped, semi-distributed, and distributed models (Cunderlik, 2003).

Lumped Model: Because the parameters of lumped hydrologic models do not vary spatially within the basin, basin response is assessed only at the outlet, leaving

individual sub-basin responses unaccounted. These models are frequently unsuitable for event-scale hydrological processes. These models can offer just as good simulations as complicated physically-based models if the focus is only on discharge prediction (Cunderlik, 2003).

Distributed Model: This method tries to account for the spatial distribution of parameter variations as well as computational procedures in order to assess the impact of distribution on simulated rainfall-runoff relationships. Depending on the user's preferences, the parameters can readily vary in space at the desired resolution. In general, distributed models require a significant amount of data (Cunderlik, 2003). The controlling physical processes, on the other hand, are precisely modelled, and when correctly applied, they may deliver the highest level of precision (Pechlivanidis et al., 2013).

Semi-Distributed Model: It acts as a bridge between Lumped model and Distributed model as the structure is more physically-based than lumped models and has less requirement of input data in comparison with fully distributed models. By dividing the basin into numerous sub-basins, the attributes of semi-distributed (simplified distributed) models are partly varied in space (Orellana et al., 2008).

2.7.2 Application of Hydrological Modelling in Sri Lanka

Hydrological models are used in a variety of applications, including water resource planning, watershed development and management, flood prediction analysis, and construction and analysis of couple's system models. In addition, in Sri Lanka, the use of mathematical models for hydrologic computations in water resource planning and forecasting has grown in popularity over the recent decades.

Herath and Wijsekera (2021) demonstrated water resources management using HEC-HMS model in the Maha Oya basin. A developed HEC-HMS hydrological model for the Giriulla watershed was utilized to simulate streamflow with approximately 75% - 80% overall accuracy.

By doing event-based and continuous modeling, De Silva et al. (2014) deployed HEC-HMS software applications in Kelani River Basin for flood control measures, disaster mitigation techniques, and water management practices. The HEC-HMS software

provides stream runoff in the basin with a greater precision of average estimated for event-based simulations NSE of 0.91 and for continuous simulations NSE of 0.88, according to their findings. Using the characteristics of the modeling approach and various data, the HEC-HMS program can be utilized to analyze future extreme circumstances.

Madhushankha and Wijesekera (2021) developed a HEC-HMS model at daily time scale for Gin Ganga at Baddegama with RMSE values of 3.0 mm/day and 3.5 mm/day during calibration and verification, respectively. The results depict HEC-HMS's capability to reproduce streamflow in the basin accurately.

Numerous studies related to the application of hydrological modelling in Sri Lanka have been conducted successfully. The HEC-HMS model has been successfully applied to various basins in Sri Lanka to analyze water resources.

2.7.3 Selection of Model and Objective Function

The availability of data, the complexity of model development, and the objective of the modeling influence the selection of a hydrological model (Garcia et al., 2017). Water managers and planners, on the other hand, like to work with models that are easily available and can be completed with minimal parameters. As it is a freely available physics-based model that can simulate with limited data, the HEC-HMS (version 4.8) model has been selected as the best suited model for this research. Furthermore, it is meant to represent the rainfall-runoff processes of catchments in a wide range of geographical regions around the world, including Sri Lanka, including huge river basins and small urban or natural watersheds (De Silva et al., 2014; Halwatura & Najim, 2013; Verma et al., 2010).

The hydrologic model performance and behaviour assessment are made by comparing simulated and observed variables, which is often referred to as the calibration process. Hydrologists need to assess model performance because: (1) to study the model's capability to (quantitatively) produce historical and future watershed behaviour quantitatively; (2) to provide a way for improving modelling approach through parameter adjustments, modification of model structure, the incorporation of additional observational data, as well as the depiction of key watershed spatial and

temporal features; (3) to compare the model outputs with the findings of the studies (Krause et al., 2005). At the catchment outlet, the most common comparisons are performed between simulated and observed streamflow. The proximity of the simulated output to the observed measurements is measured using objective functions or goodness of fit criteria, which are mathematical measures (Krause et al., 2005). In an optimization technique, the objective function's aim is to generate parameters in the response surface in order to acquire the best-suited objective function value based on its accepted optimal ranges (Baddoo et al., 2020). Servat and Dezetter (1991) described an objective function as a numerical quantity that can be used to improve calibration. The coefficient of determination (R^2) value of the efficiency criteria reflects the correlation between observed and simulated values (Meenu et al., 2013). The R^2 is calculated using Equation [2-23].

$$R^2 = \frac{\Sigma(Q_{obs} - \overline{Q_{obs}}) \times (Q_{sim} - \overline{Q_{sim}})}{\sqrt{(\Sigma(Q_{obs} - \overline{Q_{obs}})^2 \times (Q_{sim} - \overline{Q_{sim}})^2)}} \quad [2-23]$$

where, Q_{sim} is the simulated value, Q_{obs} is the observed value, $\overline{Q_{sim}}$ is the average simulated value, and $\overline{Q_{obs}}$ is the average observed value. The range of values for R^2 is 1.0 (best) to 0.0 (unacceptable). A value of zero indicates that there is no correlation at all, whereas a value of 1 indicates that the prediction's dispersion is equal to the observation's. The squared ratio between the covariance and the multiplied standard deviations of the observed and anticipated values is also known as R^2 . As a result, it compares observed and predicted series to estimate the combined dispersion (Krause et al., 2005).

Green and Stephenson (1986) described twenty-one objective functions for evaluating a hydrological model's performance and mentioned that the criteria for the selection of objective function depend on the objective of modelling. If the aim of modeling is to analyze just peak flows, low flows and even the structure of the hydrograph are given little consideration. The rising and falling limbs of the hydrographs are also stated to be significant if routing impacts are of concern. When more generic dimensionless ordinate independent metrics of fit are needed to evaluate a model's performance across a large number of events, the coefficient of efficiency or Nash Sutcliffe objective function is a good option.

The efficiency E proposed by Nash and Sutcliffe (1970) is calculated as (Equation [2-24]):

$$NSE \text{ or } E = 1 - \frac{\sum(Q_{obs} - Q_{sim})^2}{\sum(Q_{obs} - \overline{Q_{obs}})^2} \quad [2-24]$$

where, Q_{sim} is the simulated value, Q_{obs} is the observed value and $\overline{Q_{obs}}$ is the average observed value. The range in which objective function should vary is summarized in Table 2-3.

Table 2-3: HEC-HMS model performance evaluation

NSE	R ²	RMSE Std. Dev.	PBIAS	Remarks
0.75<NSE<1	0.75<R ² <1	RMSE≤0.4	PBIAS≤±10	Very good
0.65<NSE≤0.75	0.65<R ² ≤0.75	0.4<RMSE≤0.55	±10<PBIAS≤±15	Good
0.50<NSE≤0.65	0.5<R ² ≤0.65	0.55<RMSE≤0.75	±15<PBIAS≤25	Satisfactory
NSE≤0.5	R ² ≤0.5	RMSE>0.75	PBIAS>±25	Unsatisfactory

2.7.4 HEC-HMS for Continuous Hydrological Modelling

The HEC-HMS, designed by the US Army Corps of Engineers, is a physically based model that is typically used in a lumped or semi-distributed way, while it does have distributed modeling capabilities. It's designed to simulate the precipitation runoff

mechanism in dendritic watersheds (USACE, 2018). HEC-HMS has been used for various applications, including flood forecasting (Bhuiyan et al., 2017), post-fire response analysis (Cydzik & Hogue, 2009), stormwater management (McEnroe, 2010), and climate impact assessment (Meenu et al., 2013). HEC-HMS can model both continuous and event-based hydrological phenomena while neglecting evapotranspiration and groundwater seepage flow contributions to the catchment response.

The watershed model, meteorological model, data manager, and control manager are the four key input components of the HEC-HMS (Version 4.8) model. Sub-watersheds, reaches, junctions, sources, sinks, reservoirs, and diversions are all represented by real-world objects in the watershed model. These elements need specific criteria to determine their interaction in a hydrological system. These interconnected elements allow water to flow freely and form a dendritic network (USACE, 2018). If discharge prediction is the main concern, lumped models can produce just as good simulations as complicated physically-based models (Gebre, 2015; Pechlivanidis et al., 2013).

Basin model depicts the physical properties of a watershed's hydrologic components, which turns atmospheric conditions into streamflow at specific watershed locations.. Available elements of the basin model are: subbasin, reach, junction, reservoir, diversion, source, and sink. Infiltration losses can be simulated from the available list of infiltration losses. Initial constant, SCS curve number, exponential, Green Ampt, and Smith Parlange are all options for event modeling. For simple continuous modeling, the one-layer deficit constant method can be employed. The canopy component is added to represent the interception by the canopy (USACE, 2018).

The transformation of excess precipitation into surface runoff can be done from seven available methods. The Clark, Snyder, and SCS methods are examples of unit hydrograph methods. From a single or numerous sequential events, the recession method produces an exponentially declining baseflow (USACE, 2018).

Meteorological model is used for meteorologic data analysis and the available methods to analyse are shortwave radiation, longwave radiation, precipitation,

evapotranspiration, and snowmelt. Continuous events require precipitation and evapotranspiration as inputs (USACE, 2018).

Control Specifications control the period of a simulation. A starting date and time, an ending date and time, and a time interval are all included.

A simulation run is done by combining a Basin model, Meteorologic model, and control specifications.

2.7.5 Calibration of Hydrological Model

The ultimate aim of calibrating a hydrologic model is to estimate model parameters so that the simulated model outputs match the observed values as accurately as possible (Kamali et al., 2012). The technical ability of the hydrologic model and the quality of the input dataset enables a good calibration and successful application of the hydrologic watershed model (Verma et al., 2010). In HEC-HMS modelling each component requires parameter value as an input to obtain simulated results. Some variables can be approximated exactly by monitoring stream and basin features, but others cannot. Calibration is used to approximate parameters that cannot be accurately calibrated. The calibrated values are established by a systematic search for the best fit of the observed and simulated streamflow hydrographs.

Manual Calibration is carried out through visual inspection and a trial-and-error approach, which can be time consuming and tedious, and may require personal expertise and experimental data, especially when there are a lot of parameters to calibrate.

Automatic Calibration procedures are included in the HEC-HMS model. To achieve agreement between the simulated and observed flow, the approach employs an iterative technique to optimize the objective function. The Nelder and Mead (NM) approach is more commonly employed than the Univariate Gradient (UG) method, according to Gebre (2015). This is due to the fact that the NM technique uses a downhill simplex to evaluate all parameters at the same time.

Therefore, either manual or automatic calibration method can be used to find a range of the values of parameters to minimize error in volume and preserve the shape of the hydrograph.

2.7.6 Validation of Hydrological Model

Validation (also known as verification) takes place on a dataset portion not used in calibration. The objective of model validation is to ensure the model's robustness and accuracy in describing the catchment's hydrological response, as well as to identify any bias in the calibrated parameters (Gupta et al., 2005). Pechlivanidis et al. (2013) described that if the model's performance during verification is unacceptable, the initial assumptions need revision and the model structure is examined. The model's performance of model is better during calibration than during the validation period.

2.8 Trend Analysis

Detection of trends in rainfall and streamflow is an area of interest for hydrology and climatology particularly concerning climate change. Rainfall is one of the major inputs for the streamflow generation process and streamflow reflects an integrated response of the river basin. Trend assessment of streamflow identifies needs and directions for future research work and helps decision-makers/planners for better planning (Gautam & Acharya, 2012).

One of the most important measurements and analyses for studying time series data is trend analysis. Trend analysis can be done using both non-parametric and parametric and tests. A parametric test requires data normally distributed whereas a non-parametric trend test only requires data to be independent and can accommodate outliers in the data. However, parametric tests are more powerful than non-parametric ones (Hamed & Ramachandra, 1998). The advantage of the non-parametric tests is that they require fewer assumptions and data need not be normal distributed. Thus, they are more robust than parametric tests (Hipel & McLeod, 1994). Gautam and Acharya (2012) described that in developing countries, hydrological data is frequently missing, and data distribution assumptions (normality, linearity, and independence)

are frequently disregarded. As a result, in time series trend analysis for the South Asian region, non-parametric methodologies are chosen and used.

2.8.1 Mann-Kendall Trend Test

The most widely used non-parametric test for trend analysis of the time series is the Mann-Kendall test (Mann, 1945; Kendall, 1955). The Mann-Kendall trend test proposed by Kendall (1955) is derived from a rank correlation test for two groups of observations. The null hypothesis for the Mann-Kendall test is that the dataset is randomly ordered and independent which means that there is no trend or correlation among the observations. However, the correlation between the rank order of the observed values and their order in time is considered. Nevertheless, the observed data are usually auto correlated.

Mann-Kendall test function has the following input parameters (Hussain & Mahmud, 2019).

1. x: a vector (list, numpy array or pandas series) data
2. alpha: significance level (0.05 is the default)

The classical Mann-Kendall test statistic (S) for a time series, x with n number of data points is calculated as follows (Mann, 1945).

$$S = \sum_{k=1}^{n-1} \sum_{i=k+1}^n \text{sign}(x_i - x_k) \quad [2-25]$$

where,

$$\text{sign}(x_i - x_k) = \begin{cases} +1 ; (x_i - x_k > 0) \\ 0 ; (x_i - x_k = 0) \\ -1 ; (x_i - x_k < 0) \end{cases} \quad [2-26]$$

Positive values of the S-statistic signify increasing trend (wet tendencies) while negative values decrease trend (dry tendencies).

Where, n is the number of data points, m is the number of tied groups and t_j denotes the number of ties of extent j. A tied group is a set of sample data having the same

value. In cases where the sample size $n > 10$, the standard normal test statistic Z is computed using Equation [2-27].

The significance of the trend is calculated using Z statistics as follows.

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}}; & S > 0 \\ 0 & ; S = 0 \\ \frac{S-1}{\sqrt{\text{Var}(S)}}; & S < 0 \end{cases} \quad [2-27]$$

Positive Z values signify wetting conditions while negative Z values signify drying conditions.

Tau measures the strength of the monotonic relationship between the time series. Kendall's tau correlation coefficient is given by:

$$\tau = \frac{S}{n(n-1)/2} \quad [2-28]$$

The Mann-Kendall statistical test has been frequently used to quantify the significance of trends in hydro-meteorological time series (Douglas et al., 2000; Yue et al., 2002; Partal & Kahya, 2006; Modarres & Silva, 2007; Tabari et al., 2011).

2.8.2 Sen's Slope Estimator

The Mann-Kendall test identifies only the direction of the trend. To determine the trend magnitude, the non-parametric Sen's slope estimator can be applied. Sen (1968) developed the procedure for estimating the magnitude of trend slope and applied successfully in Gocic and Trajkovic (2013). The slope of trend in the sample of N pairs of data:

$$Q_i = \frac{x_j - x_k}{j - k} \text{ for } i = 1, 2, \dots, N \quad [2-29]$$

where x_j and x_k are the data values at times j and k ($j > k$), respectively.

If there is only one datum in each period, then $= \frac{n(n-1)}{2}$; where n is the number of periods. If there are multiple observations in one or more periods, then $< \frac{n(n-1)}{2}$, where n is the total number of observations.

The N values of Q_i are ranked from smallest to largest and the median of slope or Sen's slope estimator is computed as:

$$Q_{med} = \begin{cases} Q_{[(N+1)/2]}, & \text{if } N \text{ is odd} \\ \frac{Q_{[N/2]} + Q_{[(N+2)/2]}}{2}, & \text{if } N \text{ is even} \end{cases} \quad [2-30]$$

The sign of Q_{med} sign signifies data trend reflection and its value indicates the steepness of the trend. To determine whether the median slope is statistically different from zero, one should obtain the confidence interval of Q_{med} at specific probability.

CHAPTER 3

3 MATERIALS AND METHODS

3.1 Overview of Study Area

The present work is carried out in two study areas. The calculation of meteorological drought indices is done on the larger areal extent; however, the assimilation of bias-corrected satellite projections to project future streamflow from the HEC-HMS model is done on the sub-basin level. Both the study areas are described in the subsequent sections.

3.1.1 Study Area for Calculation of Drought Indices

Here, the Maduru Oya River Basin is selected as the study area. Maduru Oya, the 8th longest river in Sri Lanka, is 135 km long and spans over four administrative districts (Badulla, Polonnaruwa, Ampara and Batticaloa).

The Maduru Oya originates from Mahiyangana in the Badulla district in Sri Lanka with an overall watershed area of 1,541 km². The ecology of the area depends on the river contribution from Maduru Oya River. The basin falls under the intermediate and dry climatic zone and receives around 1,756 mm annual average rainfall. The average temperature of the study area varies between 27.4 °C.

There are one stream gauging station and five rainfall stations located in this basin. The Irrigation Department and the Meteorological Department provided data on streamflow and rainfall, respectively. The data checking procedures were carried out to assess the accuracy and consistency of the data.

The study area with one streamflow station and five rainfall gauging stations and is described in Figure 3-1.

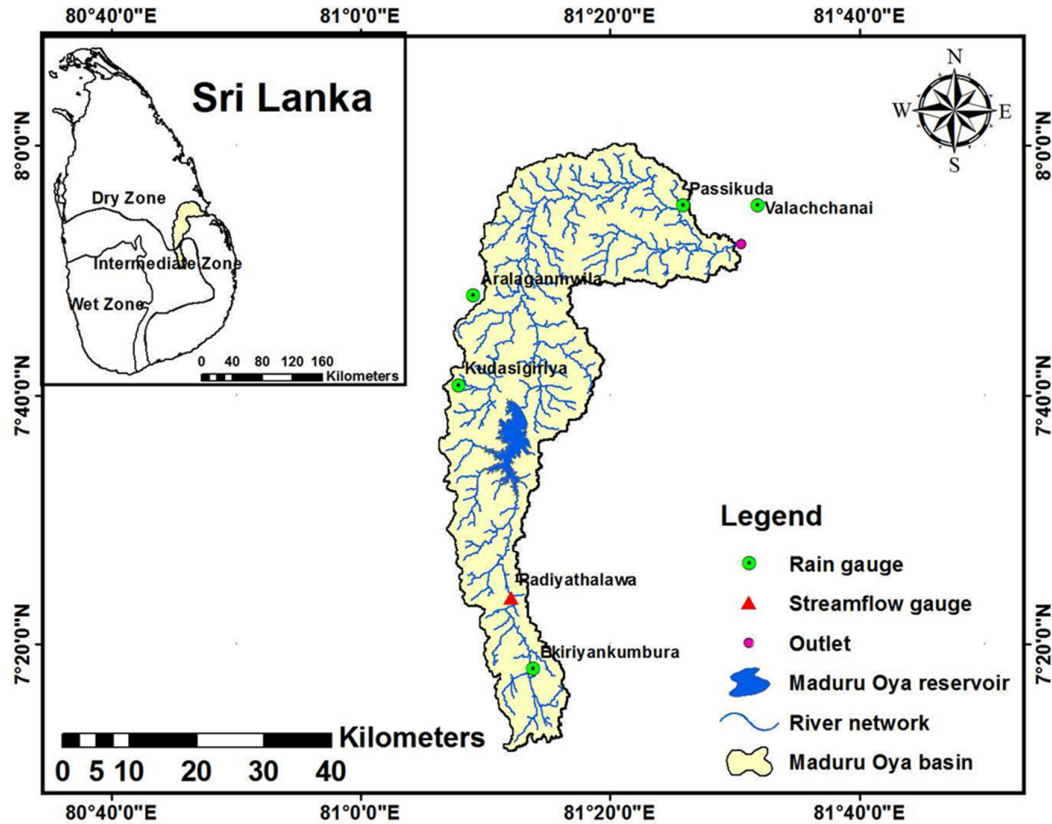


Figure 3-1: Study area of the Maduru Oya River Basin

3.1.2 Study Area for Hydrological Modelling

For the hydrological modelling and Standardized Runoff Index (SRI) calculation, Padiyathalawa watershed was considered as the study area. The watershed is situated upstream of the Maduru Oya river basin with outlet at Padiyathalawa with an aerial coverage of about 167 km² in Sri Lanka. The Padiyathalawa watershed under study is shown in Figure 3-2.

The elevation of the Padiyathalawa watershed varies from ~600 meters to ~120 meters near outlet. The average terrain slope becomes relatively mild towards the downstream of the Maduru Oya river basin. The longest flow path in the Padiyathalawa watershed is of ~28 km.

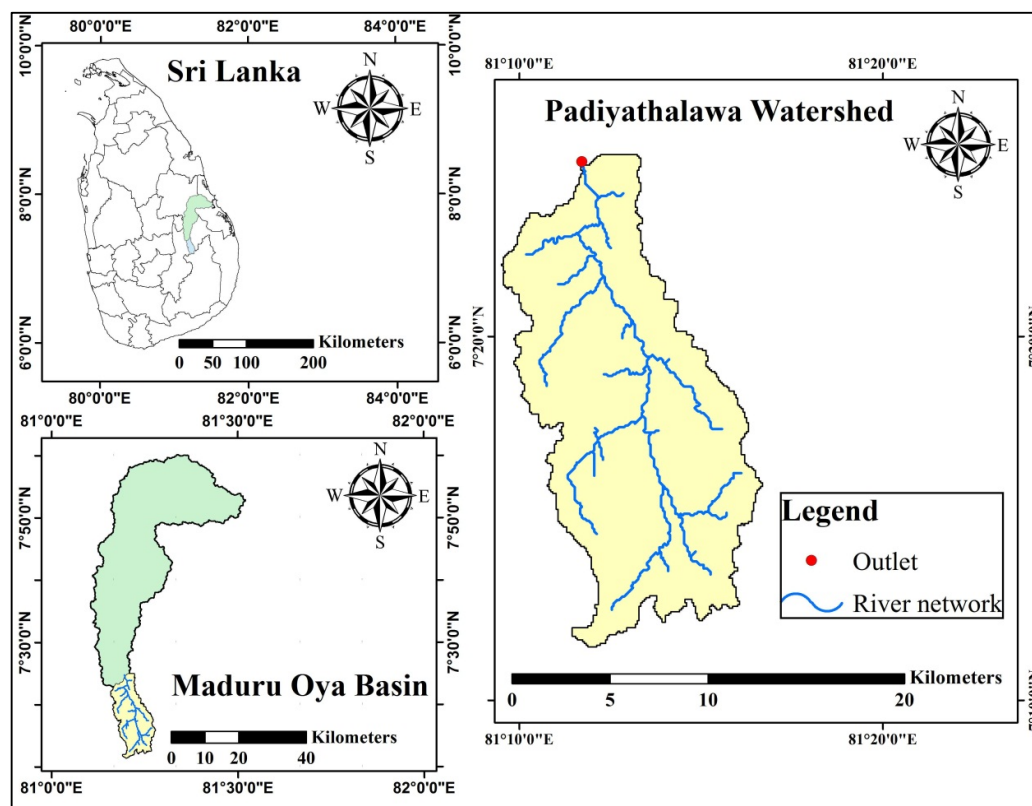


Figure 3-2: The Padiyathalawa sub-watershed area for hydrological modelling

3.2 Data and Data Sources

The major types of data used in this study are Potential Evapotranspiration (PET), Rainfall and Streamflow. The location of the five rainfall gauging stations (Aralaganwila, Ekiriyanakumbura, Kudasigiriya, Pasikuda and Valachchanai) and one river gauging station (Padiyathalawa) is given in Table 3-1.

Table 3-1: Coordinates of Meteorological stations

Gauging Stations	Coordinates
Aralaganwila	7°48' 0" N, 81°9' 0" E
Ekiriyankumbura	7°18' 0" N, 81°13' 48" E
Kudasigiriya	7°40' 48" N , 81°7' 48" E
Pasikuda	7°55' 48" N, 81°33' 0" E
Valachchanai	7°55' 12" N, 81°31' 48" E
Padiyathalawa	7°23' 0" N, 81°11' 30" E

Table 3-2: Data sources and Resolution

S. No	Data	Spatial Resolution	Data Source
1	Land Use	1:500,000	Survey Department of Sri Lanka(1999)
2	Digital Elevation Model	30 m	Shuttle Radar Topography Mission
3	Soil Map	1:500,000	Survey Department of Sri Lanka (1999)
4	Rainfall	Daily	Department of Meteorology(1981-2018); GFDL-RegCM4(IITM, RCP 4.5, RCP 8.5)(1951-2099)
5	Streamflow	Daily	Department of Irrigation (1984-2018)
6	Potential Evapotranspiration	Daily	MPI (IITM, RCP 4.5, RCP 8.5)(1951-2099)

3.2.1 Land Use

For study purposes, here, the land use is classified into nine classes (Figure 3-3). About 47% is scrub land of the study area while 35.2% is Forest area. It is considered that 100% of the rock areas and homestead areas are impervious. The percentage of various land use aerial coverage is described in Table 3-3.

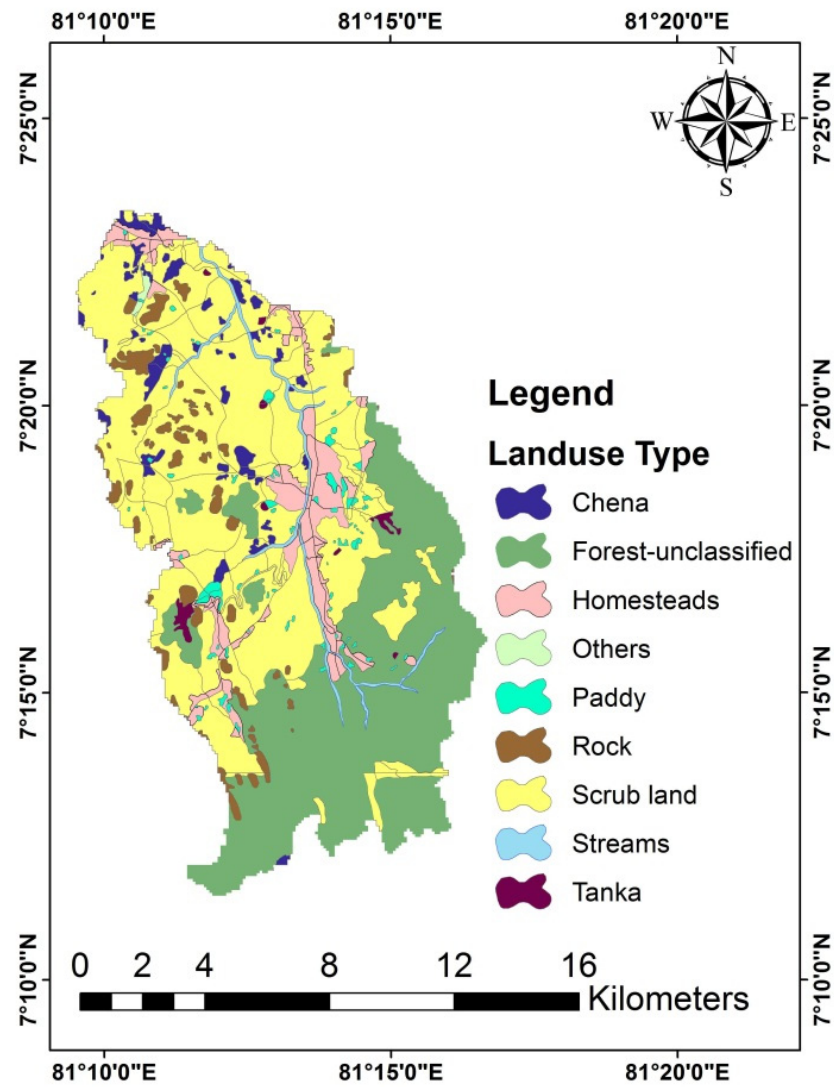


Figure 3-3: Land use land cover map of the Padiyathalawa watershed area

Table 3-3: Land Use classification of the Padiyathalawa watershed

Land-use Type	Area (km²)	Area (%)
Chena	4.88	2.9%
Forest-unclassified	58.74	35.2%
Homestead	12.14	7.3%
Others	0.29	0.2%
Paddy	2.15	1.3%
Rock	6.55	3.9%
Scrub land	78.46	47.0%
Streams	2.75	1.6%
Tanks	1.01	0.6%
Total	166.97	100%

3.2.2 Digital Elevation Model (DEM)

The DEM is required to retrieve the general information of the topography. It represents the continuous elevation values over a region in a regular array of z values. Digital elevation model is utilized in the basin delineation, drainage line generation, and estimating elevation of each grid for the model input file.

The DEM utilized in the current study is the Shuttle Radar Topography Mission (SRTM) 1 arc-second (~30 m) DEM. It spans between 56° South and 50° North latitude.

3.2.3 Soil Map

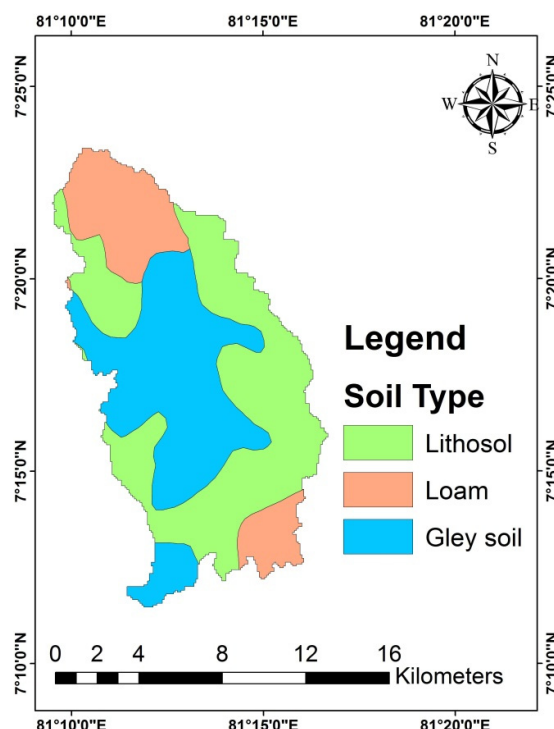


Figure 3-4: Soil Map of the Padiyathalawa watershed

3.2.4 Hydro-meteorological Datasets

World Climate Research Programme (WCRP) states that regional downscaling as an opportunity to include the broader scientific community in climate research. In this regard the Coordinated Regional Climate Downscaling Experiment (CORDEX) has catalysed the process of downscaling. WCRP-CORDEX dataset for the South Asia region is provided to assist the scientific community over climate change and create public awareness in projecting probable future climate patterns. The Regional Climate model used in this study is IITM-RegCM4 RCM by the Center for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM), Pune, India. This contributing CORDEX Modelling is downscaled by the use of NOAA-GFDL-GFDL-ESM2M as the CMIP5 model inputs. This downscaled data after several quality checks are published on the CCCR-IITM Earth System Grid Federation (ESFG) Data Node for public access and use (Sanjay et al., 2017). The RCP4.5 and RCP8.5 scenarios are used for the present study. The static bias correction in CORDEX was done using real-

time data and RCP4.5 is the closest scenario suitable for the static bias correction. The data utilized for the current research is from 1951 – 2099. Figure 3-5 shows Region 6: South Asia of the CORDEX project.

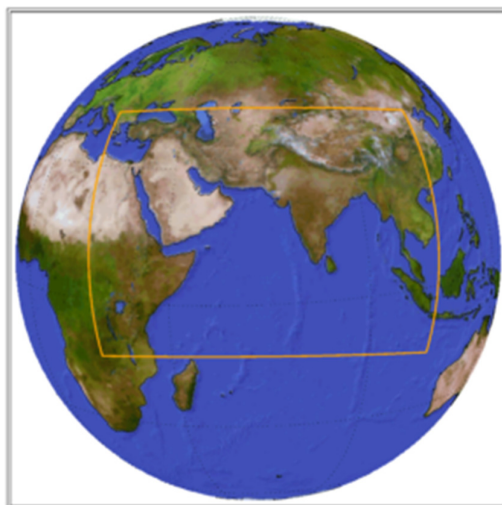


Figure 3-5: Region 6-South Asia

(Source: <http://www.cordex.org/domains/region-6-south-asia/>)

3.3 Tools/Software Used

The initial data processing and data analysis were performed using Python 3.7 with numerical computation libraries such as numpy and scipy, geospatial data handling libraries such as Geospatial Data Abstraction Library (GDAL), NetCDF4, Rasterio and Geopandas, data analysis and visualization libraries such as Pandas, Matplotlib and Seaborn, parallel processing library (multiprocessing) and other libraries such as glob, os, math and tqdm. The geospatial analysis was carried out in GIS platforms, such as ArcGIS 10.3 (proprietary). The hydrological modelling part was carried out using the HEC-HMS model. Finally, Microsoft Office 2010 was used for reporting, typesetting and spreadsheet purposes.

3.4 Data Checking

The observed datasets require the process of data checking before further application. The percentage of rainfall missing data is calculated and filled accordingly. There is a

temporal variation of rainfall datasets from stations Valachchanai, Passikuda, Kudasigiriya, Ekiriyankumbura and Aralaganwila (Figure 3-6). The period which comprises the maximum number of rainfall stations data and streamflow station data availability (2004–2015) is selected for calibration and validation of the hydrological model. Visual inspections were also performed to look for data errors. For each year, the streamflow response to rainfall was plotted using Thiessen weighted average rainfall (Figure 3-7).

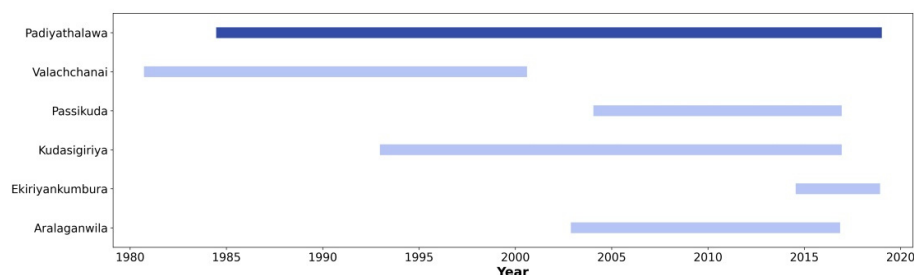


Figure 3-6: Time-period of Streamflow and Rainfall data availability

Four of the five rainfall gauging stations have missing data, which was filled using Inverse Distance Weighting (IDW) method and Linear interpolation. It was observed that there is an eleven-month period of missing data in the streamflow dataset of Padiyathalawa station for the year 1992-1993, following the preliminary data analysis and data checking, this year was removed from the data set. The details of missing data are given in Table 3-4.

3.4.1 Details of Missing Data

Table 3-4: Description of Missing data

Data Type	Station Name	No. of missing months	Percentage
Rainfall	Aralaganwila	0	0 %
	Ekiriyankumbura	2	13 %
	Kudasigiriya	12	3.47 %
	Passikuda	21	14 %
	Valachchanai	3	1 %
Streamflow	Padiyathalawa	11	8 %

3.4.2 Thiessen Average Rainfall

Rainfall intensity and duration vary from place to place, hence it is never consistent across the basin or catchment area. As a result, the rainfall recorded by each rain gauge station should be weighted based on the station's area coverage. The rainfall data obtained at each station is given a weightage based on the station's area nearest to or covered by the Thiessen weighted mean method (Chow et al., 1988). Thiessen polygons and the assigned weights in the Maduru Oya river basin are shown in Figure 3-7.

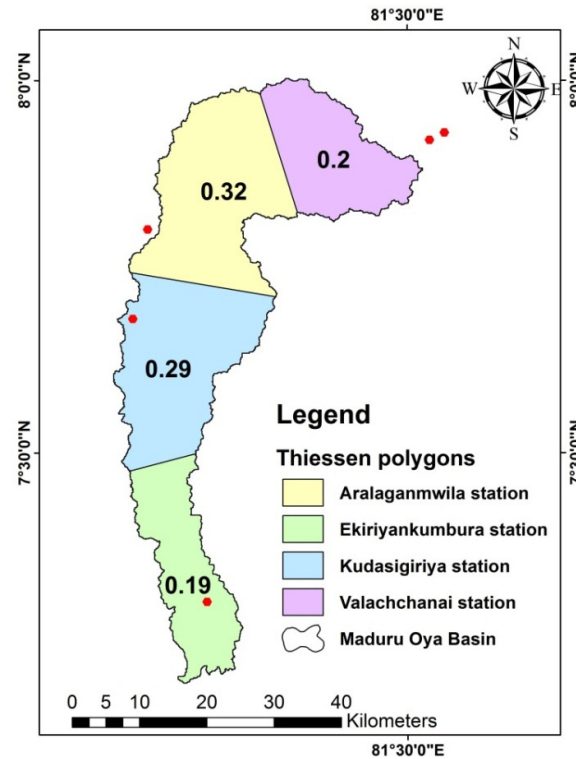


Figure 3-7: Thiessen polygons and assigned weights for the Maduru Oya Basin

3.5 Filling of Missing Data

Rainfall is considered as one of the most significant hydrologic data. Observational rainfall data is collected by a network of rainfall stations. However, due to a lack of rainfall stations in the research area or missing rainfall data, rainfall records are frequently incomplete.

The concept of Inverse Distance Weighting (IDW) is based on Tobler's first law (the first law of geography). Everything is interconnected, yet close things are more related than far things, according to the definition. The IDW is a deterministic approach developed by the United States National Weather Service in 1972. This is due to the calculation's lack of requirements to meet precise statistical assumptions. As a result, IDW differs from stochastic approaches (e.g., Kriging and TRA) (Chen & Liu, 2012). Therefore, the period for which multiple rainfall station data is available, the IDW method is used for interpolation of rainfall data. Equation [3 1] is used for the IDW process.

$$R_p = \sum_{i=1}^N w_i * R_i \quad [3-1]$$

$$w_i = \frac{d_i^{-\alpha}}{\sum_{i=1}^N d_i^{-\alpha}} \quad [3-2]$$

where,

R_p = unknown rainfall data (mm),

R_i = rainfall data of known rainfall stations (mm); N = number of rainfall stations

and

d_i = the distance from each rainfall station to an unknown site; $\alpha = 2$.

Different interpolation methods such as linear, polynomial, quadratic, and cubic were applied for the period when only a single rainfall station data is available. The RMSE and R^2 obtained are tabulated in Table 3-5 and it was observed that Linear interpolation is the most suitable method to fill missing data for the region.

Table 3-5: Application of interpolation methods

Method of Interpolation	RMSE	R^2
Linear	5.394	0.899
Polynomial(2 nd order)	6.678	0.846
Polynomial(3 rd order)	7.047	0.828
Quadratic	6.678	0.846
pchip	5.541	0.894
Akima	5.573	0.893
Cubic	7.047	0.828
Normal distribution	6.636	0.847
Gamma distribution	9.892	0.662

Data was checked monthly, seasonally, annually and single mass curve was plotted after filling missing data and summarized in further sections for each Rainfall station.

3.5.1 Aralaganwila Station

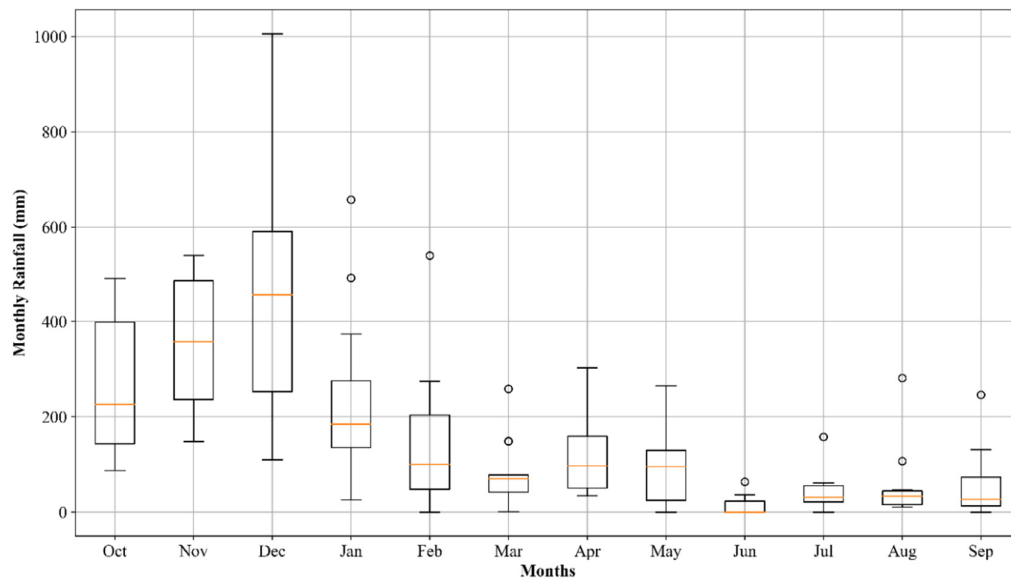


Figure 3-8: Monthly variation of rainfall at the Aralaganwila station

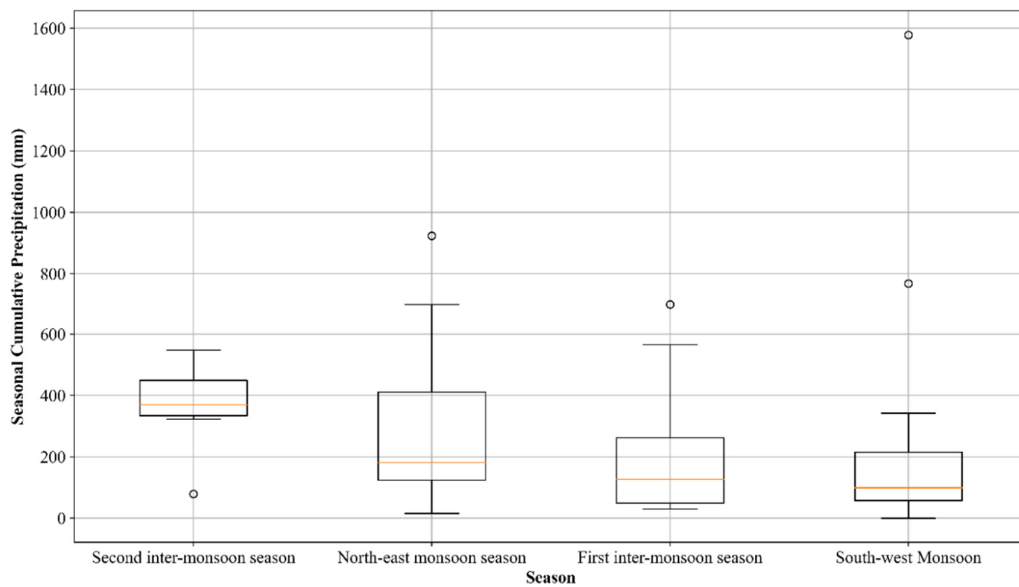


Figure 3-9: Seasonal variation of rainfall at the Aralaganwila station

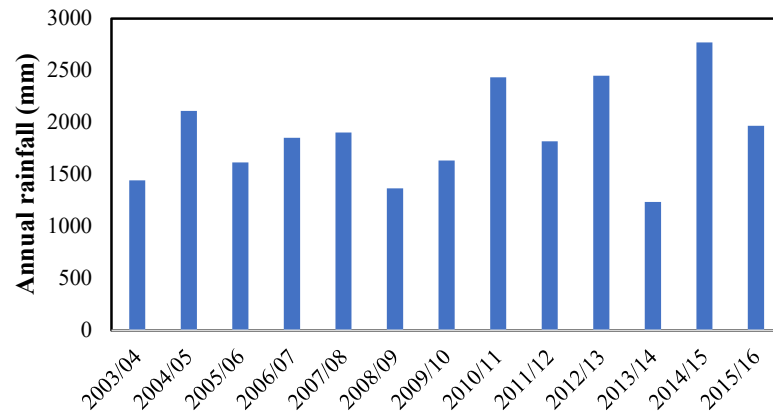


Figure 3-10: Annual variation of Rainfall at the Aralaganwila station

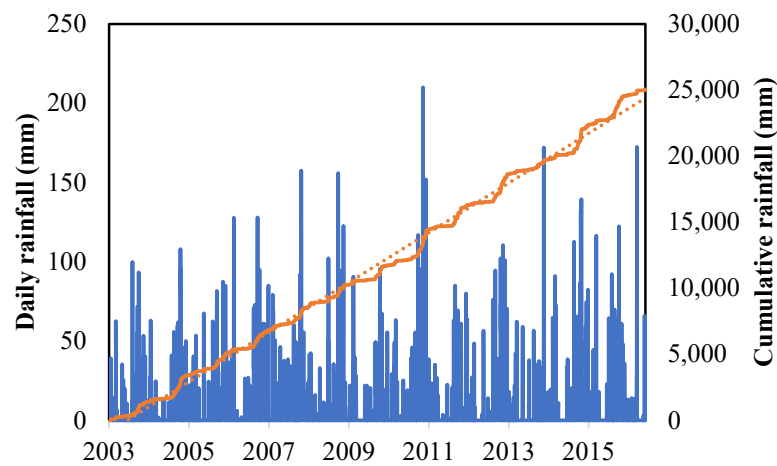


Figure 3-11: Daily Rainfall time series and single mass curve

It was observed that the Aralaganwila station receives the highest rainfall in December, with an annual average rainfall of about 1,893 mm. The Northeast monsoon season is the wettest while the Southwest is the driest. The highest daily rainfall was recorded in 2011. No rainfall trend was observed after applying the Mann-Kendall (M-K) test and Sen Slope's Estimator for the Aralaganwila rainfall station.

3.5.2 Ekiriyankumbura Station

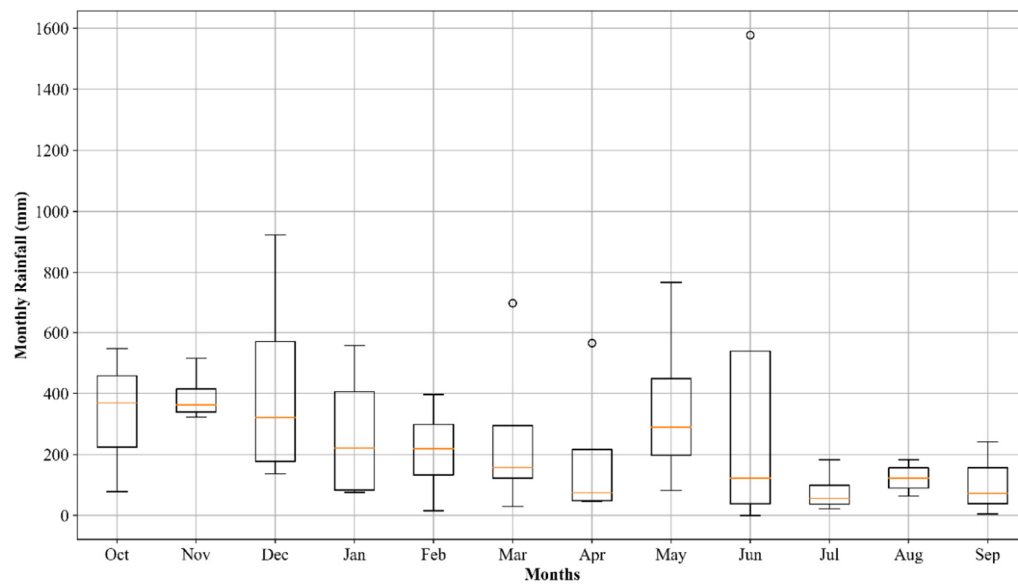


Figure 3-12: Monthly variation of rainfall at the Ekiriyankumbura station

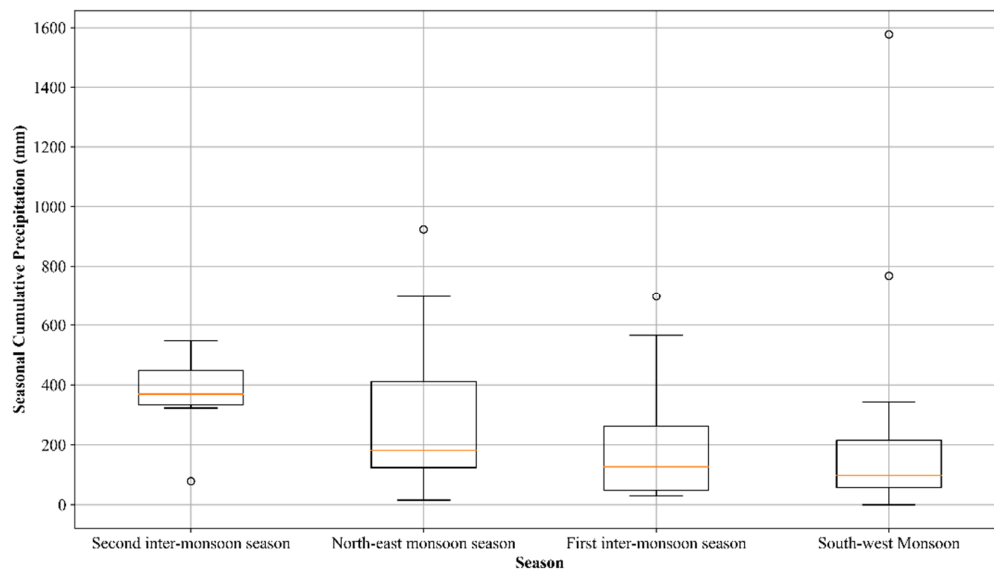


Figure 3-13: Seasonal variation of Rainfall at the Ekiriyankumbura station

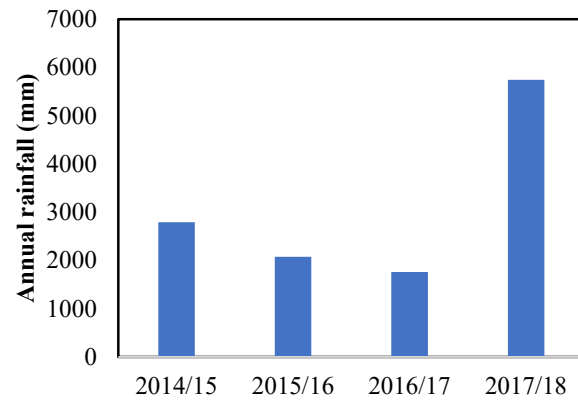


Figure 3-14: Annual variation of Rainfall at the Ekiriyankumbura station

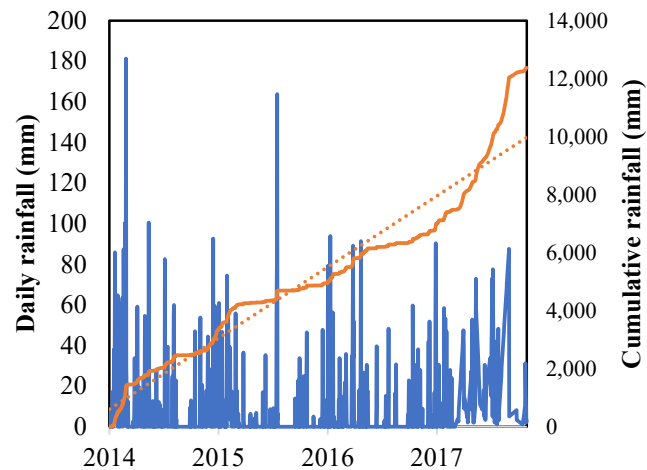


Figure 3-15: Daily Rainfall time series and single mass curve

It was observed that the Ekiriyankumbura station receives the highest amount of rainfall in December, with an annual average rainfall of about 2,210 mm. Northeast monsoon season and Second-inter monsoon season are the wettest seasons, whereas the Southwest monsoon season is the driest. An increasing rainfall trend was observed after applying the M-K test and Sen Slope's Estimator for the Ekiriyankumbura rainfall station.

3.5.3 Kudasigiriya Station

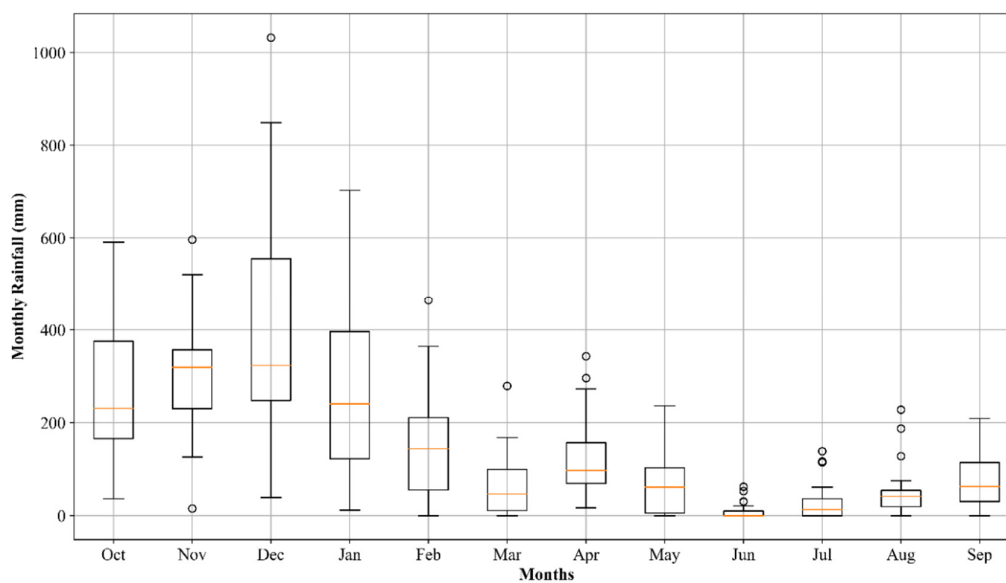


Figure 3-16: Monthly variation of rainfall at the Kudasigiriya station

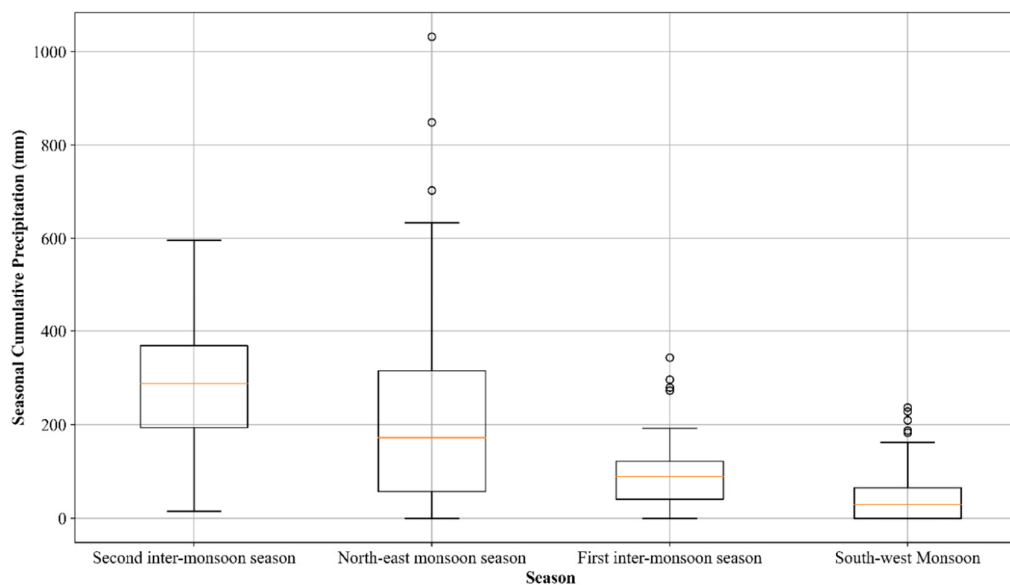


Figure 3-17: Seasonal variation of Rainfall at the Kudasigiriya station

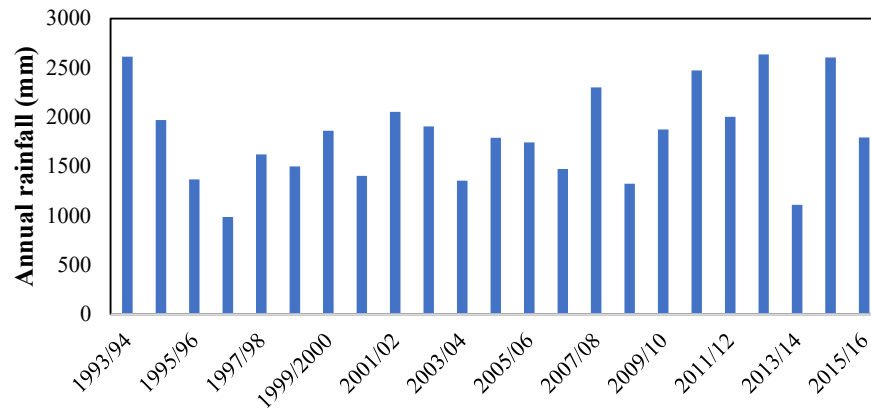


Figure 3-18: Annual variation of Rainfall at the Kudasigiriya station

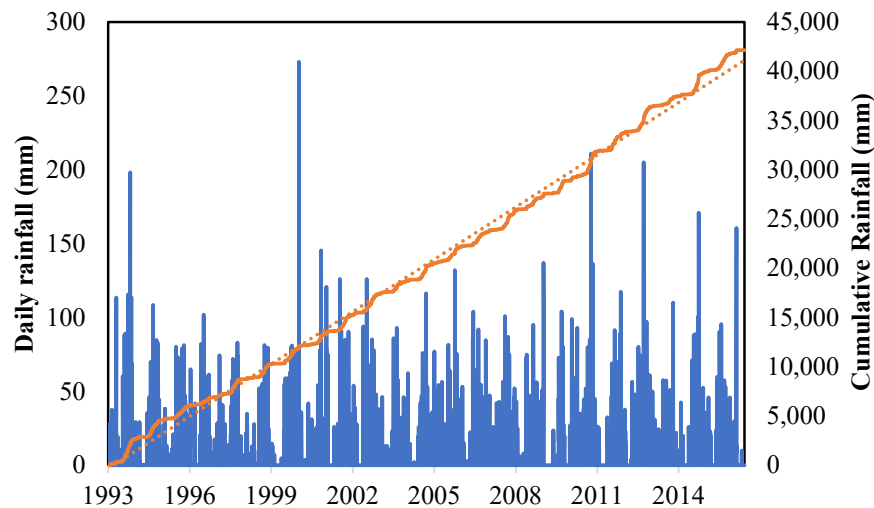


Figure 3-19: Daily Rainfall time series and single mass curve

It was observed that the Kudasigiriya station receives the highest amount of rainfall in the December with an annual average rainfall of about 1,816 mm. North-east monsoon season and Second-inter monsoon season are the wettest seasons, whereas the South-west monsoon season is the driest. The highest daily rainfall was recorded in 2000. A decreasing rainfall trend was observed after applying the M-K test and Sen Slope's Estimator for the Kudasigiriya rainfall station.

3.5.4 Passikuda Station

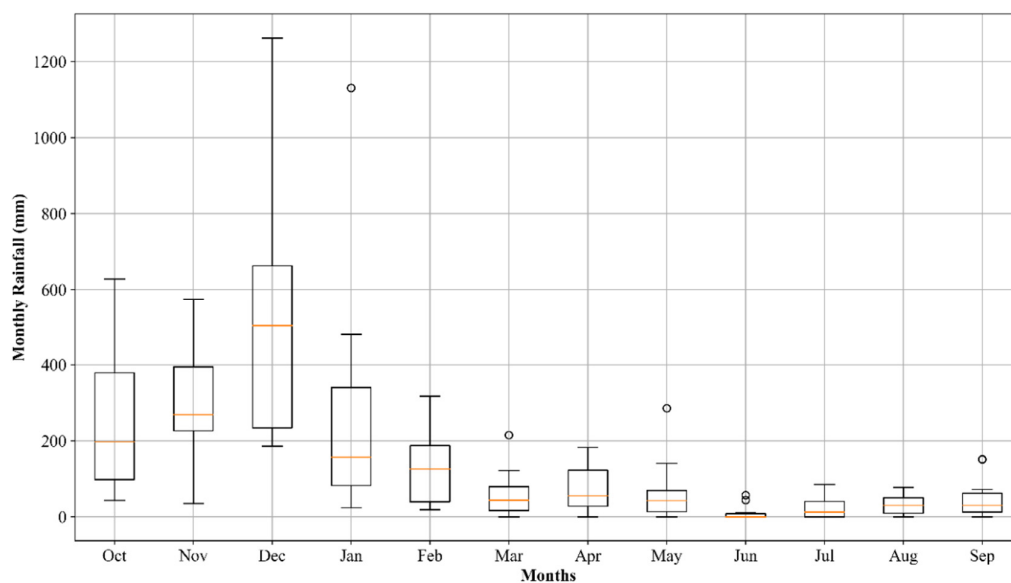


Figure 3-20: Monthly variation of rainfall at the Pasikuda station

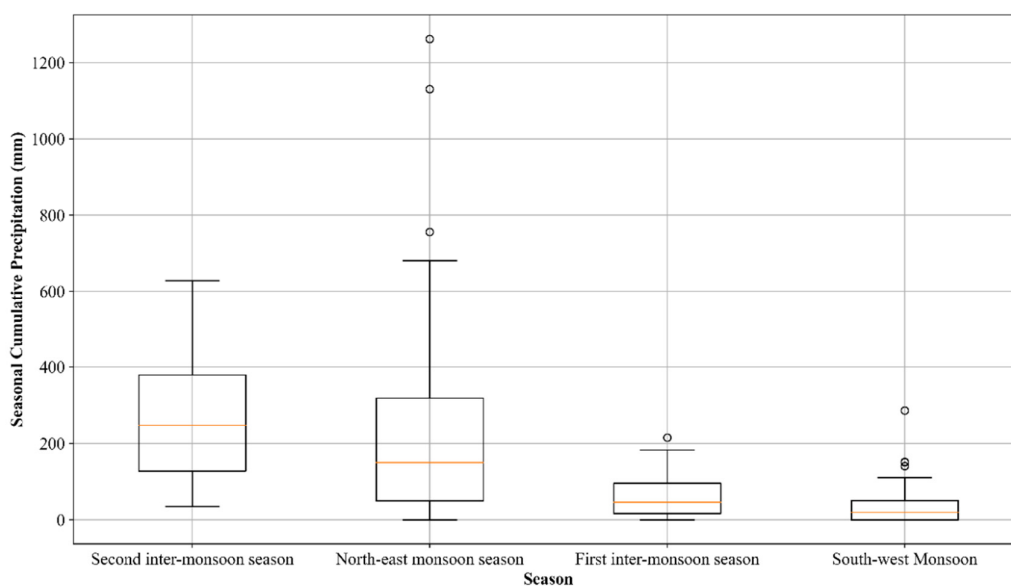


Figure 3-21: Seasonal variation of rainfall at the Pasikuda station

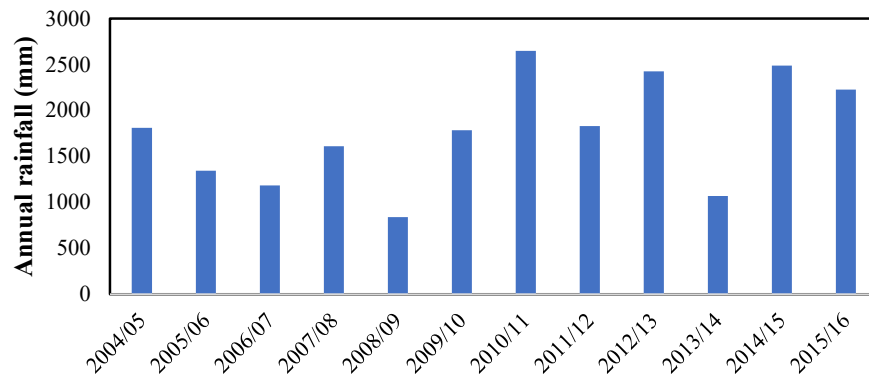


Figure 3-22: Annual variation of Rainfall at the Pasikuda station

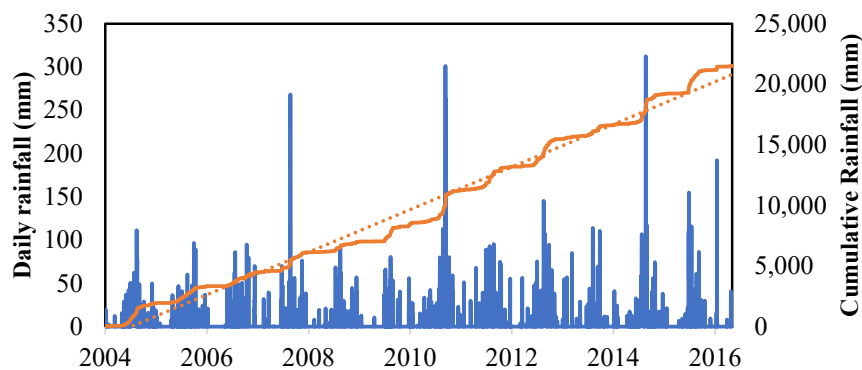


Figure 3-23: Daily Rainfall time series and single mass curve

It was observed that the Pasikuda station receives the highest amount of rainfall in the December, with an annual average rainfall of about 1,772 mm. Northeast monsoon season and Second-inter monsoon season are the wettest seasons, while the Southwest monsoon season is the driest. The highest daily rainfall was recorded in 2015. No rainfall trend was observed after applying the M-K test and Sen Slope's Estimator for the Pasikuda rainfall station.

3.5.5 Valachchanai Station

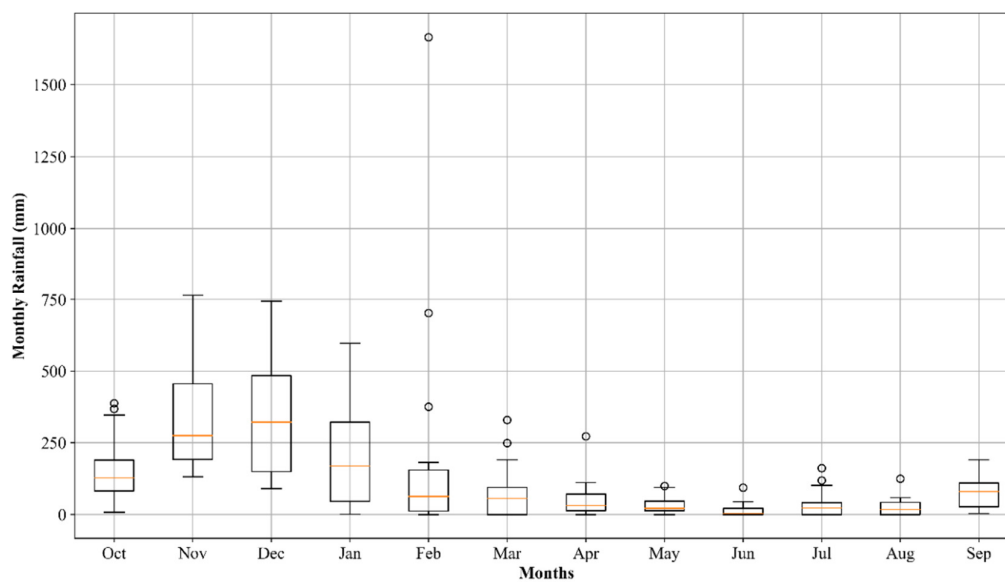


Figure 3-24: Monthly variation of rainfall at the Valachchanai station

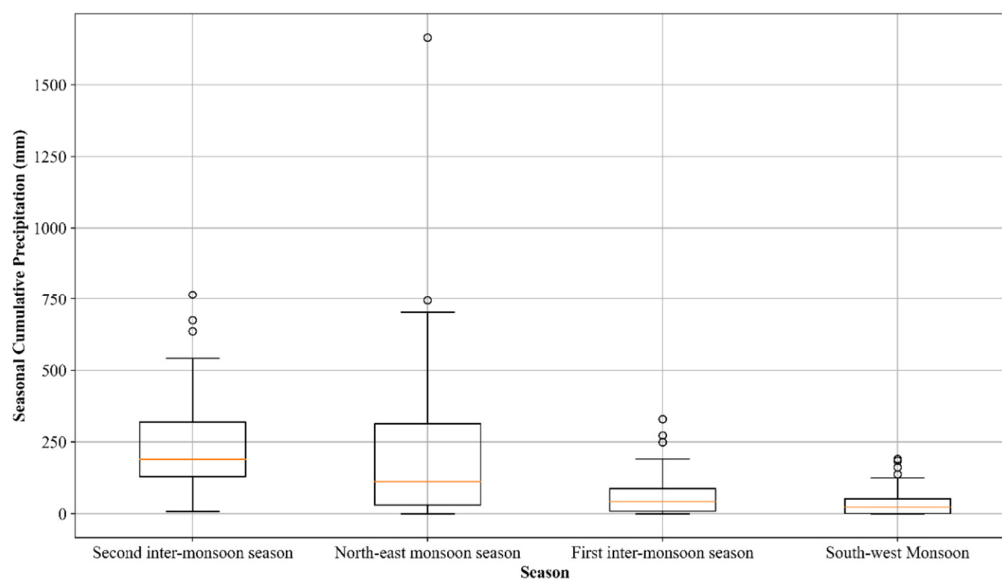


Figure 3-25: Seasonal variation of rainfall at the Valachchanai station

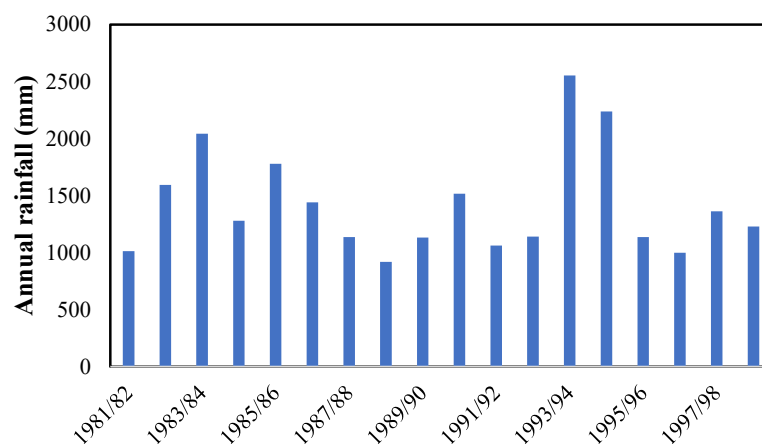


Figure 3-26: Annual variation of Rainfall at the Valachchanai station

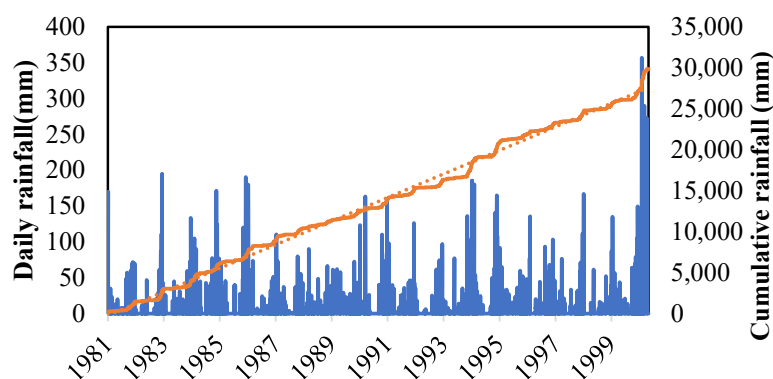


Figure 3-27: Daily Rainfall time series and single mass curve

It was observed that the Valachchanai station receives the highest amount of rainfall in the November and December, with an annual average rainfall of about 1,420 mm. North-east monsoon season is the wettest season while the South-west monsoon season is the driest. The highest daily rainfall was recorded in 2000. No rainfall trend was observed after the applying the M-K test and Sen Slope's Estimator for the Valachchanai rainfall station.

Double Mass Curve

The double-mass curve can be used to identify and adjust precipitation data that is inconsistent. As long as the relationship between the variables is a fixed ratio, the graph

of cumulative data of one variable versus cumulative data of a related other variable is a straight line. The double mass curve is a common method for determining the consistency and long-term trend of hydrometeorological time series (Gao et al., 2017). A shift in the constant of proportionality between the two variables has developed, or perhaps the proportionality is not a constant value at all rates of cumulation, is indicated by a break in the slope of the double-mass curve.

The double mass curve is plotted for each rainfall station to assess the consistency of the data sets for each rainfall station. The double mass curves of Aralaganwila (Figure 3-28), Kudasigiriya (Figure 3-29) and Pasikuda (Figure 3-30) station implies that the rainfall data is consistent and can be used for further study.

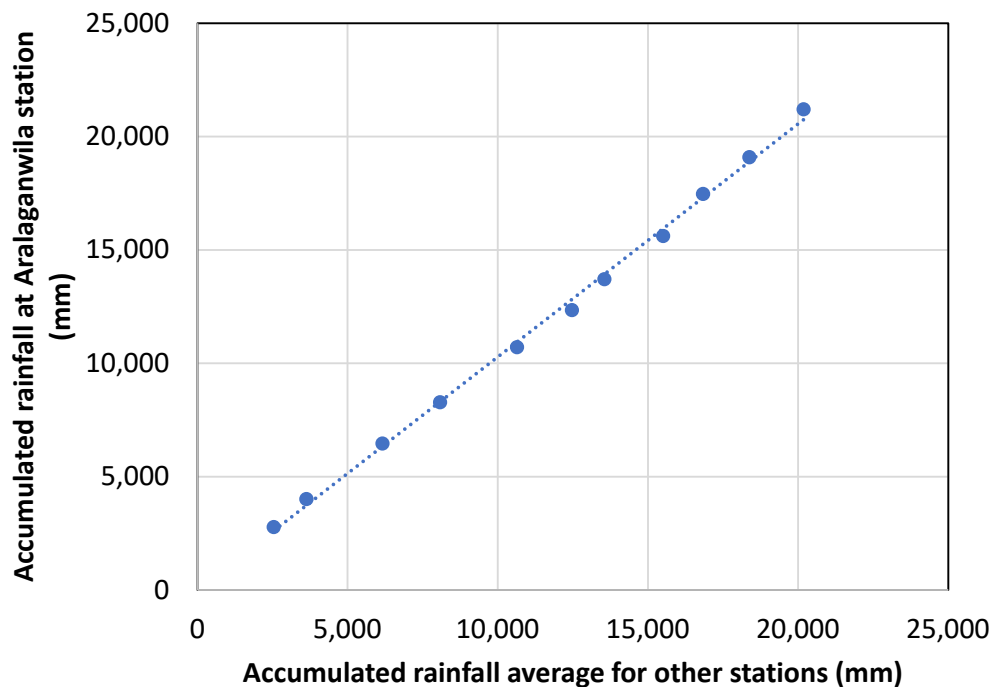


Figure 3-28: Double mass curve for Aralaganwila station

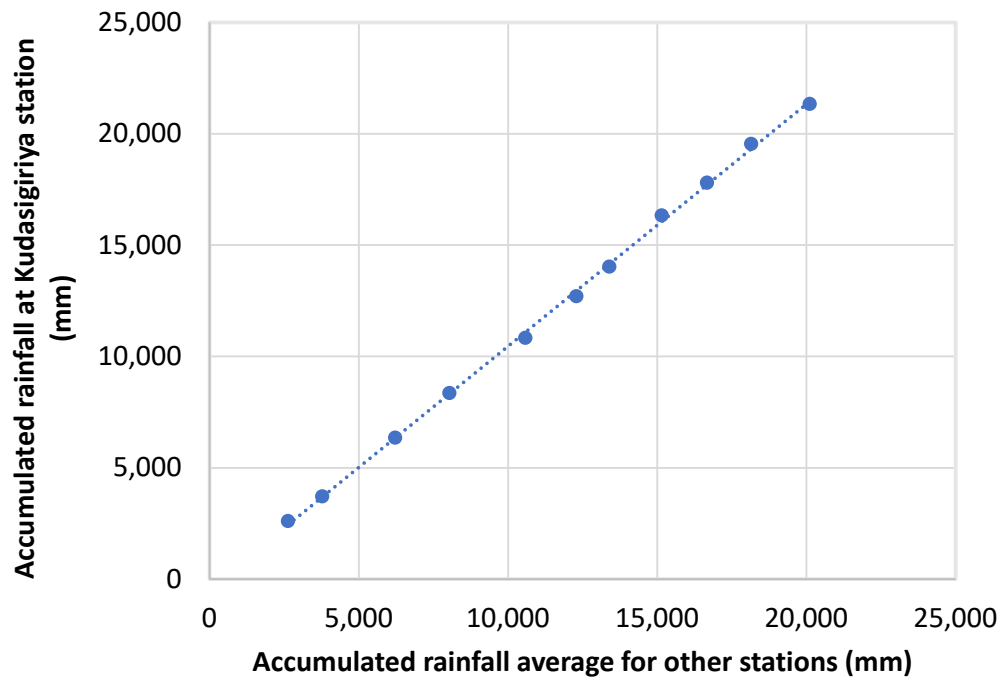


Figure 3-29: Double mass curve for Kudasigiriya station

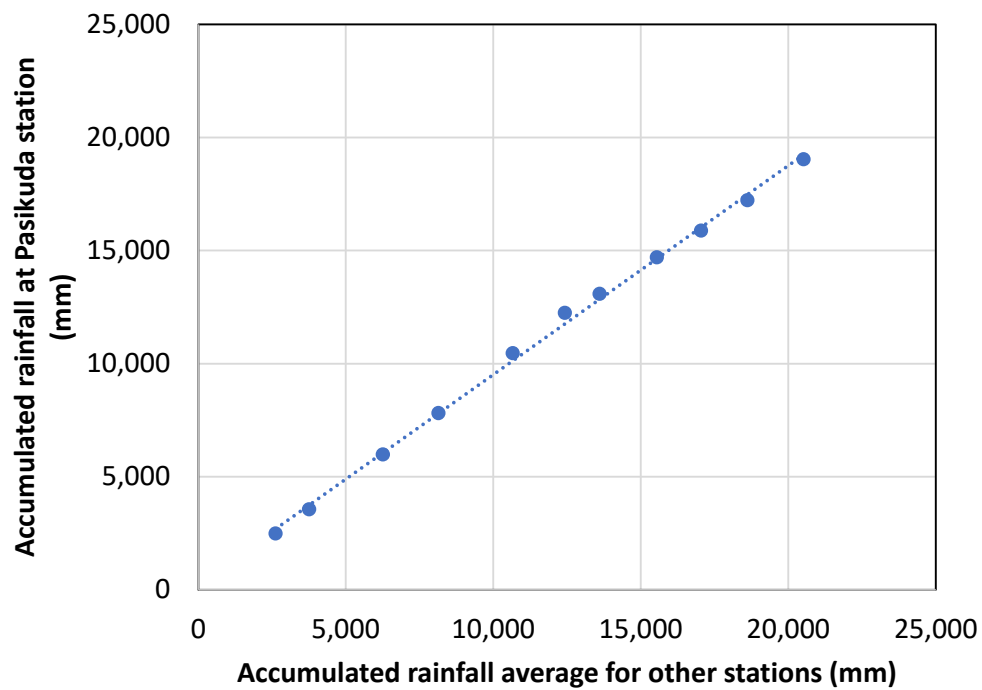


Figure 3-30: Double mass curve for Pasikuda station

3.5.6 Padiyathalawa Station

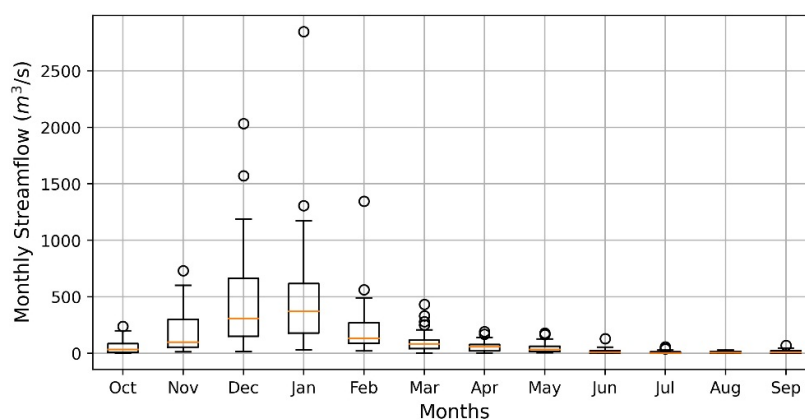


Figure 3-31: Monthly variation of Streamflow at the Padiyathalawa station

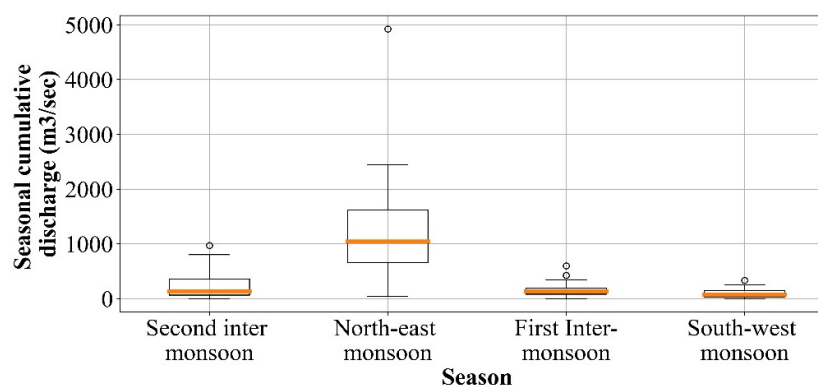


Figure 3-32: Seasonal variation of Streamflow at the Padiyathalawa station

It was observed that the Padiyathalawa station records the highest amount of rainfall in December and January. The northeast monsoon season records the highest discharge values, while the southwest monsoon season records the lowest. The highest annual average streamflow and daily streamflow was recorded in 2011.

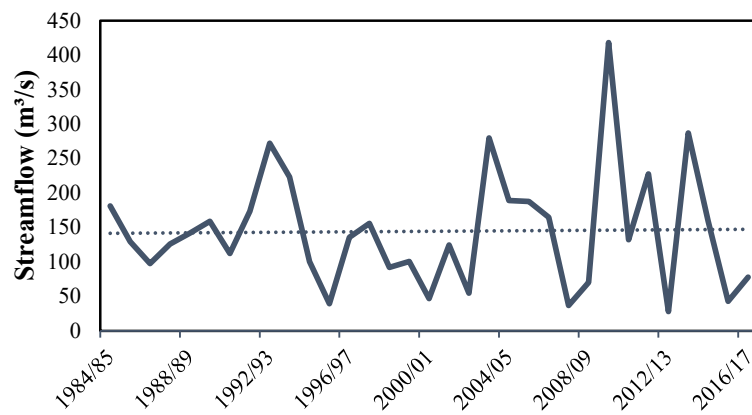


Figure 3-33: Annual average variation of Streamflow at the Padiyathalawa station

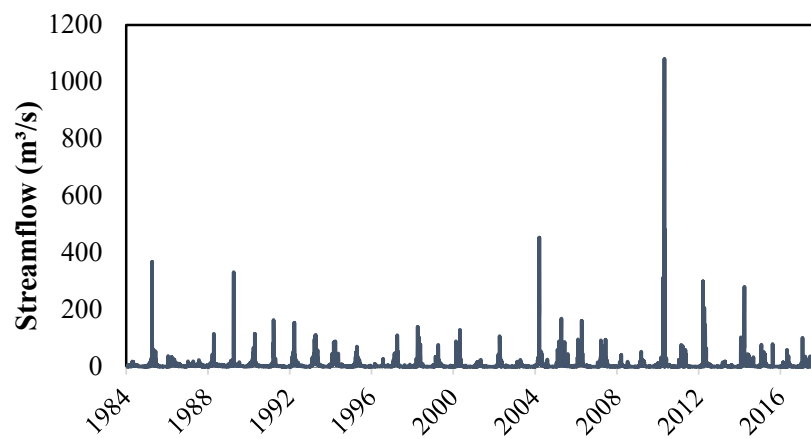


Figure 3-34: Daily streamflow variation of Streamflow at the Padiyathalawa station

3.6 Research Methodology

A literature review was undertaken to (a) determine the research problem and (b) assess the present state of research in the subject of climate change impacts on drought, (c) determine commonly used RCM models for climate studies within the region and their application and (d) select a suitable hydrologic model for the present study. The projected daily RCM data (precipitation) was bias-corrected concerning observed daily data using the mean-based method for radiative forcing scenarios RCP 4.5 and RCP 8.5. For the assessment of existing drought and future risk of drought in the study area, four meteorological drought indices (viz., Standardized Precipitation Index, Standardized Precipitation Evapotranspiration Index, Reconnaissance Drought Index and Effective Drought Index) and one hydrological drought index (i.e., Standardized Runoff Index) were selected following an assessment of research publications for various regions.

The three main components were considered when developing the HEC-HMS model: the Basin model, Meteorologic model and Control Specifications. A lumped model was developed up to the Padiyathalawa river gauging station. Model calibration was carried out using four years of data (01-October-2004 to 30-September-2008), and another four years of data (01-October-2008 to 30-September-2012) for model validation. The RMSE was selected as the objective function to evaluate model performance. In addition, Nash-Sutcliffe coefficients (NSE) and Coefficient of Determination (R^2) were also calculated for comparison/model performance evaluation. With the calibrated and validated HEC-HMS model, future variation of streamflow was projected under varied climatic scenarios over the 21st-century. The M-K test and Sen's slope estimator detected the indices and projected streamflow trends. Drought analysis (1951-2099) provides the most suitable index to study drought intensity, frequency and severity in the study area. The results were analysed to provide suitable drought mitigation measures/recommendations for the Maduru Oya River Basin planners/managers to minimize the future drought-related impacts.

3.7 Methodology Flowchart

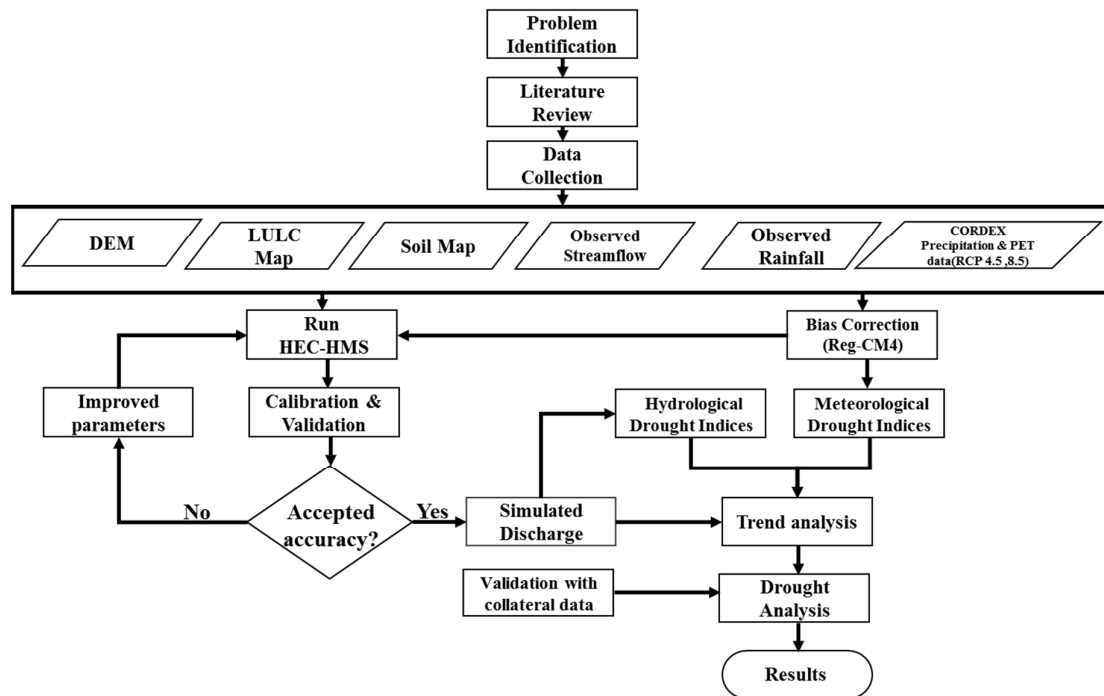


Figure 3-35: Methodology Flowchart

3.8 Development of the Basin Model

A lumped model for river flow up to the Padiyathalawa station, where daily streamflow data is available, was developed for the study. A lumped model is sufficient for this study concerning river discharge projections it can provide good simulations as complex physical models (Gebre, 2015; Pechlivanidis et al., 2013). There are no reach and junction components since river routing is not considered for the lumped model.

3.8.1 Development of the Canopy Model

In continuous modeling, canopy interception should be integrated with a deficit and constant method (USACE, 2000). Simple canopy is preferable over dynamic and gridded simple method because of the compatibility with the loss method and applicability in continuous process (USACE, 2018). Two inputs are needed for the canopy method: Initial storage (%) and Maximum Storage (mm). Initial storage is

concerning the input representing the percentage of the maximum canopy storage filled at the beginning of the simulation. Here, 0% was used as the initial value to start the simulation after a no rainfall period (Ahbari et al., 2018). The maximum Storage parameter represents the maximum depth of water that can be intercepted by vegetation (Ahbari et al., 2018). The calculated values are shown in Table 3-6.

Table 3-6: Maximum canopy storage calculation

According to USACE(2000)		Application to the Padiyathalawa watershed		
Type of vegetation	Max canopy storage (mm)	Area (km ²)	Weight coefficient	Basin average value(mm)
General vegetation	1.270	85.49	0.51	1.37
Grasses & Deciduous trees	2.032	58.74	0.35	
Coniferous trees	2.540	-	-	
Others	-	22.74	0.14	

The average basin value for maximum canopy storage is 1.37 mm. Evapotranspiration is determined using both Wet and Dry Periods.

3.8.2 Development of the Precipitation Loss Model

To estimate precipitation loss, there are twelve available methods. For primary continuous modelling, the deficit and constant loss method is usually used with the Canopy method (USACE, 2018). The deficit and constant method is most suitable for continuous simulation and requires less number of parameters (Madhushankha & Wijesekera, 2021). There are four sets of inputs required for the loss method: Impervious (%), Constant Rate (mm/hr), Maximum Deficit (mm) and Initial Deficit (mm).

Impervious (%) is determined by the percentage of the homestead and rock land use from land-use distribution. Here, this value is computed as 11.2 %. The constant rate (mm/hr) initial value is taken as 1.27 mm/hr, which is the minimum loss rate for hydrological soil type C (USACE, 2000).

Table 3-7: Weighted Curve Number Calculation

Land-use Type	Area(km²)	Area (%)	Soil Group	CN	CN*Area
Chena	4.88	2.9%	C	88	429.44
Forest- unclassified	58.74	35.2%	C	70	4111.80
Homestead	12.14	7.3%	C	80	971.20
Others	0.29	0.2%	C	80	23.20
Paddy	2.15	1.3%	C	78	167.70
Rock	6.55	3.9%	C	89	582.95
Scrub land	78.46	47.0%	C	64	5021.44
Streams	2.75	1.6%	C	97	266.75
Tanks	1.01	0.6%	C	97	97.97
Total	166.97	100%		Weighted CN	69.91

The maximum deficit and watershed characteristics are related through CN (USACE, 2000). The SCS abstraction method formula is used to calculate maximum deficit and it is found to be ~109 mm. The initial deficit is taken as one-fifth of the maximum retention times (Salvadore et al., 2015). For this study, the above-mentioned value is 21.87 mm.

3.8.3 Development of the Transform Model

The SCS UH method is used out of seven options to covert excess rainfall into a direct runoff because: (a) in diverse environments, the SCS method adapts to produce better

outcomes, (b) easy calculation due to two parameters only, (c) reliable and good outcomes can be attained (Salvadore et al., 2015). The only parameter required as input is the Lag Time (min) and the relationship of lag time with the time of concentration (T_c) was used for lag time calculation (Equation [3-3]) (USACE, 2018). The value of T_c was calculated using the Kirpich formula as shown in Equation [3-3]. Here, the Lag time for the Padiyathalawa watershed was calculated as 148 min.

$$T_c = 0.0078 * L^{0.77} * S^{-0.385} \quad [3-3]$$

where, L= length of longest channel path (ft); S= average watershed slope (ft/ft). The L for Padiyathalwa watercourse is 91,119 ft and the average watershed slope is 0.0171 ft/ft. Lag time is calculated using the Equation [3-4].

$$T_L = 0.6 * T_c \quad [3-4]$$

3.8.4 Development of Baseflow Model

The baseflow method selected as recession. This method is preferred because: (a) its applicability in a continuous process that resets automatically after each storm event, (b) requires less number of parameters, and (c) its compatibility with the loss model (Ali et al., 2011). The inflection point on the retreating limb of a hydrograph is used in this method to determine when surface flow has stopped contributing to runoff. The retreating limb shows the contributions of interflow and groundwater flow after this point. Three inputs are needed for the recession method: recession constant, initial discharge, and threshold ratio. The initial flow can be the average annual flow in the channel (USACE, 2000), which is 4.65 m³/s for the Padiyathalawa watershed. Here, the groundwater flow recession constant is considered as 0.95 (USACE, 2000). The threshold ratio is estimated by examining of hydrographs and the flow at which the recession limb is approximated by a straight line (USACE, 2000). Initially, it is estimated to be 0.2.

3.9 Development of Precipitation Model

In the precipitation model, the Thiessen method was used. Arc-GIS was used to create Thiessen polygons for the Maduru Oya Basin, and Thiessen weights for each sub-basin were determined in Table 3-8.

Table 3-8: Thiessen weight of rainfall stations

Station Name	Thiessen area (km ²)	Thiessen weight
Aralaganwila	474.04	0.32
Ekiriyankumbura	281.46	0.19
Kudasigiriya	429.60	0.29
Valachchanai	296.28	0.20

For each rain gauging station in the precipitation model, the daily Thiessen rainfall data was used as input to the HEC-HMS model. The model was calibrated using time series discharge data from the Padiyathalawa river gauging station. The simulation time interval was set to 30 minutes, and the starting and ending dates for model calibration were set to 1-October-2004 and 30-September-2008, respectively.

3.10 Model Calibration

On the basis of the data, the model was calibrated from 2004 ~ 2008. Following the selection of various components for model development, model calibration was carried out to improve the model's efficiency, which is dependent on the parameters. Manual calibration was completed first, followed by optimized calibration. For matching the results, NSE, RMSE and R^2 were selected as the objective functions to evaluate the performance. This study uses the Nelder and Mead (NM) method for automatic calibration. By adjusting the parameter's initial values until the change in the objective function was negligible, the optimum parameters were determined.

CHAPTER 4

4 ANALYSIS AND RESULTS

The daily precipitation obtained from RCM data was bias-corrected using the observed dataset of the same period. The RMSE was used to evaluate the bias-corrected results. The monthly and seasonal time-series of meteorological drought indicators were calculated using bias-corrected precipitation and potential evapotranspiration as input. The lumped model was developed for the watershed. The selected period for calibration was from 01-October-2004 to 30-September-2008, and the period of validation was selected from 01-October-2008 to 30-September-2012. The R^2 , NSE and RMSE were checked for the model outputs. Future streamflow simulations were obtained for both RCP 4.5 and RCP 8.5 scenarios. SRI time-series was plotted from the projected streamflow. Trend Analysis was done for hydrological and meteorological drought indices.

4.1 Bias Correction

The bias-correction results were obtained using the mean-based method. The comparison of observed precipitation, RCM data before bias correction and after bias correction for RCP 4.5 and RCP 8.5 are plotted in Figure 4-1 and Figure 4-2, respectively. Bias was reduced for the March to August, where RMSE was reduced to less than one (Figure 4-7 and Figure 4-8). For the remaining months, there is still bias in the RCM dataset as tabulated in Table 4-1. Since the current study focuses on the dry months of the study area (i.e., March to August for the drought-related studies, the bias correction results for RCP 4.5 and RCP 8.5 can be used for further steps. The results show satisfactory performance of the mean-based method.

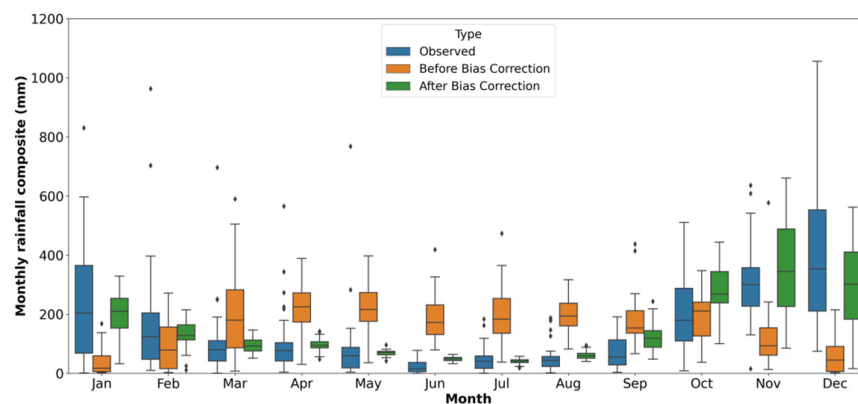


Figure 4-1: Bias correction of the historical period and RCP 4.5 scenario (1981-2018)

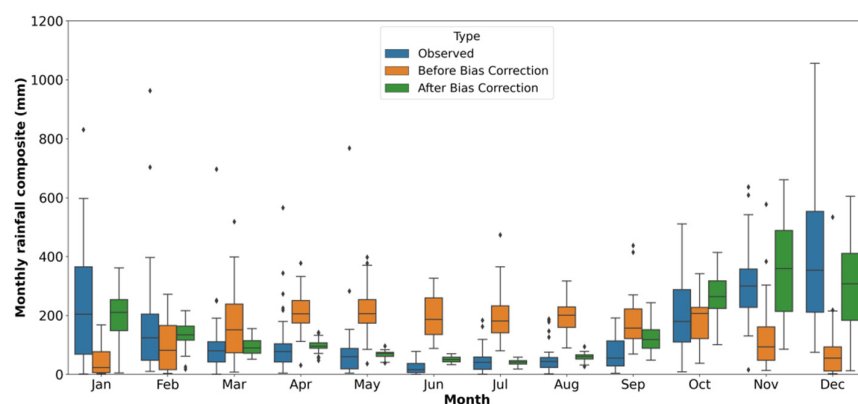


Figure 4-2: Bias correction of the historical period and RCP 8.5 scenario (1981-2018)

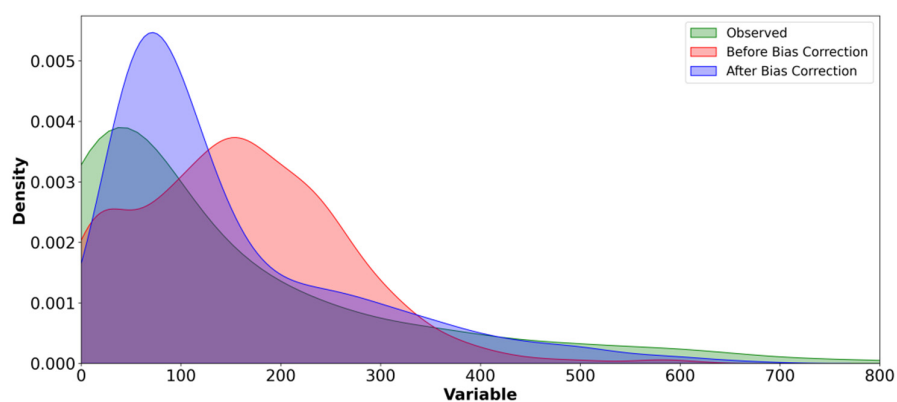


Figure 4-3: PDF plot for the historical period and RCP 4.5 scenario (1981-2018)

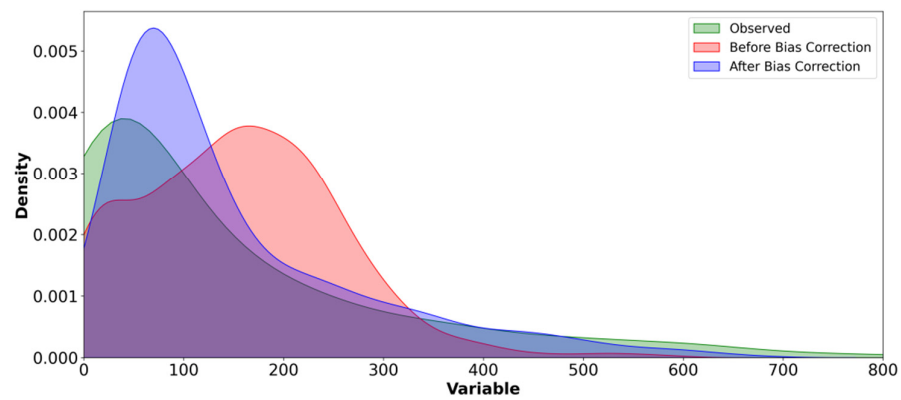


Figure 4-4: PDF plot for the historical period and RCP 8.5 scenario (1981-2018)

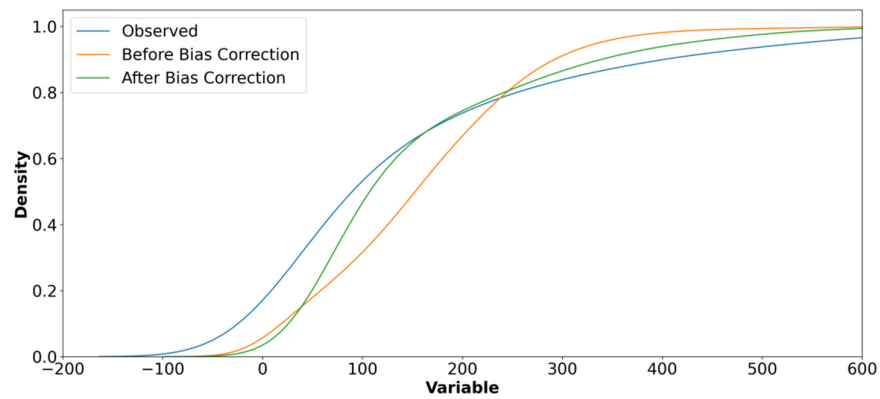


Figure 4-5: CDF plot for the historical period and RCP 4.5 scenario (1981-2018)

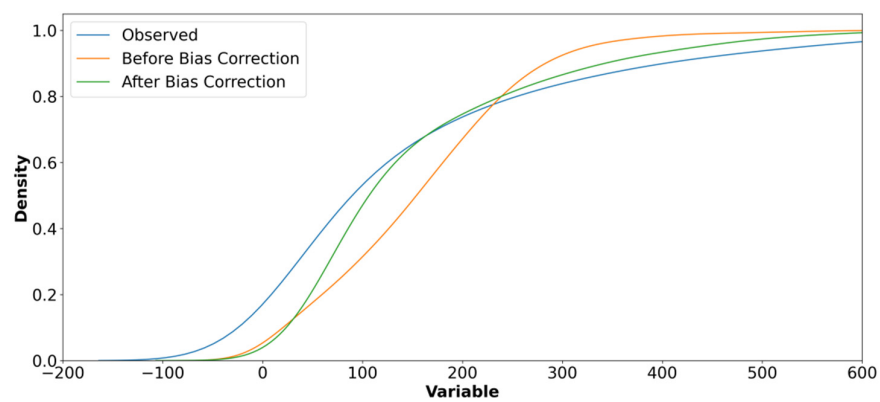


Figure 4-6: CDF plot for the historical period and RCP 8.5 scenario (1981-2018)

The distribution of the observed rainfall, RCM distribution before bias correction and after bias correction shows the reduction of bias in RCM data for both RCP 4.5 and RCP 8.5 scenarios (Figure 4-3 and Figure 4-4). The distribution of RCM data is close to observed data after applying the mean-based bias correction technique.

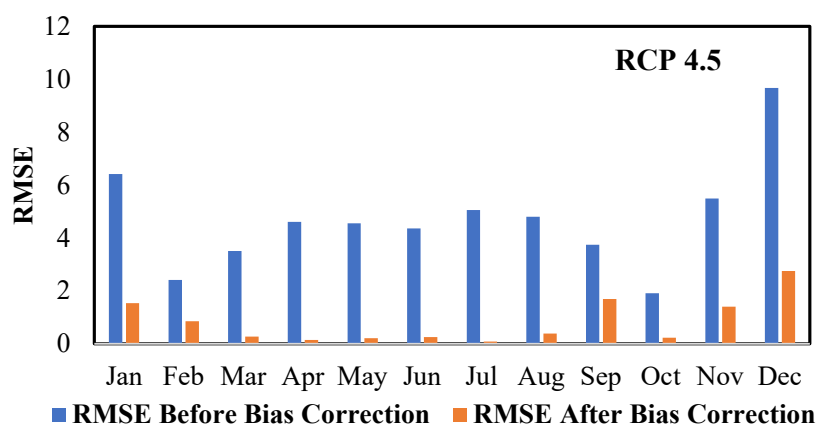


Figure 4-7: Monthly RMSE values in CORDEX data (1981-2018)

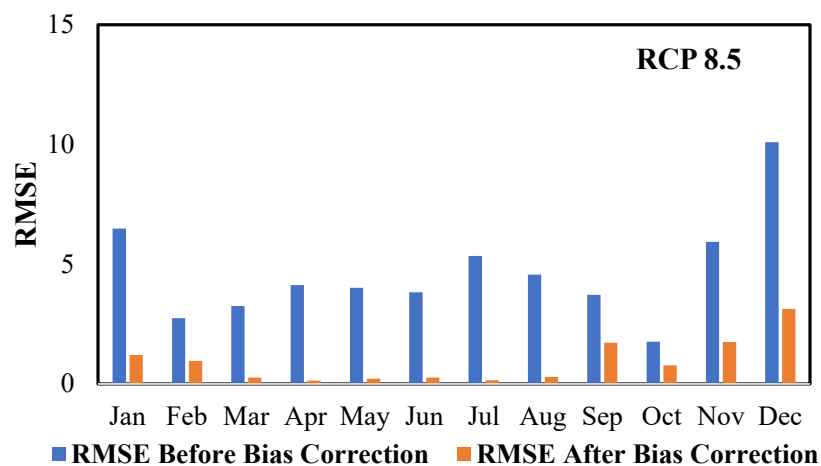


Figure 4-8: Monthly RMSE values in CORDEX data (1981-2018)

Table 4-1: Monthly RMSE values in CORDEX data before and after bias correction

Month	RMSE Before and After Bias Correction			
	RCP 4.5		RCP 8.5	
	Before	After	Before	After
Jan	6.41	1.53	6.49	1.21
Feb	2.41	0.85	2.74	0.96
Mar	3.51	0.27	3.26	0.27
Apr	4.61	0.14	4.13	0.14
May	4.55	0.22	4.01	0.22
Jun	4.36	0.25	3.83	0.27
Jul	5.05	0.08	5.35	0.15
Aug	4.81	0.39	4.56	0.29
Sep	3.75	1.70	3.72	1.73
Oct	1.91	0.23	1.76	0.78
Nov	5.49	1.41	5.93	1.75
Dec	9.67	2.75	10.10	3.13

4.2 Standardized Precipitation Index (SPI)

With the computation of SPI by the process mentioned in the previous chapter, the results obtained are utilized to analyse the area for dry and wet spells according to the classification of SPI values as mentioned in Table 2-2. Here the values are classified into monthly and seasonal scales over the 1951-2099 period.

The bias-corrected rainfall values serves as input for the calculation of SPI. The SPI time series at monthly and seasonal timescales for the Maduru Oya river basin are discussed in sections for the historical period, existing conditions and future drought risk. The future drought risk time series are obtained using the projected precipitation of RCM for the RCP 4.5 and RCP 8.5 scenarios.

4.2.1 SPI for Monthly Timescale

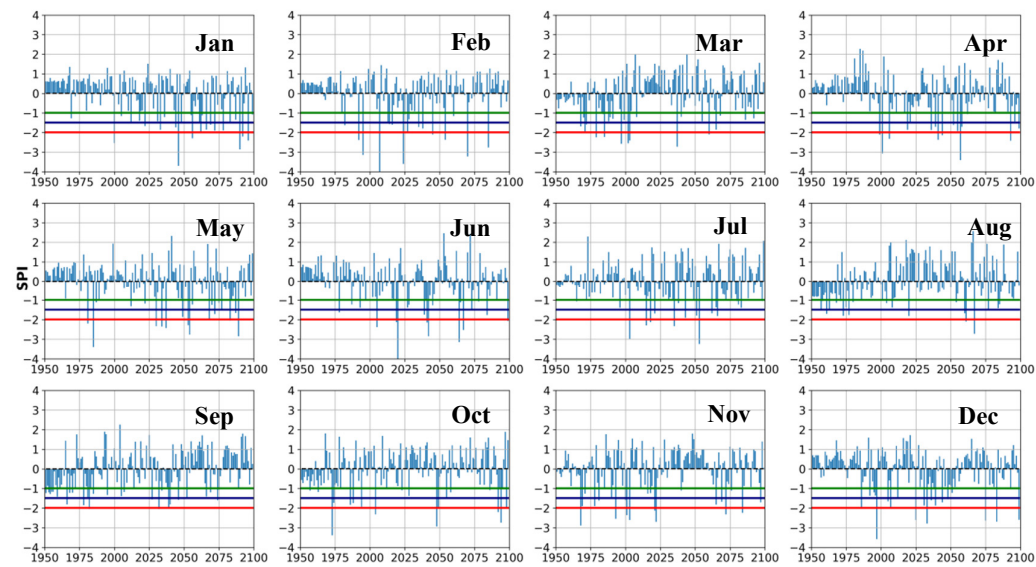


Figure 4-9: The SPI values at monthly timescale for the historical period and RCP 4.5 scenario

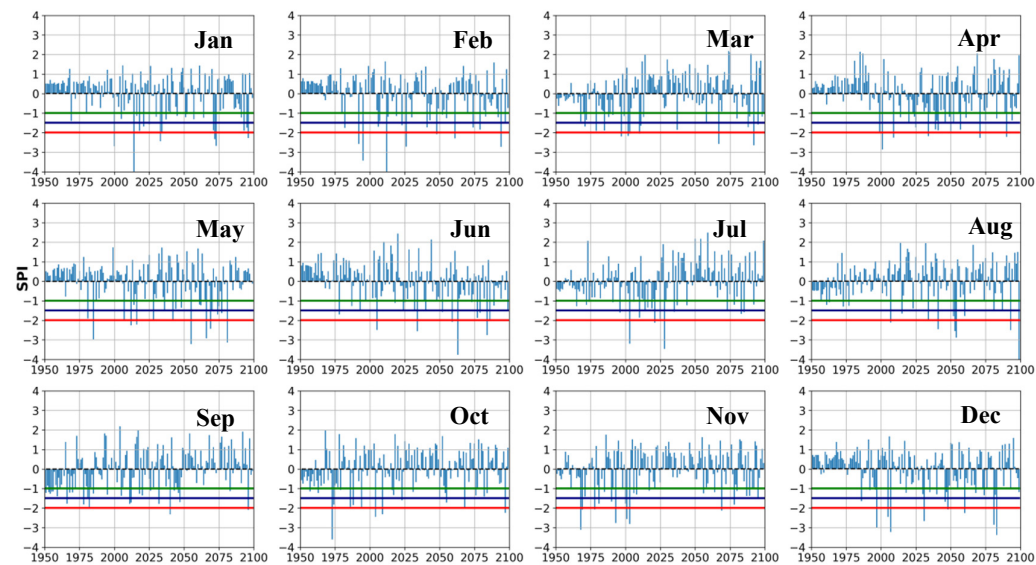


Figure 4-10: The SPI values at monthly timescale for the historical period and RCP 8.5 scenario

The monthly SPI plots shown in Figure 4-9 and Figure 4-10 indicate January, February, April, May, June and December with wet condition (i.e., $SPI > 0$) during the 1951-2005 period. It is observed for the existing conditions that the mild drought and

moderate drought frequency is increased in comparison to the historical period with wet conditions. For the future period (2006-2100), the frequency of negative SPI values is projected to increase with a high number of severe (i.e., $SPI < -1.5$) and extreme drought ($SPI < -2$) conditions for RCP 4.5 (110 drought events) and RCP 8.5 (104 drought events) compared to the historical/reference (45 drought events) period.

The months of March (8), August (5), September (4), October (6) and November (9) have negative SPI (severe and extreme droughts) values over the historical period (1951-2005). The frequency of wet conditions has increased during the recent period (2006-2020) for the dry months (compared to the historical period). The trend analysis for SPI values depicting the future drought risk of the RCP 4.5 and RCP 8.5 scenarios at monthly timescale is presented in Annexure 8 - 1 and Annexure 8 - 2.

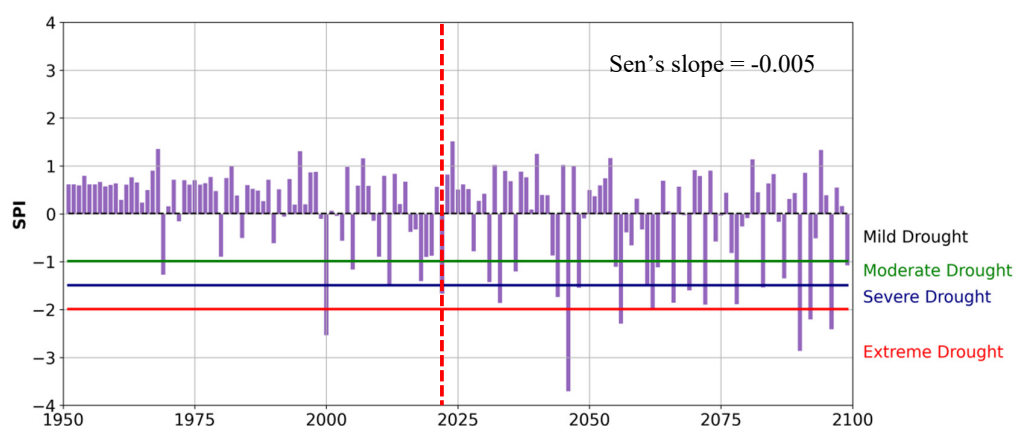


Figure 4-11: SPI values of the monthly timescale for the historical period and RCP 4.5 (January)

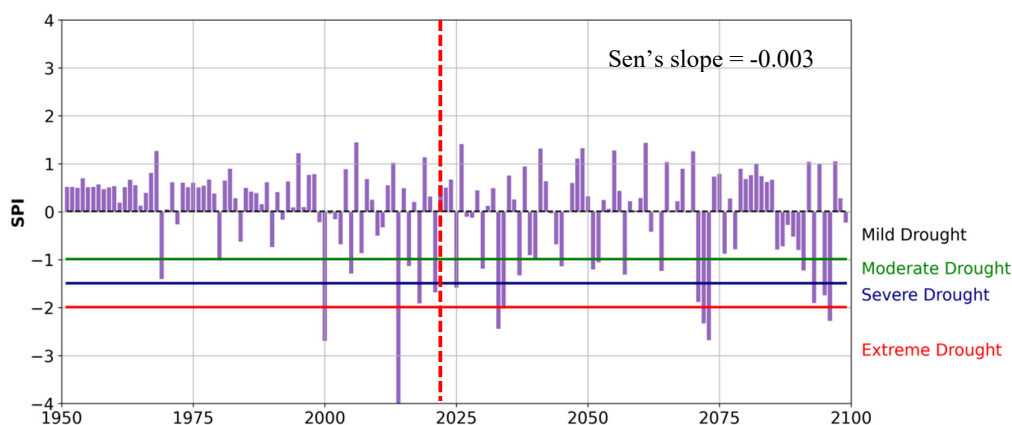


Figure 4-12: SPI values of the monthly timescale for the historical period and RCP 8.5 (January)

The SPI time series for January is shown in Figure 4-11 and Figure 4-12. The SPI values over the historical period (1951- 2005) are mostly positive in January. For the future period (2022-2099), SPI values are projected to decrease more in RCP 4.5 (Sen's slope=-0.005) than in RCP 8.5 (Sen's slope=-0.003), depicted by Sen's slope values. The frequency of severe and extreme drought (17 under RCP 4.5 and 12 under RCP 8.5) is projected to increase for both scenarios compared to the historical (2) period. The SPI time series of every month is depicted in Annexure 2 - 1 to Annexure 2 - 24 for RCP 4.5 and RCP 8.5 scenarios.

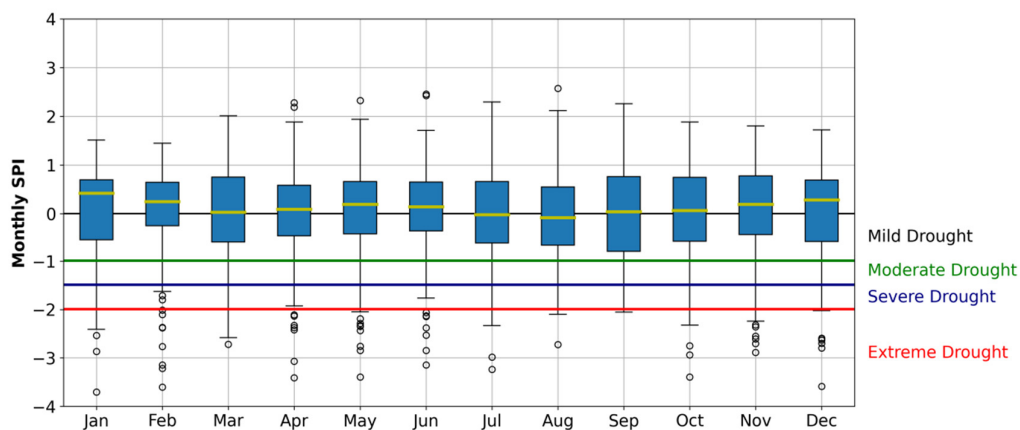


Figure 4-13: The projected monthly variation of SPI for RCP 4.5 (2022-2100)

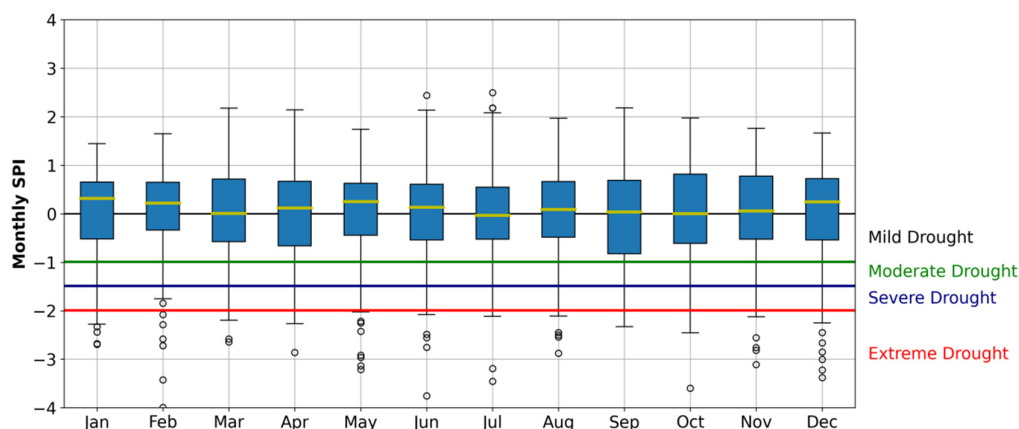


Figure 4-14: The projected monthly variation of SPI for RCP 8.5 (2022-2100)

The number of severe and extreme drought events is projected to be high for January (17,12), February (12,10), April (10,13), May (12,9), June (9,13), and December (13,6) (Figure 4-13 and Figure 4-14) under RCP 4.5 and RCP 8.5.

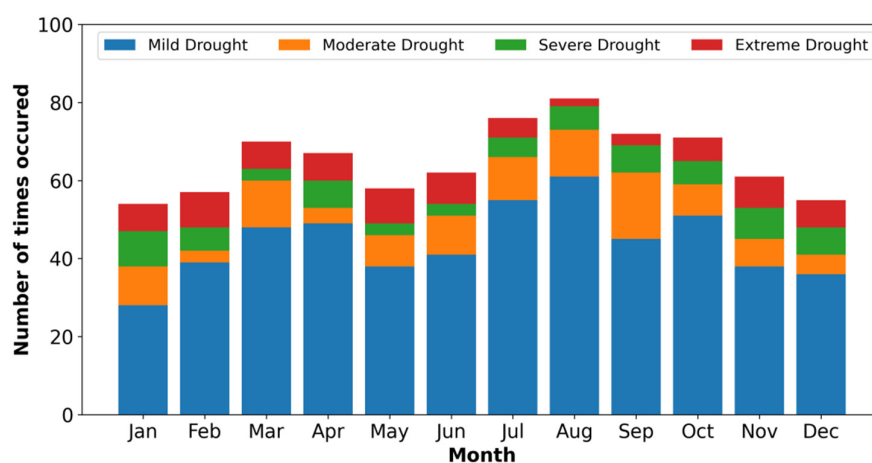


Figure 4-15: Projected frequency and severity of drought events (RCP 4.5) over 2022-2100 period

According to the SPI projections under RCP 4.5, it is observed that August is the month with the highest frequency (80) of drought within the Maduru Oya River Basin (Figure 4-15). The comparison of historical drought events (108) with mid-century (101) and end-century (99) RCP 4.5 is shown in Figure 4-16. It indicates that more severe droughts and extreme droughts may occur during the mid (29)- than during end

(19)-century periods (compared to the historical period (24)). The frequency analysis for RCP 8.5 projections is shown in Annexure 2 - 26 and Annexure 2 - 28.

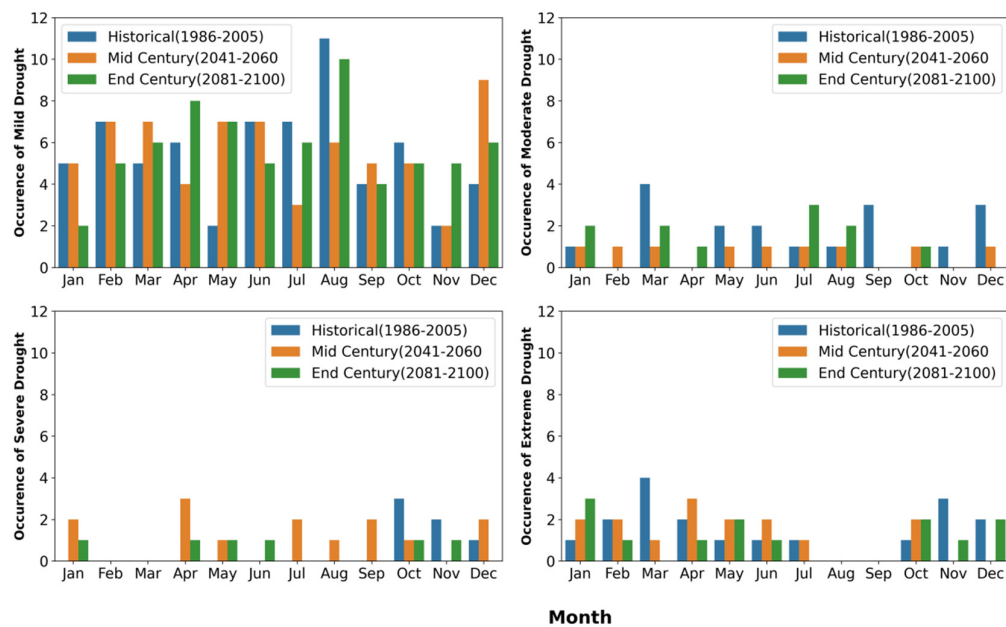


Figure 4-16: Comparison of the historical, mid-, and end-century period drought events under RCP 4.5

4.2.2 SPI for Seasonal Timescale

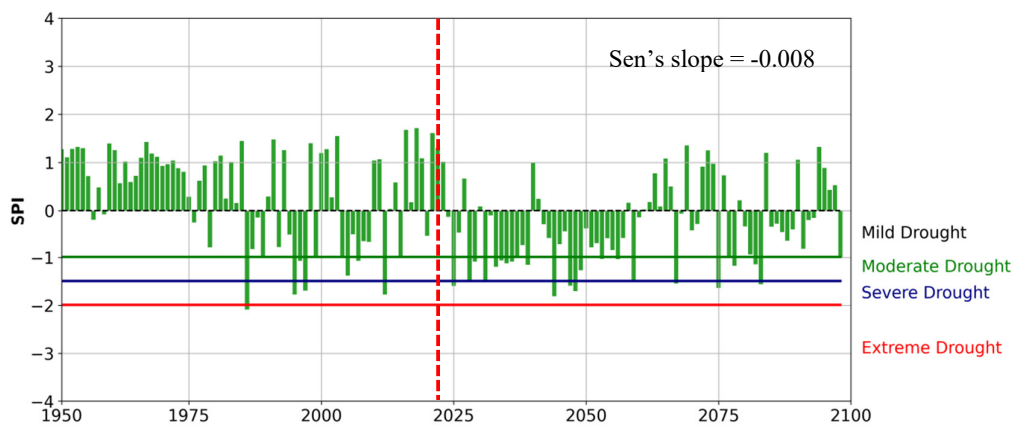


Figure 4-17: SPI for the historical period and Northeast Monsoonal period (Dec.-Mar.) under RCP 4.5

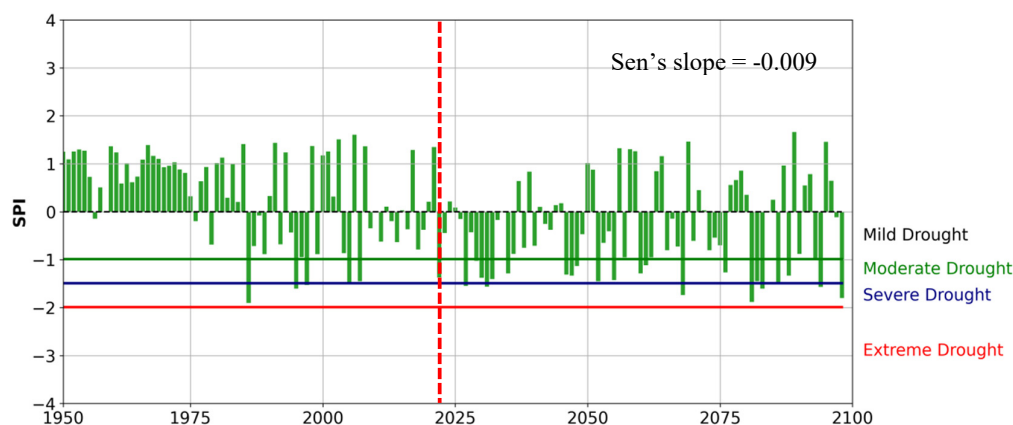


Figure 4-18: SPI for the historical and Northeast Monsoonal period (Dec-Mar) under RCP 8.5

The SPI values of Northeast Monsoon season are mostly positive for the historical period (1951-2005) with a trivial frequency (3 severe and extreme droughts) of drought events. For the future period, the trend of SPI is decreasing, highlighting an increase of projected drought events, especially over the mid-century for RCP 4.5 and RCP 8.5 (Figure 4-17 and Figure 4-18). It is observed that the SPI values are negative for the Southwest Monsoon for the historical period with a high frequency (6) of severe and extreme droughts. The SPI trend increases in future periods, indicating a decrease of drought events (compared to the historical period (7)) for both RCP 4.5 (6) and RCP 8.5 (4) (Figure 4-19 and Figure 4-20). The seasonal time series of SPI for all the seasons and RCP scenarios is shown in Annexure 2 - 29 to Annexure 2 - 36.

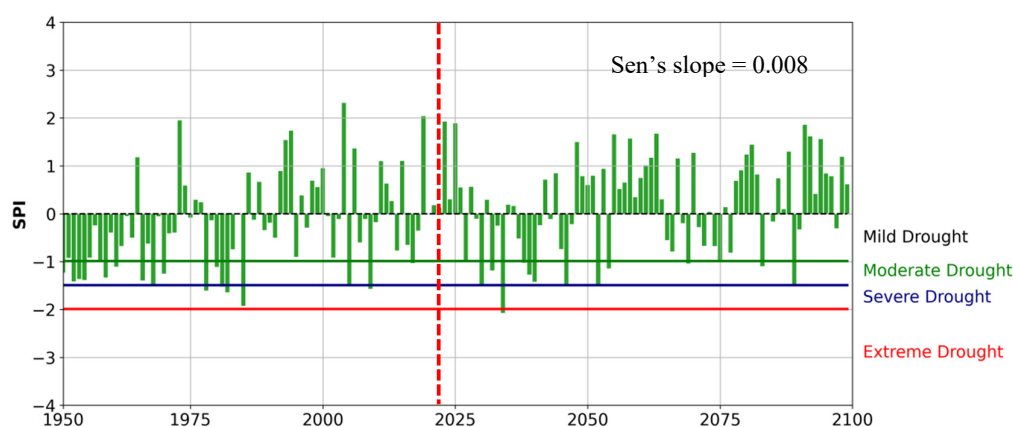


Figure 4-19: The SPI for the historical Southwest Monsoonal period (May-Sep) for RCP 4.5

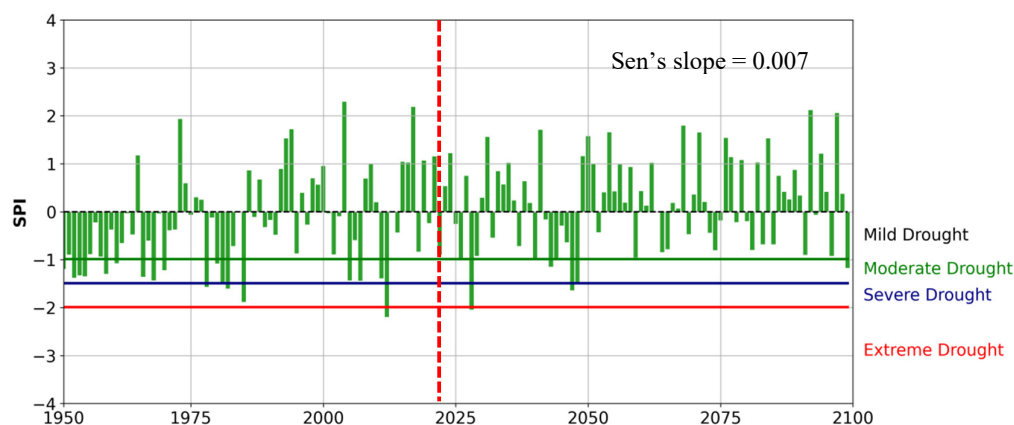


Figure 4-20: The SPI for the historical Southwest Monsoonal period (May-Sep) for RCP 8.5

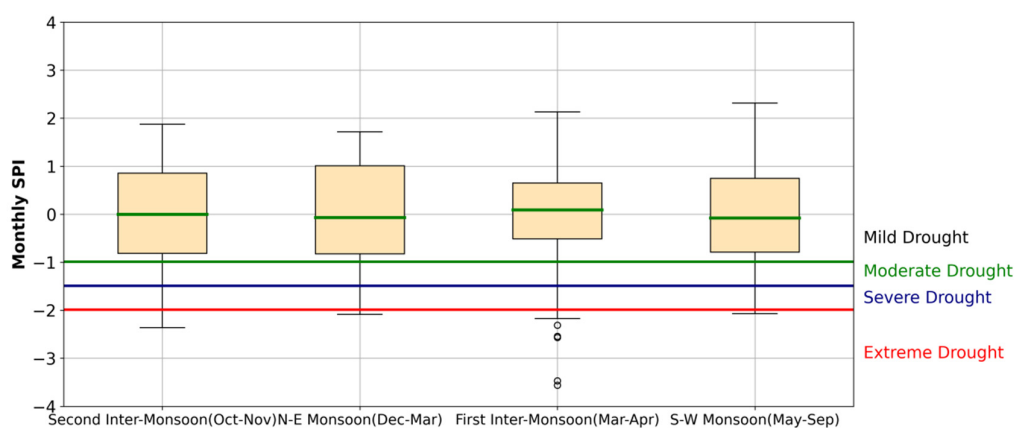


Figure 4-21: Seasonal variation of SPI for RCP 4.5 (2022-2100)

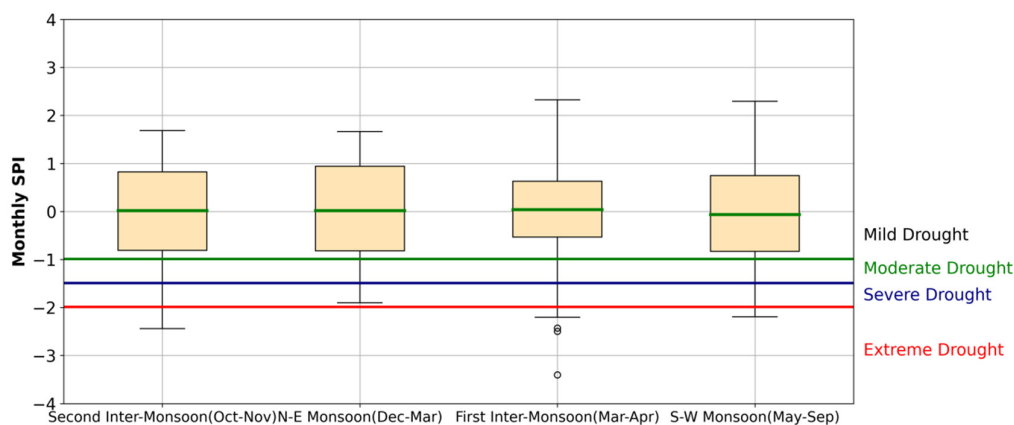


Figure 4-22: Seasonal variation of SPI for RCP 8.5 (2022-2100)

The boxplot of seasonal variation of SPI values indicates extreme drought events in every season, especially in the First Inter-Monsoon season for RCP 4.5 (5) and RCP 8.5 (6) (Figure 4-21 and Figure 4-22). The median SPI value is less than one for Northeast Monsoon season and Southwest Monsoon season under RCP 4.5, indicating the projected droughts' high drought frequency and severity.

The seasonal trend analysis of SPI using the M-K test and Sen Slope estimator are summarized in Annexure 8 - 3 and Annexure 8 - 4, respectively.

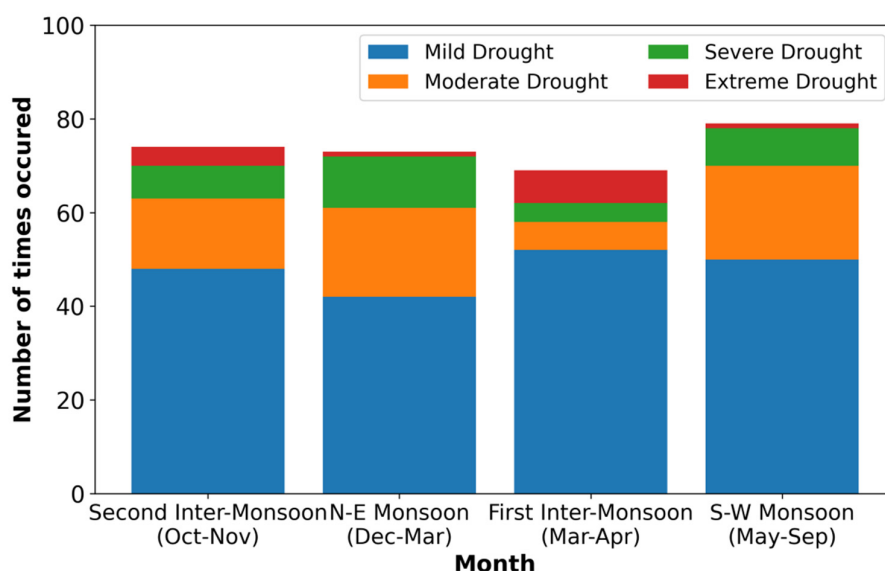


Figure 4-23: Projected frequency and severity of seasonal drought events under RCP 4.5 for 2022-2100 period

The above figure indicates that the Southwest monsoonal period may experience the highest frequency of drought events under RCP 4.5. The First-Inter Monsoon season is projected to have the highest frequency of extreme drought events under RCP 4.5. The frequency analysis under RCP 8.5 is presented in Annexure 2 - 38.

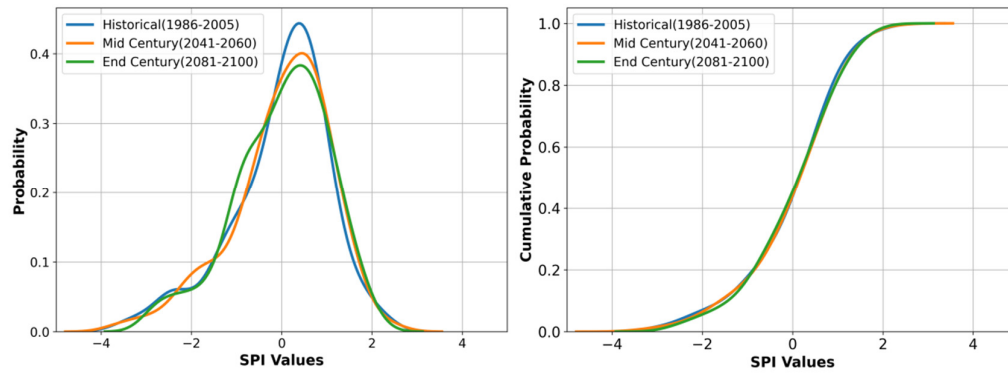


Figure 4-24: Probability of occurrence of droughts during the mid-century (left) and end-century (right) periods under RCP 4.5

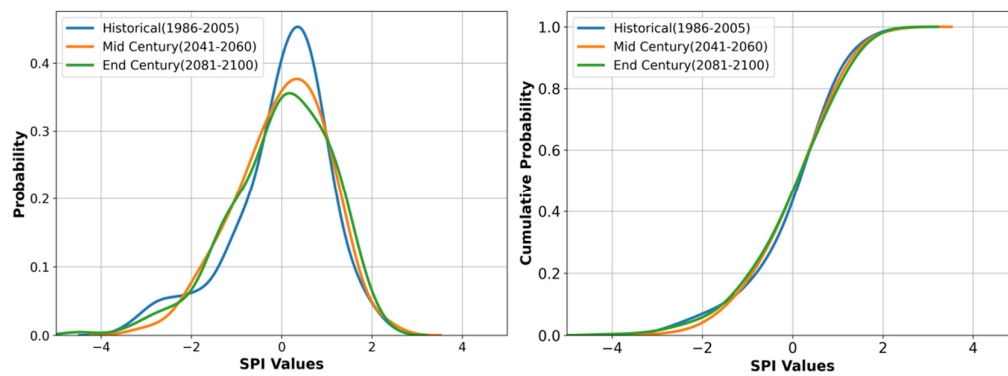


Figure 4-25: Probability of occurrence of droughts during the mid-century (left) and end-century (right) periods under RCP 8.5

The probability of zero SPI value (i.e., wet conditions) is the highest for the historical period for RCP 4.5 and RCP 8.5 (Figure 4-24 and Figure 4-25). The probability of wet conditions reduces for the mid- and end-century while skewing towards the negative SPI values for RCP 4.5 and RCP 8.5. The end-century period is projected to have a higher frequency and severity of drought events than the mid-century and historical periods. The values ($SPI < 0$) indicates drought risk and values ($SPI > 0$) indicates wet period.

4.3 Standardized Precipitation Evapotranspiration Index (SPEI)

The computation of SPEI is undertaken according to the process mentioned in Section 2.6.2. The results obtained are utilized to analyse the area for dry and wet spells according to SPEI classifications (Table 2-2) for monthly and seasonal scales over the 1950-2099 period.

The bias-corrected rainfall values and potential evapotranspiration values serve as the inputs for the SPEI calculation. The SPEI time series at monthly and seasonal timescales for the Maduru Oya river basin are discussed in the following sub-sections, concerning the historical (1951-2005), recent (2006-2021) and future drought (2022-2099) risk. The future drought risk time series are obtained using the projected precipitation of RCM for the scenarios of RCP 4.5 and RCP 8.5.

4.3.1 SPEI for Monthly Timescale

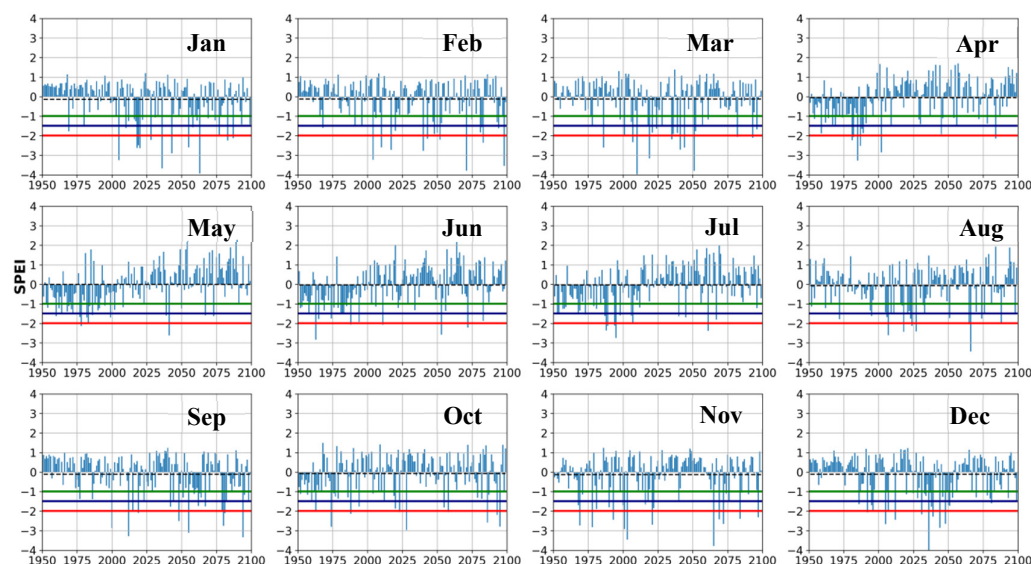


Figure 4-26: SPEI values of the monthly timescale for the historical period and RCP 4.5

Figure 4-26 and Figure 4-27 show wet conditions in January, February, September and December months of the 1951-2005 period. The frequency of mild and moderate droughts has increased recently (2006-2021) (compared to the historical period with wet conditions). For the future period, the frequency of negative SPEI values is

projected to increase with a high number of severe and extreme drought conditions for RCP 4.5 (128) and RCP 8.5 (122) (compared to the historical and recent periods (67)).

The months of April (9 severe and extreme drought events), May (9 severe and extreme drought events), June (9 severe and extreme drought events), Jul (9 severe and extreme drought events) and November (9 severe and extreme drought events) have negative SPEI values during the historical period (1951-2005). The frequency of wet conditions has increased recently (2006-2021) during the dry months (compared to the historical period). The trend analysis for SPEI values depicting the future drought risk of the RCP 4.5 and RCP 8.5 scenarios at monthly timescale is summarized in Annexure 8 - 5 and Annexure 8 - 6.

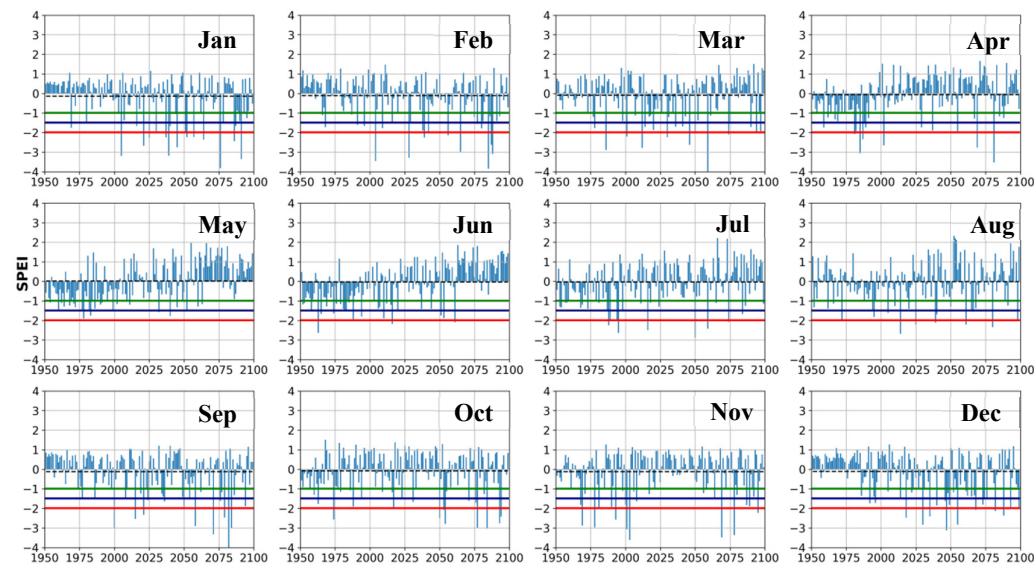


Figure 4-27: SPEI values of monthly timescale for the historical and future periods under RCP 8.5

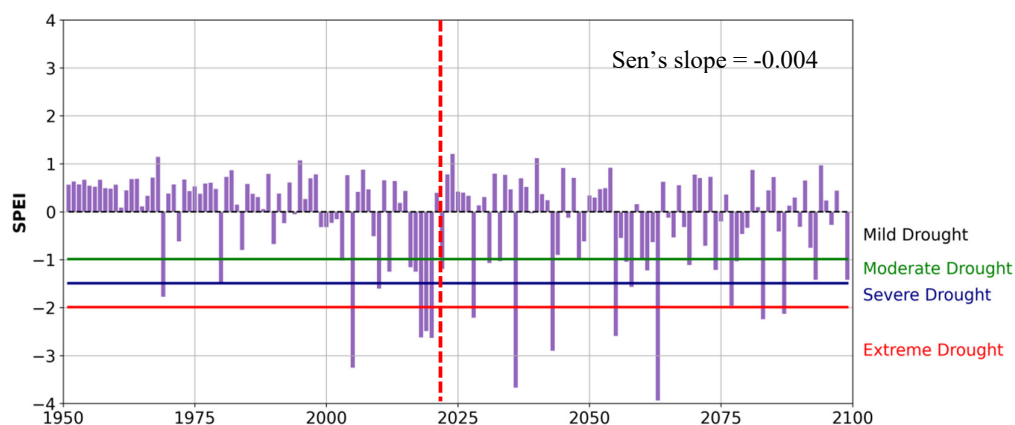


Figure 4-28: SPEI values of January for historical and future periods under RCP 4.5

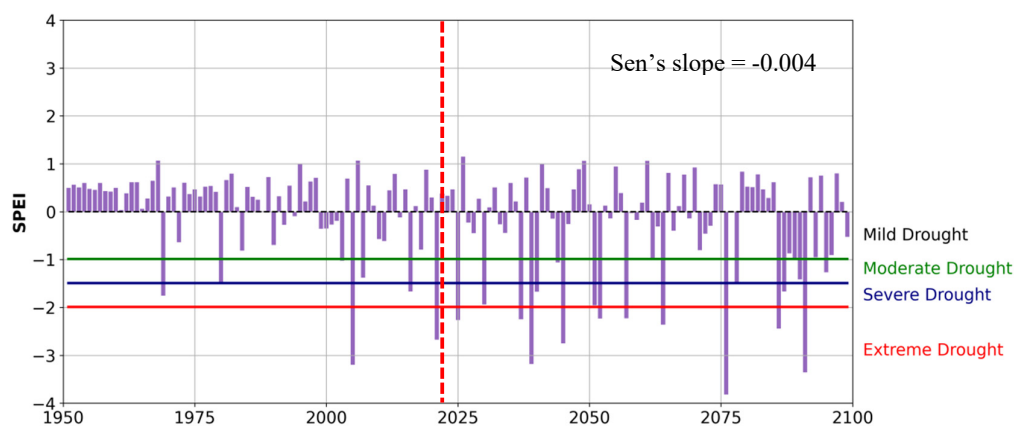


Figure 4-29: SPEI values of January for the historical and future periods under RCP 8.5

The SPEI time series for January is shown in Figure 4-28 and Figure 4-29. In general, the historical period (1951- 2005) has positive SPEI values. For the future period (2022-2099), SPEI values are projected to decrease under RCP 4.5 (13 severe and extreme drought events) and RCP 8.5 (17 severe and extreme drought events), as depicted by Sen's slope values. The frequency of severe and extreme droughts is projected to increase for both scenarios (with respect to historical period). The SPEI time series of every month is depicted in Annexure 3 - 1 to Annexure 3 - 24 for RCP 4.5 and RCP 8.5 scenarios, respectively.

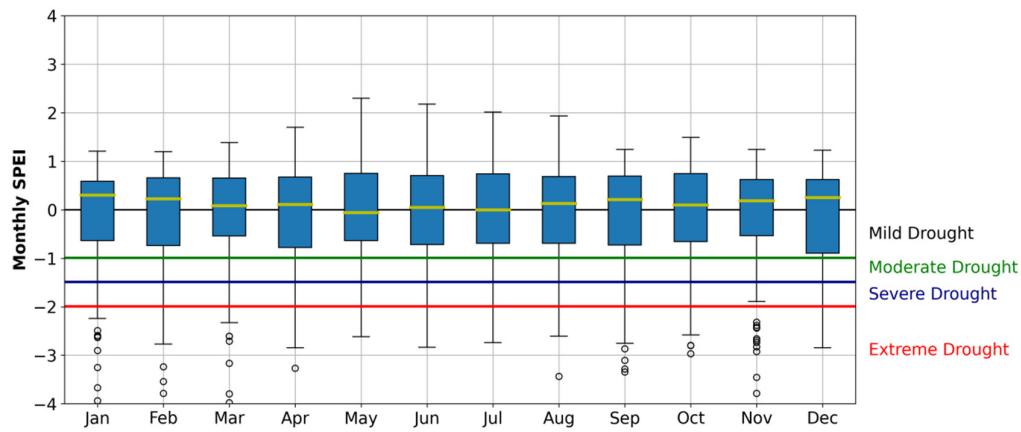


Figure 4-30: Monthly variation of SPEI for RCP 4.5 scenario over 2022-2100 period

The number of extreme drought events is projected to be high during January (13,17), February (14,14), March (17,14), September (16,14), October (9,12) and December (13,16) (Figure 4-30 and Figure 4-31) under RCP 4.5 and RCP 8.5 scenarios with respect to the historical period.

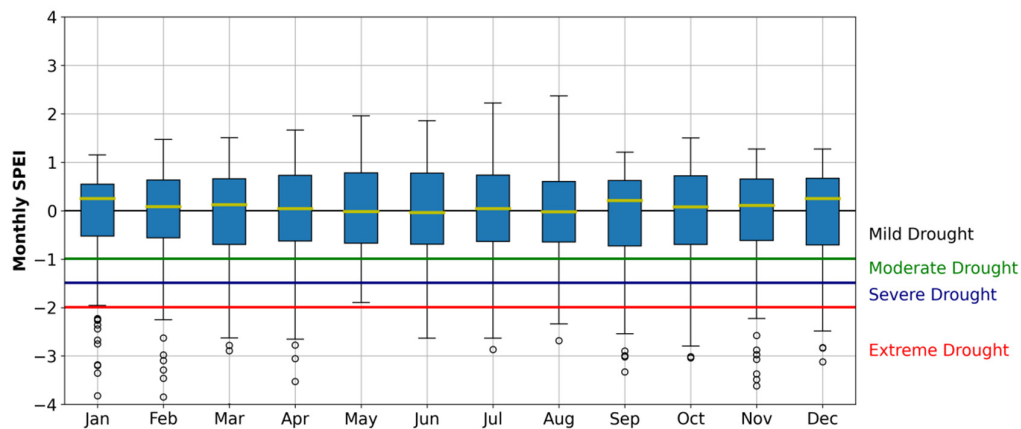


Figure 4-31: Monthly variation of SPEI under RCP 8.5 over 2022-2100 period

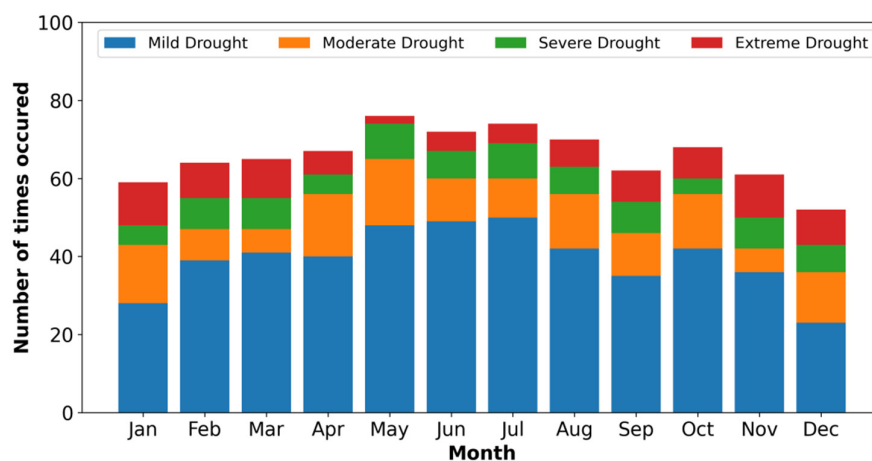


Figure 4-32: Projected frequency and severity of drought events under RCP 4.5 over 2022-2100 period

Figure 4-32 shows that under RCP 4.5, May is the month with the highest projected frequency (78) of drought in the Maduru Oya River Basin. The comparison of historical drought events with mid-century and end-century RCP 4.5 scenario (Figure 4-33) indicates the occurrence of more severe and extreme droughts during mid- and end-century. The frequency analysis for RCP 8.5 is depicted in Annexure 3 - 26 and Annexure 3 - 28.

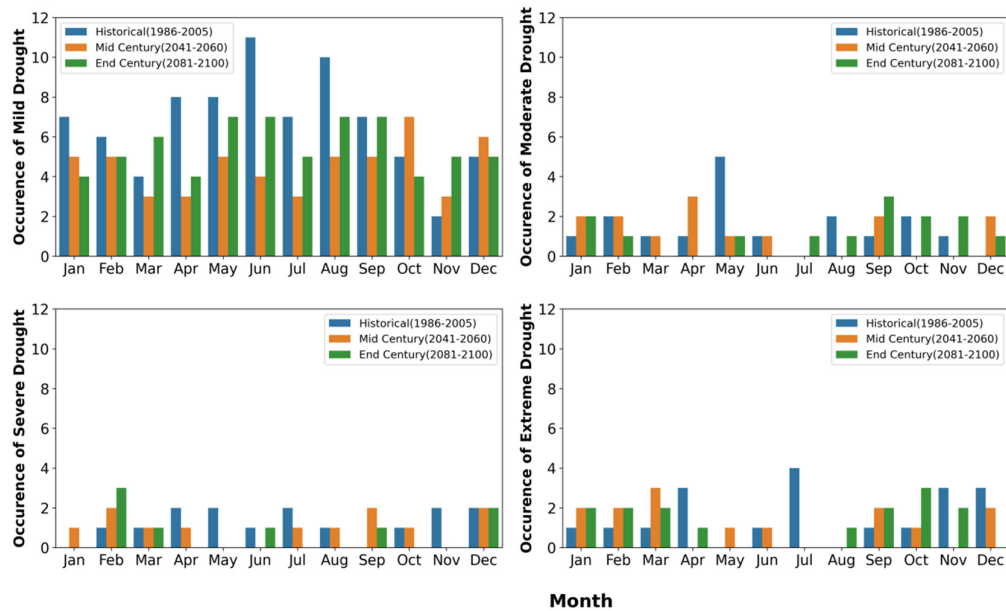


Figure 4-33: Comparison of the historical, mid-century and end-century drought events under RCP 4.5

4.3.2 SPEI for Seasonal Timescale

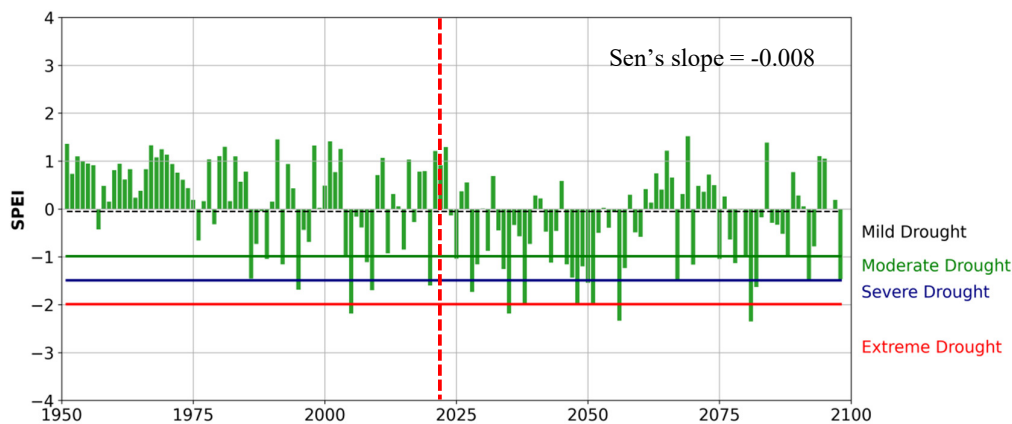


Figure 4-34: SPEI for the historical and Northeast Monsoonal period (Dec-Mar) under RCP 4.5

The SPEI values of the Northeast Monsoon season are positive for the historical period (1951-2005) with less frequency (3 severe and extreme drought events) of drought events. For the future period, the trend of SPEI is decreasing which means increase of drought events is projected especially for both RCP 4.5 (14 severe and extreme drought

events) and RCP 8.5 (14 severe and extreme drought events) (Figure 4-34 and Figure 4-35).

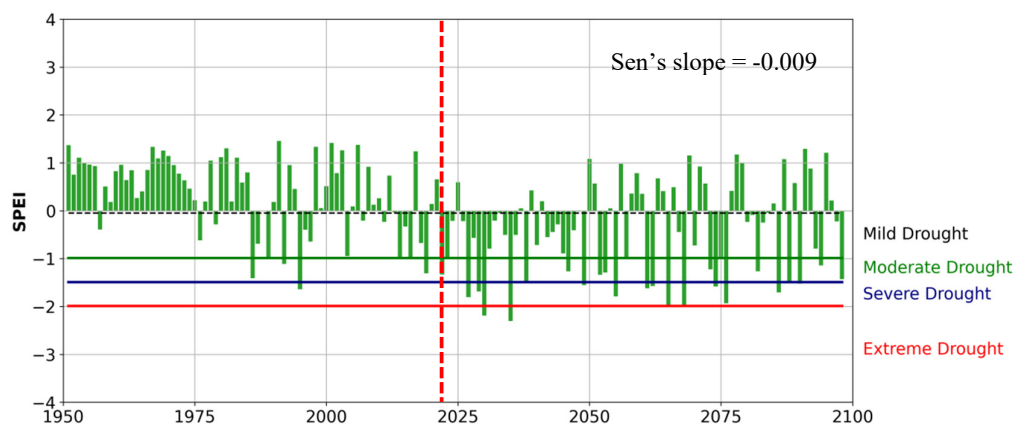


Figure 4-35: SPEI for the historical and Northeast Monsoonal period (Dec-Mar) under RCP 8.5

SPEI values are negative for Southwest Monsoon for the historical time period with high frequency (8) of severe and extreme drought events. The SPEI trend is increasing which means decrease of drought events (in comparison to historical period) for both RCP 4.5 and RCP 8.5 (Figure 4-36 and Figure 4-37). The seasonal time series of SPEI for all the seasons and RCP scenarios is depicted in Annexure 3 - 29 to Annexure 3 - 36.

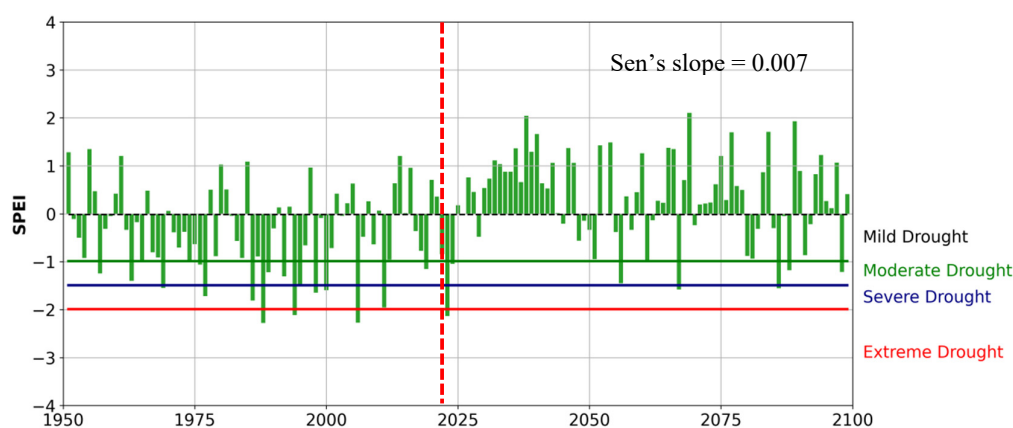


Figure 4-36: SPEI for the historical and Southwest Monsoonal period (May-Sep) under RCP 4.5

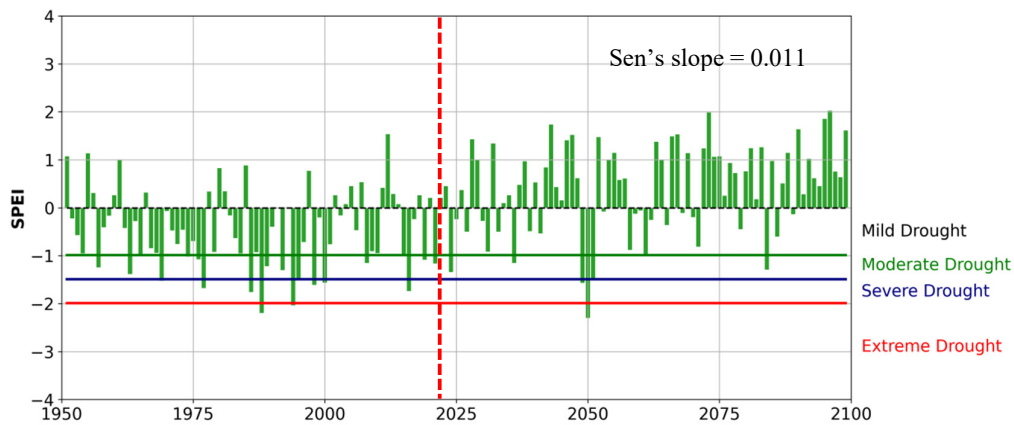


Figure 4-37: SPEI for the historical and Southwest Monsoonal period (May-Sep) under RCP 8.5

The boxplot of seasonal variation of SPEI values indicate extreme drought events in every season especially in the First inter-monsoon season for both RCP 4.5 (4) and RCP 8.5 (2) as shown in Figure 4-38 and Figure 4-39. The seasonal trend analysis of SPEI using M-K test and Sen Slope estimator is summarized in

Annexure 8 - 7 and Annexure 8 - 8.

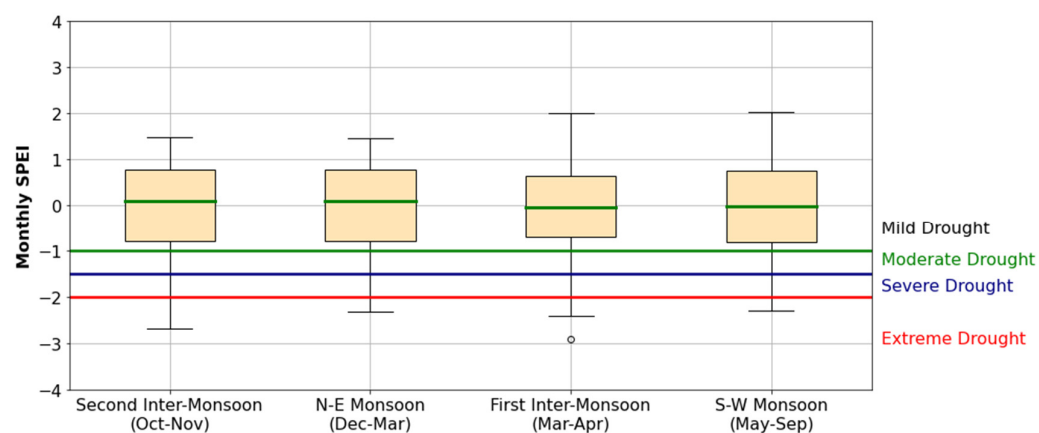


Figure 4-38: Seasonal variation of SPEI for RCP 4.5 (2022-2100)

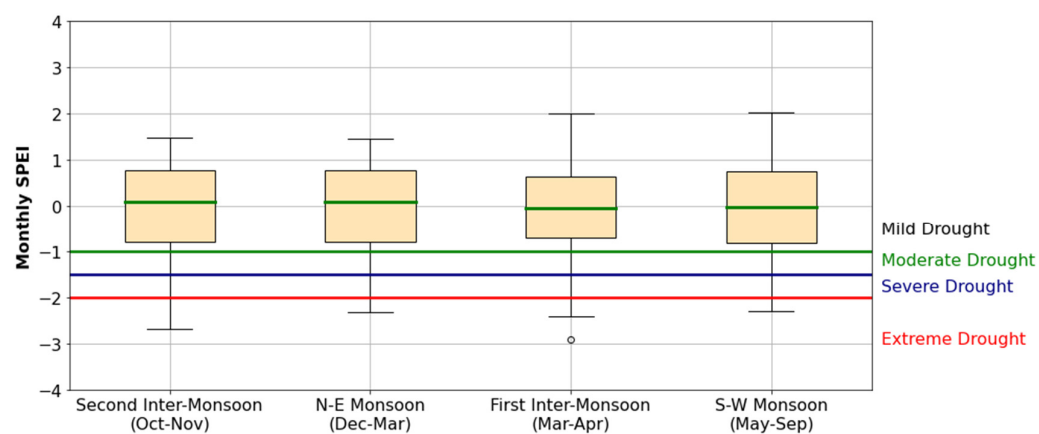


Figure 4-39: Seasonal variation of SPEI for RCP 8.5 (2022-2100)

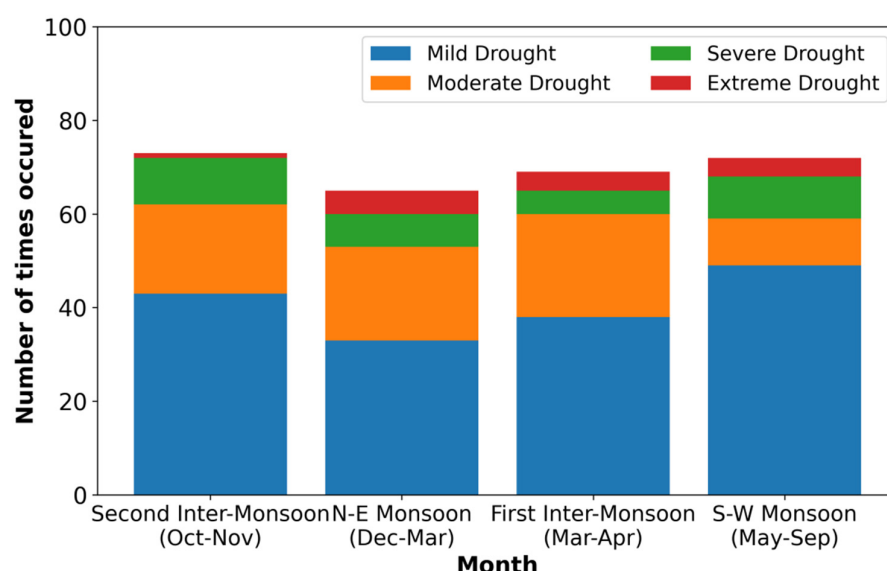


Figure 4-40: Projected frequency and severity of seasonal drought events under RCP 4.5 for 2022-2100 period

The seasonal projections indicate that, under the RCP 4.5, the highest frequency (74) of drought events may occur during the Second Inter-Monsoon (Oct-Nov). The Northeast Monsoon season is projected to have the highest frequency of extreme drought events (10). The frequency analysis for the projection under RCP 8.5 scenario is shown in Annexure 3 - 38.

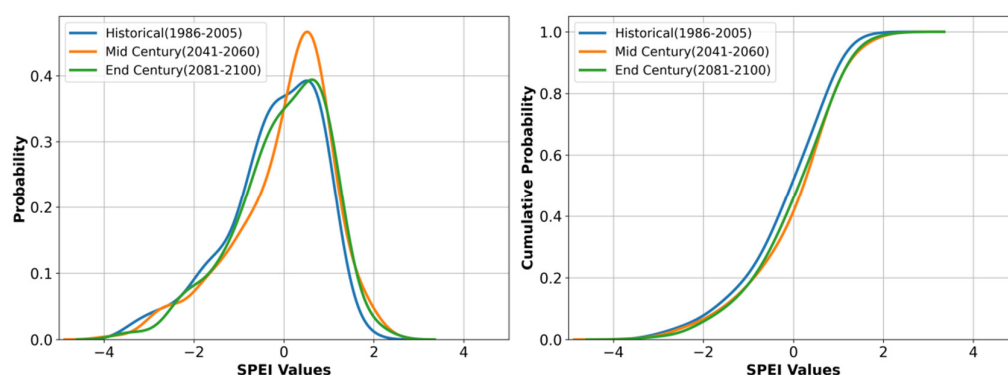


Figure 4-41: Probability of occurrence of droughts during mid-century (left) and end-century (right) periods under RCP 4.5

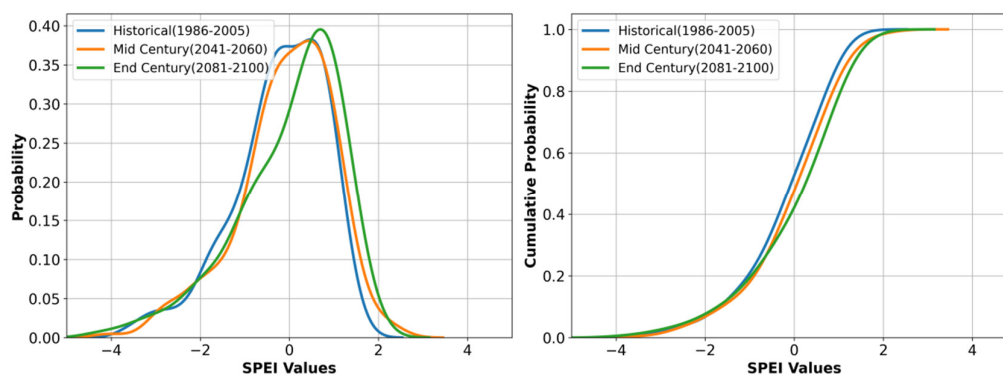


Figure 4-42: Probability of occurrence of droughts during mid-century (left) and end-century (right) periods under RCP 8.5

Figure 4-41 and Figure 4-42 indicate that the probability of zero SPEI value (i.e., wet conditions) is highest under the RCP 4.5 scenario during the mid-century period and under RCP 8.5 for the end-century period. The probability distribution of drought occurrence is skewed towards negative SPEI values for the end-century under RCP 4.5 and during the mid-century with RCP 8.5. The end- and mid-century periods are projected to be wetter than the historical period for both RCPs. The values ($SPEI < 0$) indicate droughts and values ($SPEI > 0$) indicate wet conditions.

4.4 Reconnaissance Drought Index (RDI)

The RDI time series at monthly and seasonal timescales for the Maduru Oya river basin are discussed in the following sub-chapters concerning historical, recent, and future periods' drought risk. The future drought risk time series are obtained using the projected precipitation of RCM for the scenarios of RCP 4.5 and RCP 8.5.

4.4.1 RDI for Monthly Timescale

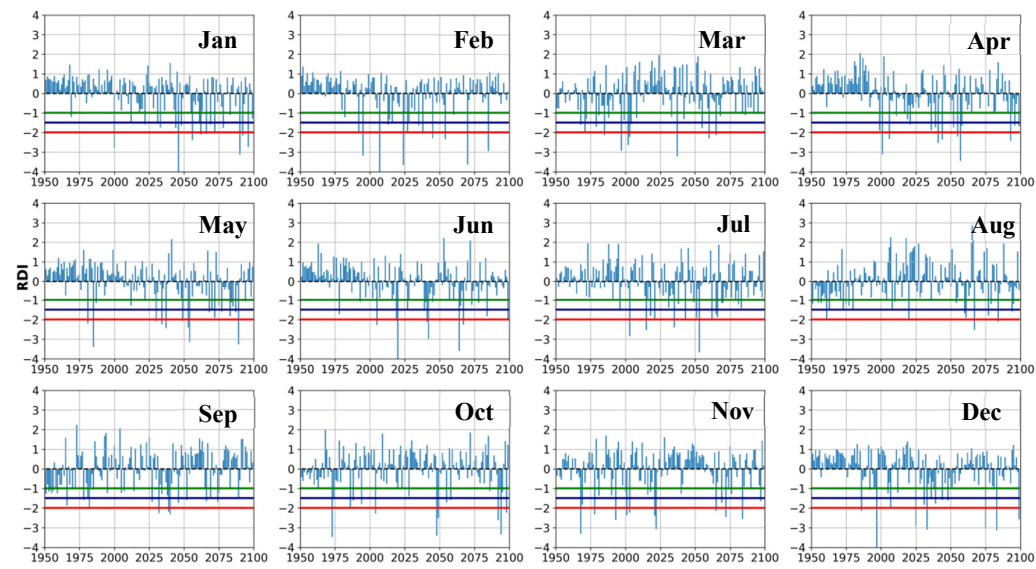


Figure 4-43: RDI values of monthly timescale for the historical and future periods under RCP 4.5

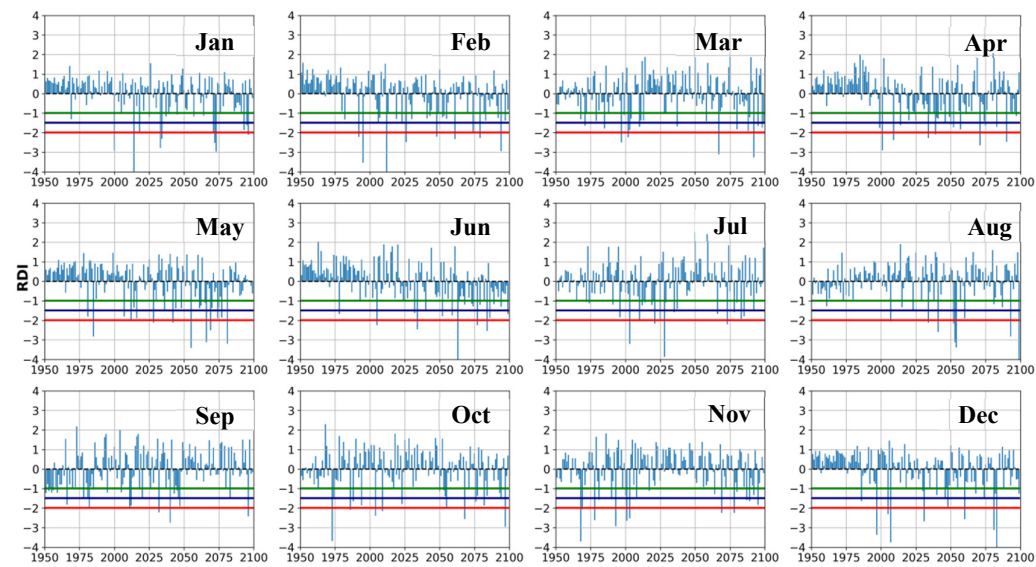


Figure 4-44: RDI values of monthly timescale for the historical and future periods under RCP 8.5

The RDI plots of the monthly scale (Figure 4-43 and Figure 4-44) show that January, February, April, May, June and December months with wet conditions for the historical period (1951-2005). Those figures also show that mild and moderate drought

frequencies have increased recently (2006-2021) (compared to the historical period with wet conditions). For the future periods, the frequency of negative RDI values is projected to increase with a high number of severe and extreme drought conditions for RCP 4.5 (119) and RCP 8.5 (107) (compared to the historical and recent times (40)).

The months of March (8), August (4), September (4), October (5) and November (6) have negative RDI values (i.e., dry conditions) for the historical period (1951-2005). The frequency of wet conditions is increased during the recent dry months (compared to the historical period). The trend analysis for RDI values depicting the future drought risk of the RCP 4.5 and RCP 8.5 scenarios at monthly timescale is summarized in Annexure 8 - 9 and Annexure 8 - 10, respectively.

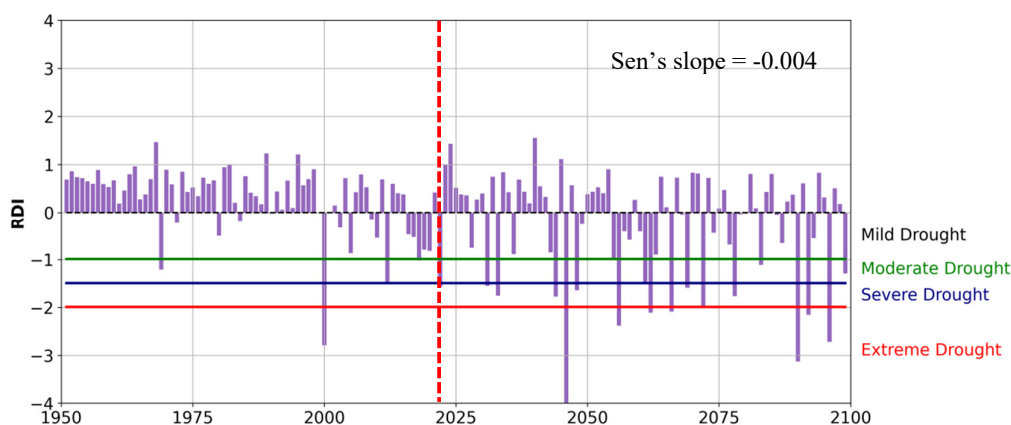


Figure 4-45: RDI values of January for historical and future periods under RCP 4.5

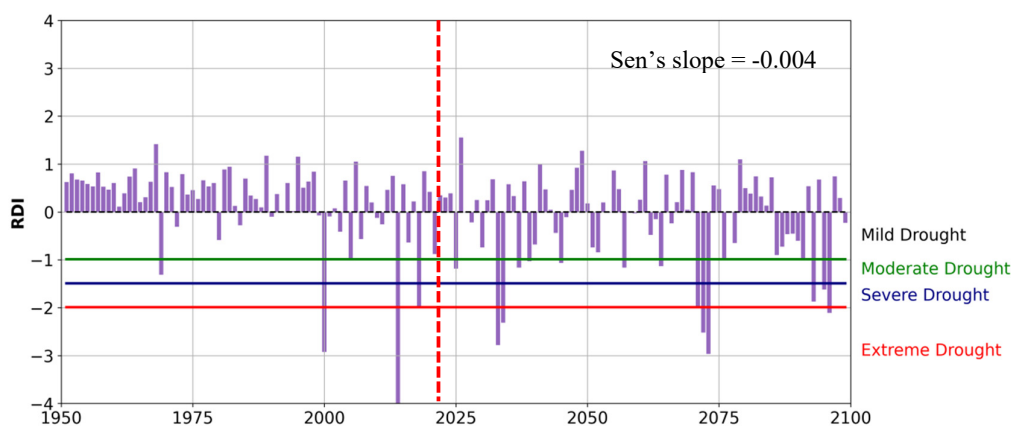


Figure 4-46: RDI values of January for historical and future periods under RCP 8.5

The RDI time series for January under RCP 4.5 and 8.5 (including the historical period of 1950-2021) are shown in Figure 4-45 and Figure 4-46, respectively. The historical period (1951- 2005) primarily consists of positive RDI values. For the future period (2022-2099), RDI values are projected to decrease under both RCPs, which is depicted by Sen's slope values. The frequency of severe and extreme drought is projected to increase for both scenarios (119 for RCP 4.5, 107 for RCP 8.5) with respect to the historical period (40). The RDI time series of all months are shown in Annexure 4 - 1 to Annexure 4 - 24 for RCP 4.5 and RCP 8.5 scenarios.

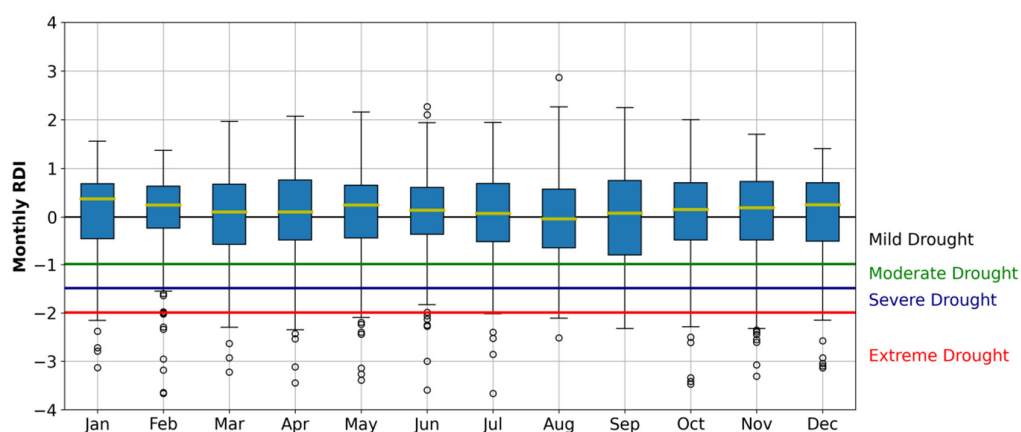


Figure 4-47: Monthly variation of RDI for RCP 4.5 scenario over 2022-2100 period

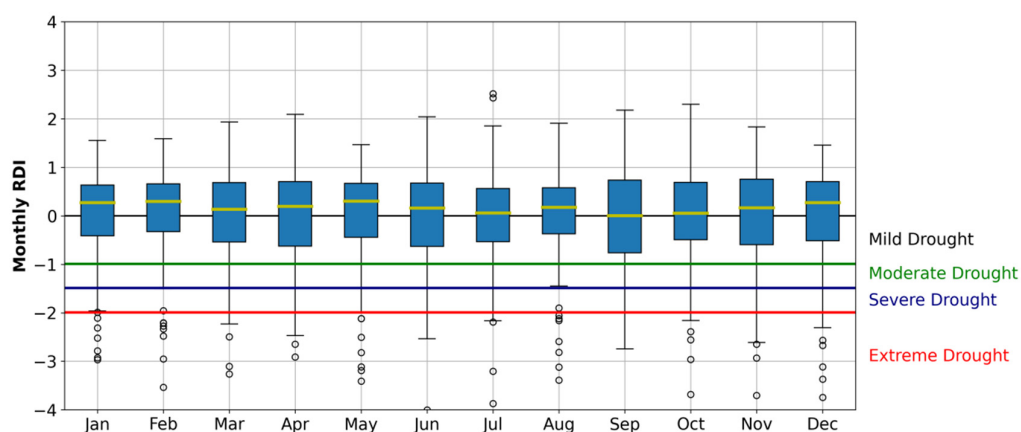


Figure 4-48: Monthly variation of RDI for RCP 4.5 scenario over 2022-2100 period

According to the monthly RDI plots shown in Figure 4-47 and Figure 4-48, the number of severe and extreme drought events is projected to be high during January (17,10), February (12,8), April (13,12), May (13,11), October (7,7) and December (11,6) for RCP 4.5 and RCP 8.5, respectively.

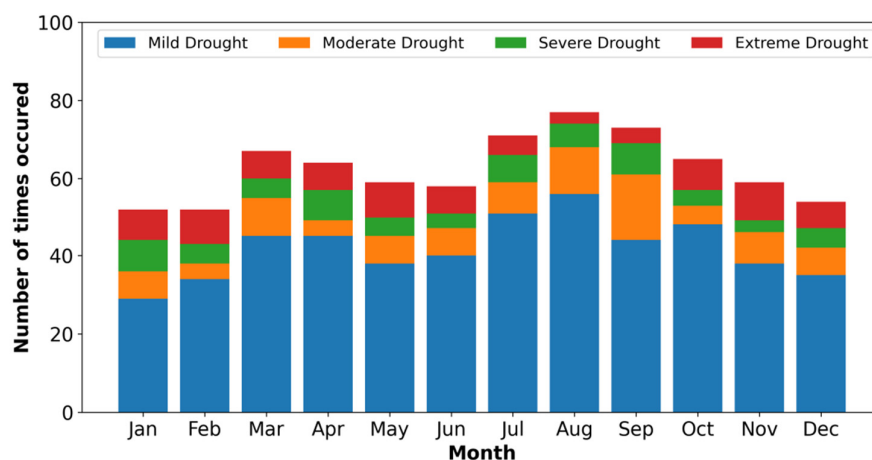


Figure 4-49: Projected frequency and severity of drought events (RCP 4.5) over 2022-2100 period

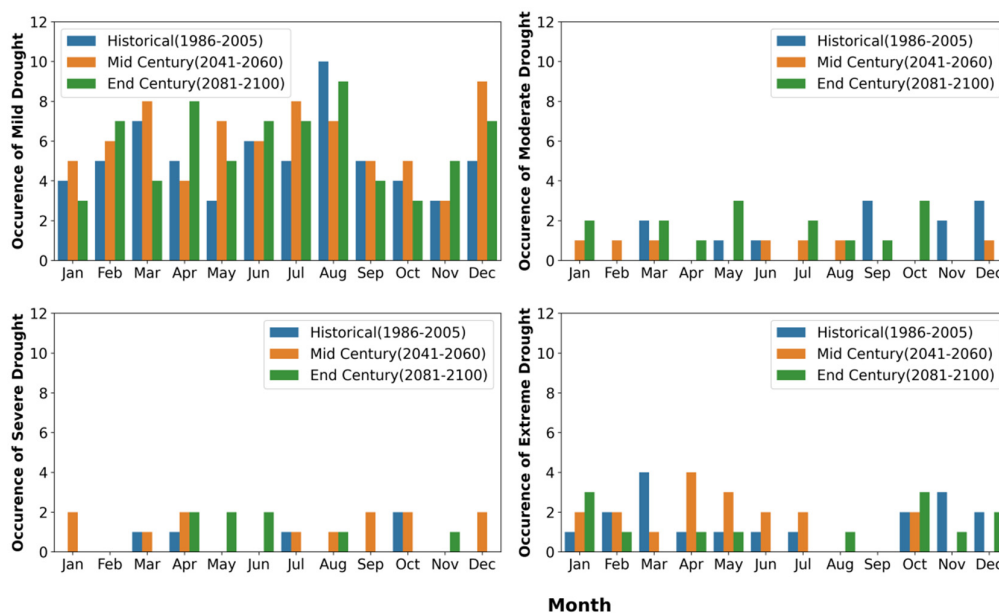


Figure 4-50: Occurrence of mild (top-left), moderate (top-right), severe (bottom-left), and extreme (bottom-right) droughts over the historical period (1950-2021) and future period (2022-2100) under RCP 4.5

As shown in Figure 4-49, under RCP 4.5, August is the month with the highest projected frequency of droughts (10) within the Maduru Oya River Basin. According to the findings presented in Figure 4-50 under RCP 4.5, more severe and extreme droughts may occur during the mid- and end-century periods (compared to the historical period). The mild droughts are projected to increase during the mid-century (70) compared to the historical and end-century periods. The frequency analysis under RCP 8.5 is depicted in Annexure 4 - 26 and Annexure 4 - 28.

4.4.2 RDI for Seasonal Timescale

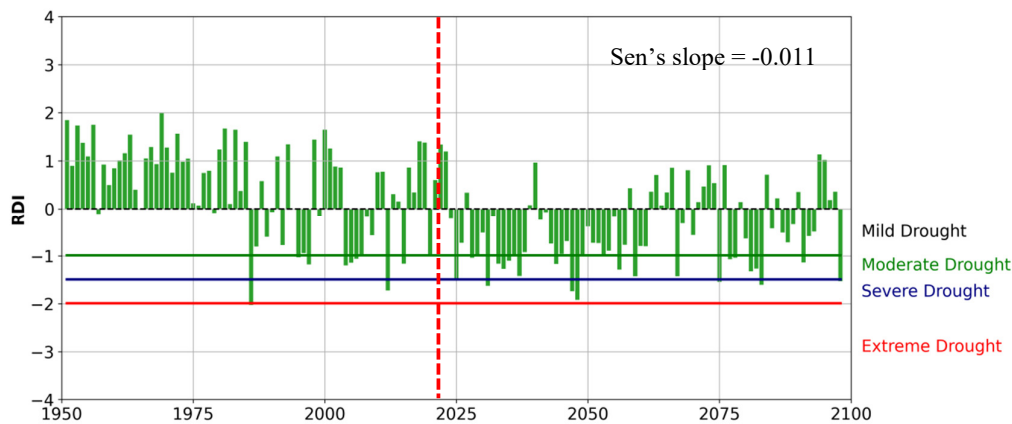


Figure 4-51: RDI for the historical Northeast Monsoonal period (Dec-Mar) for RCP 4.5

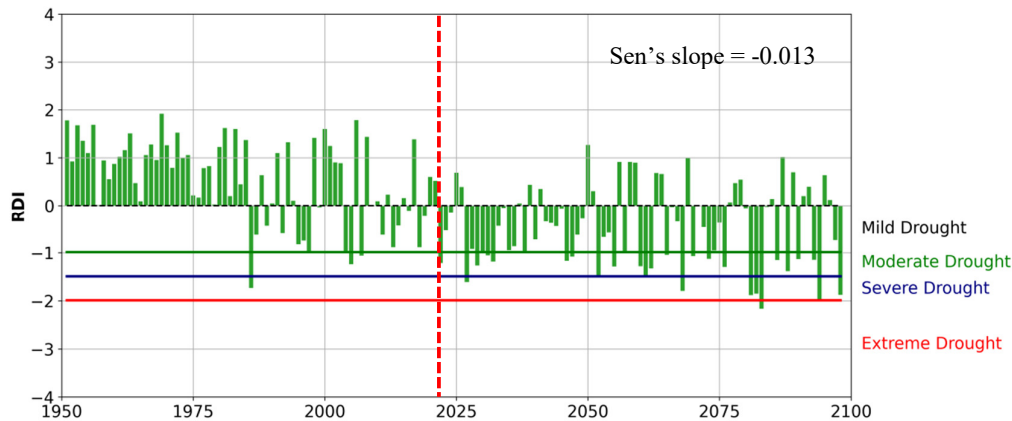


Figure 4-52: RDI for the historical Northeast Monsoonal period (Dec-Mar) for RCP 8.5

The RDI values of the Northeast Monsoon season are positive for the historical period (1951-2005) with less frequency of drought events (10). For the future period, the trend

of RDI is decreasing which means an increase of drought events is projected especially over the mid-century for both RCP 4.5 (8) and RCP 8.5 (9) (Figure 4-51 and Figure 4-52).

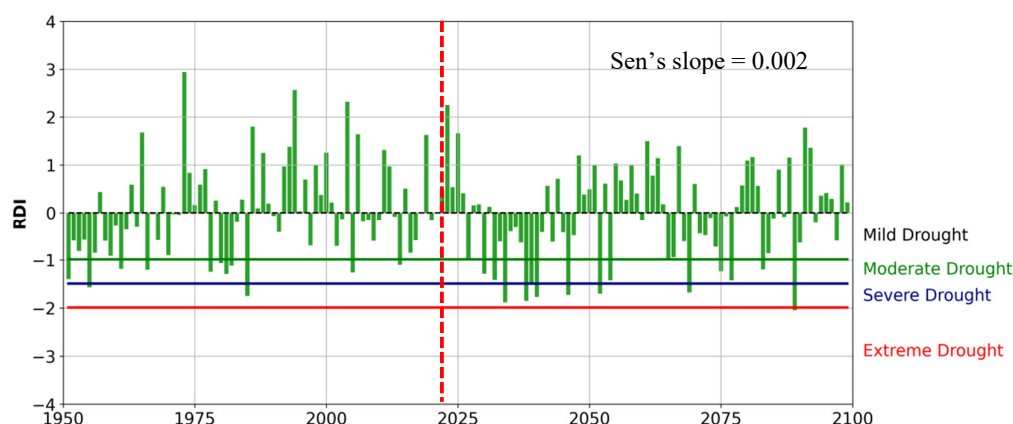


Figure 4-53: RDI for the historical Southwest Monsoonal period (May-Sep) for RCP 4.5

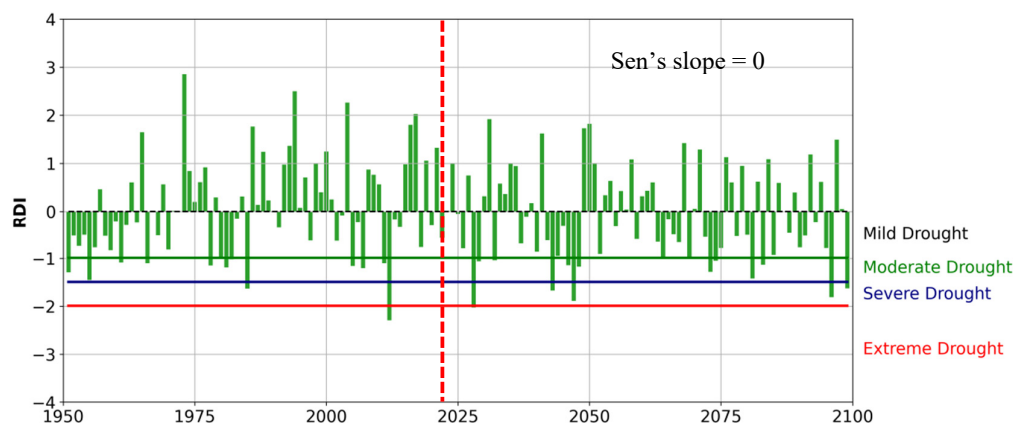


Figure 4-54: RDI for the historical Southwest Monsoonal period (May-Sep) for RCP 4.5

The above figure shows that most RDI values are negative for Southwest Monsoon for the historical period with a high frequency of mild (20) and moderate (10) drought events. The RDI trend increases under RCP 4.5 (Figure 4-53) which means a decrease in the frequency of drought events (compared to the historical period). There is no trend of RDI under RCP 8.5 (Figure 4-53). The RDI seasonal time series of the Second Inter-Monsoon, Northeast Monsoon, First Inter-Monsoon and Southwest Monsoon for both RCP scenarios are shown in Annexure 4 - 29 to Annexure 4 - 36.

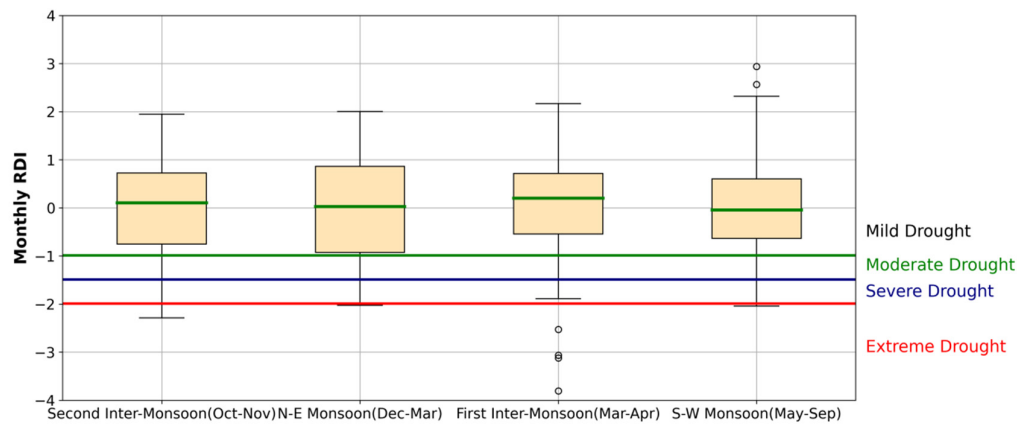


Figure 4-55: Seasonal variation of RDI for RCP 4.5 (2022-2100)

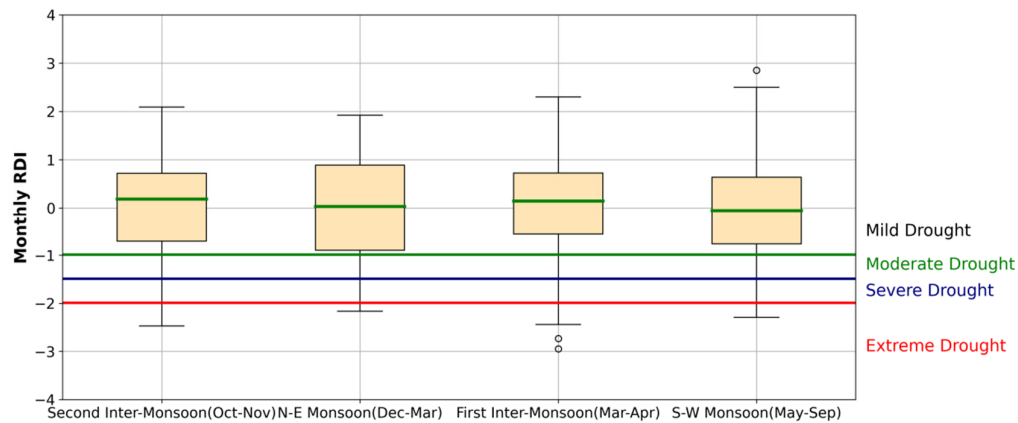


Figure 4-56: Seasonal variation of RDI for RCP 8.5 (2022-2100)

The boxplot of seasonal variation of RDI values indicate extreme drought events for every season especially in the First Inter-Monsoon under RCP 4.5 (4) and RCP 8.5 (10) (Figure 4-55 and Figure 4-56). The seasonal trend analysis of RDI using the M-K test and Sen Slope estimator is shown in

Annexure 8 - 11 and Annexure 8 - 12, respectively.

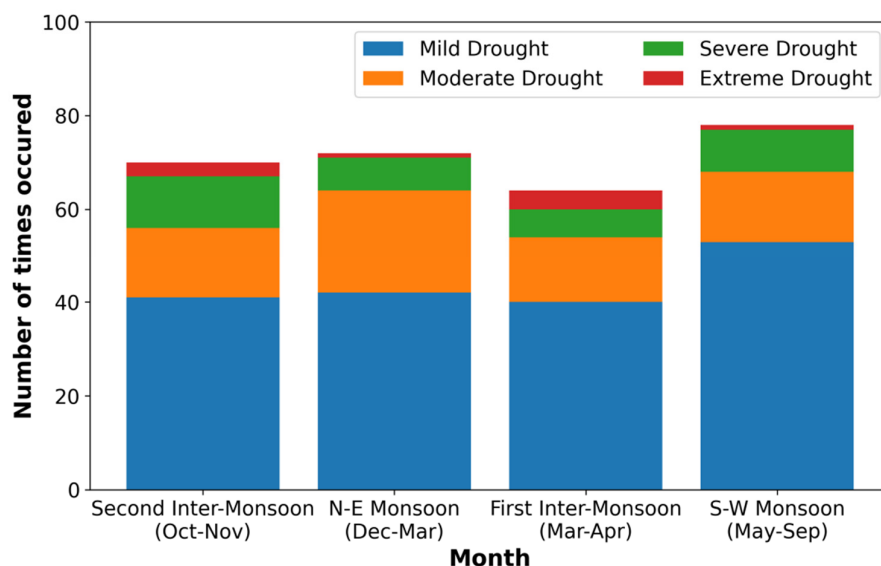


Figure 4-57: Projected frequency and severity of seasonal drought events under RCP 4.5 for 2022-2100 period

The Southwest monsoon season is projected to have the highest frequency of drought events under RCP 4.5 (70). The frequency analysis of RCP 8.5 is depicted in Annexure 4 - 38.

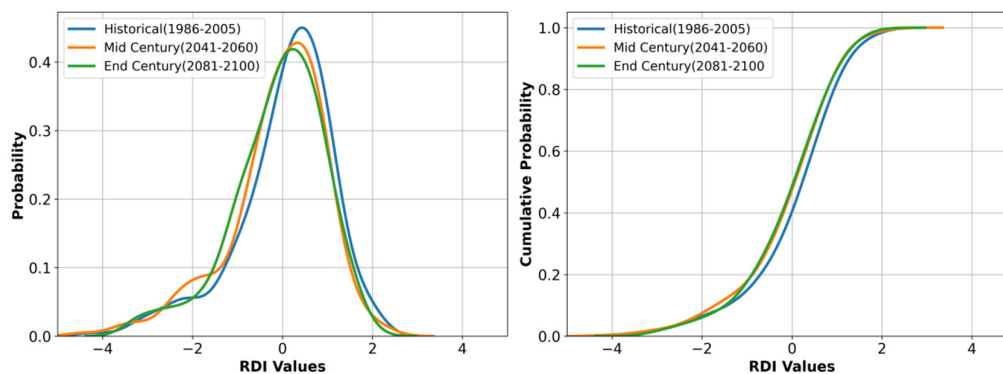


Figure 4-58: Probability of occurrence of droughts during the mid-century (left) and end-century (right) periods under RCP 4.5

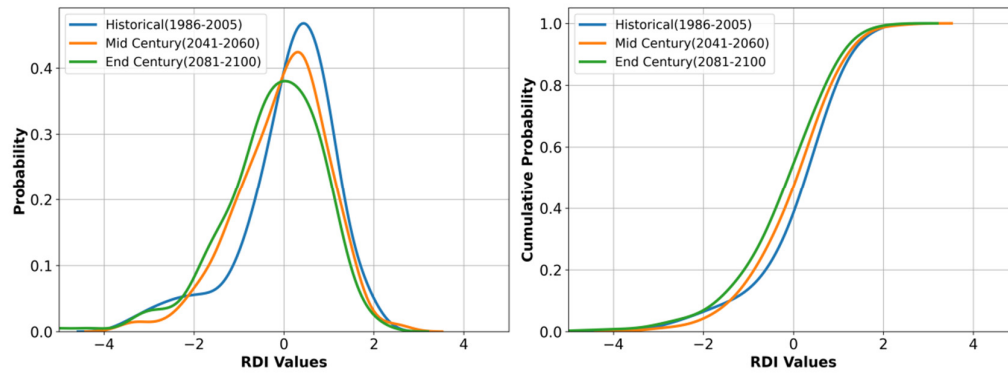


Figure 4-59: Probability of occurrence of droughts during the mid-century (left) and end-century (right) periods under RCP 8.5

The probability of zero RDI value (i.e., wet conditions) is highest for historical period as depicted in Figure 4-58 and Figure 4-59.

The probability of distribution of drought occurrence is skewed towards negative values for mid- and end-century periods under RCP 4.5 and RCP 8.5. The end-century and mid-century periods are projected to be under higher drought risk than the historical period. The end-century period is projected to have the highest drought probability (0.4) and frequency (70) under both scenarios of RCP 4.5 and RCP 8.5.

4.5 Effective Drought Index (EDI)

The bias-corrected rainfall values are used as inputs for the EDI calculation. The EDI time series at monthly timescale for the Maduru Oya river basin concerning the historical (1950-2100), recent (2006-2021) and future (2022-2100) drought risks are presented in the following sub-sections. The future drought risk time series is obtained using the projected precipitation of RCM for the RCP 4.5 and RCP 8.5.

4.5.1 EDI for Monthly Timescale

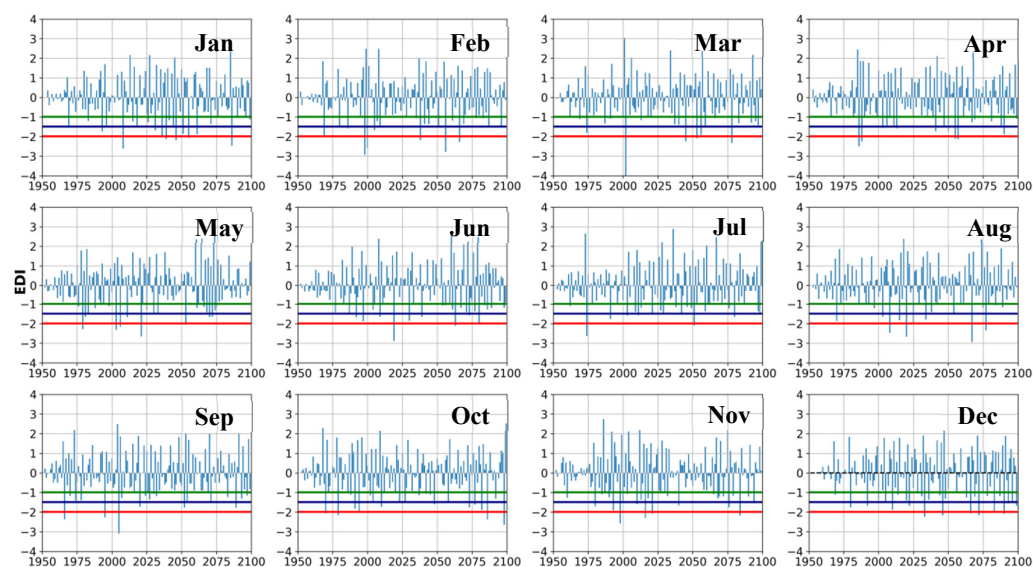


Figure 4-60: EDI values of monthly timescale for historical period and future periods under RCP 4.5

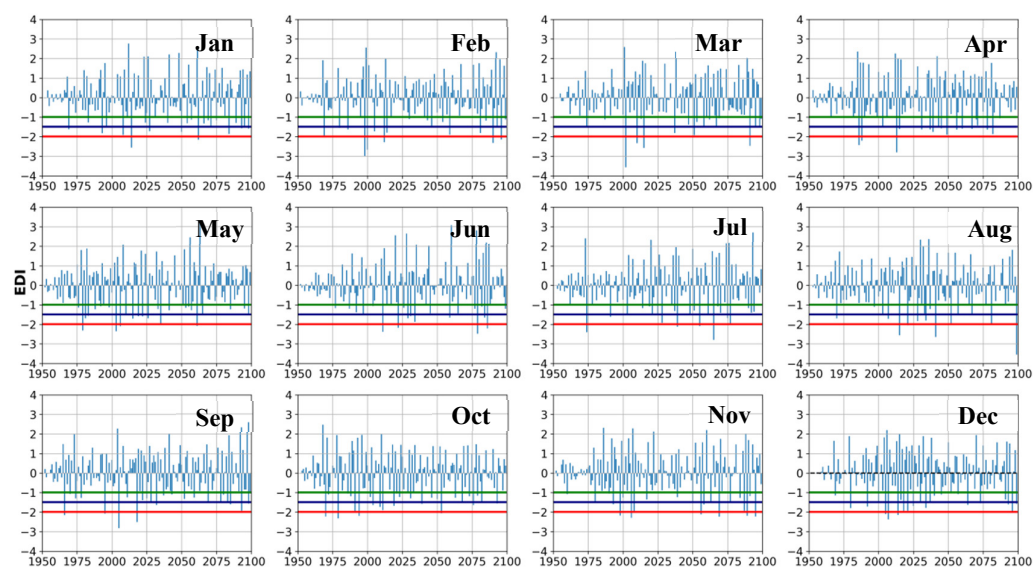


Figure 4-61: EDI values of monthly timescale for historical period and future periods under RCP 8.5

Figure 4-60 and Figure 4-61 show the EDI values at the monthly scale. It indicates that there is no particular trend of EDI for the historical (1951-2005) and recent (2006-2021) periods, as well as the future conditions under RCP 4.5 and RCP 8.5.

The trend analysis for EDI values depicting the future drought risk of the RCP 4.5 and RCP 8.5 scenarios at the monthly timescale is presented in Annexure 8 - 13 and Annexure 8 - 14. The detailed one-month time series of RCP 4.5 and RCP 8.5 are shown in Annexure 5 - 1 and Annexure 5 - 24, respectively.

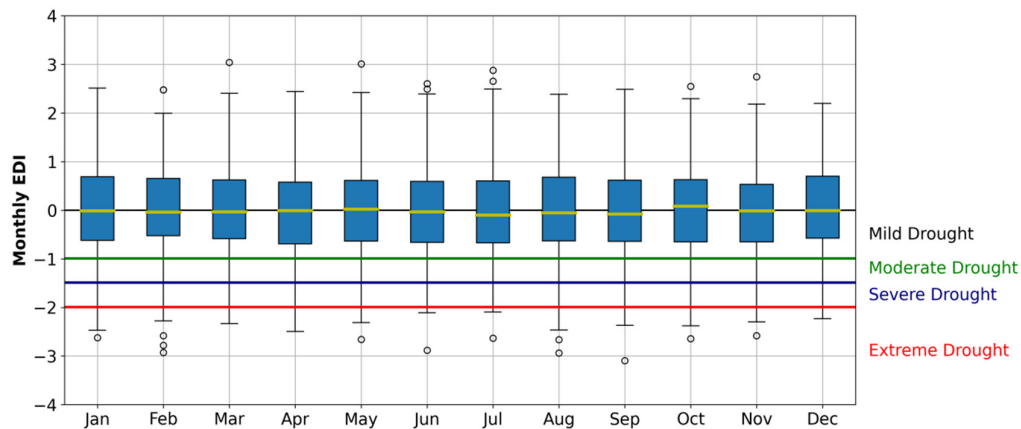


Figure 4-62: Monthly variation of EDI for RCP 4.5 scenario over 2022-2100

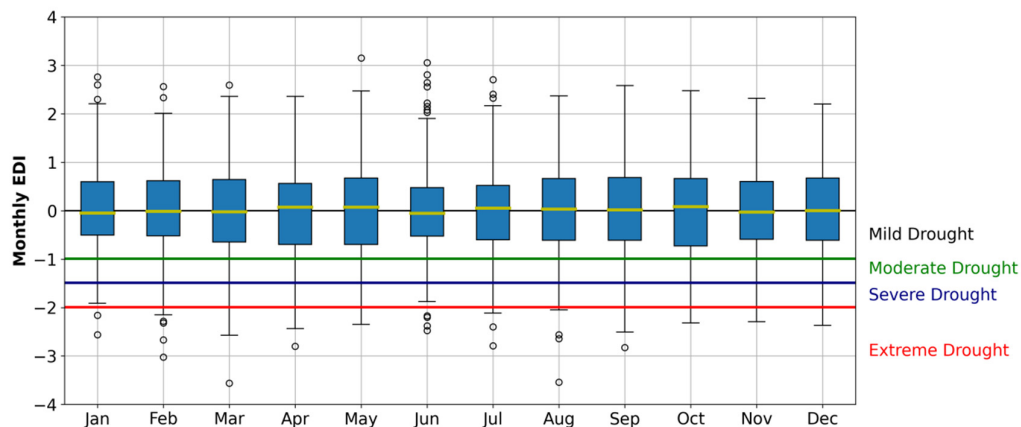


Figure 4-63: Monthly variation of EDI for RCP 8.5 scenario over 2022-2100

The number of severe and extreme drought events is projected to be high for January (10,10), April (9,13), September (5,10), October (9,9), November (7,12) and December (11,13) under RCP 4.5 and RCP 8.5, respectively (Figure 4-62 and Figure 4-63).

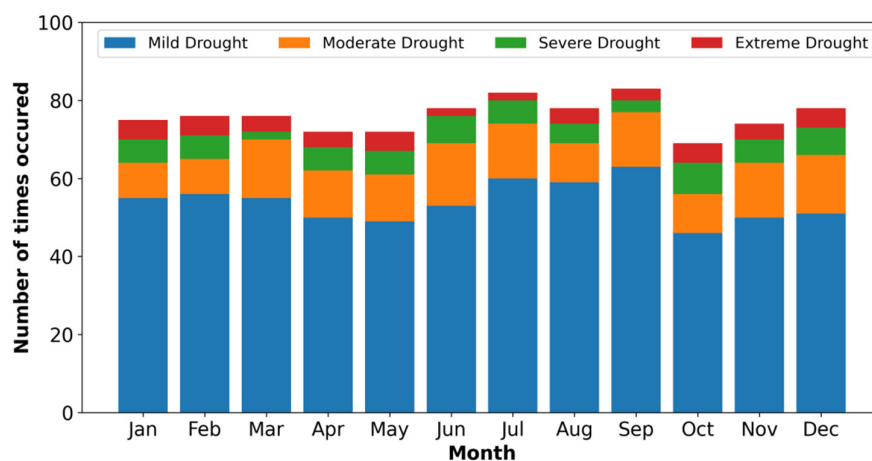


Figure 4-64: Projected frequency and severity of drought events under RCP 4.5 over 2022-2100 period

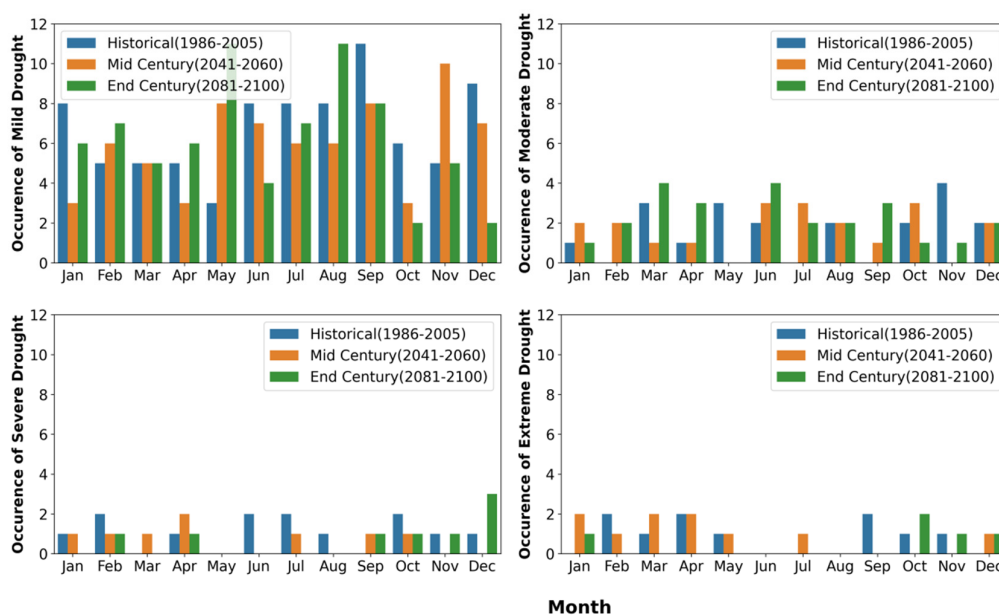


Figure 4-65: Occurrence of mild (top-left), moderate (top-right), severe (bottom-left), and extreme (bottom-right) droughts over the historical period (1950-2021) and future period (2022-2100) under RCP 4.5

Figure 4-64 shows that, under RCP 4.5, July (80) and September (80) are projected to have the highest frequency of droughts within the Maduru Oya River Basin. The comparison of historical drought events with the mid- and end-century projections under RCP 4.5 is shown in Figure 4-65. It indicates the occurrence of more moderate

(30), severe (10) and extreme (5) droughts during the future end-century periods (compared to the historical period). The frequency analysis concerning RCP 8.5 projections is shown in Annexure 5 - 26.

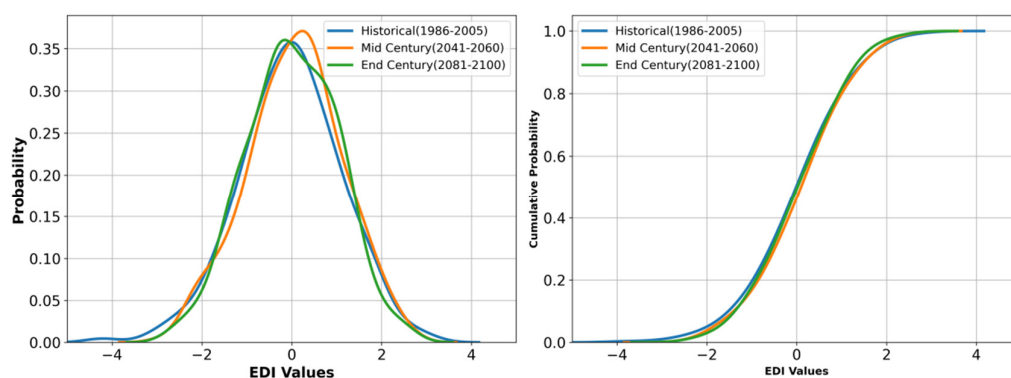


Figure 4-66: Probability of drought occurrence during mid and end-century (RCP 4.5)

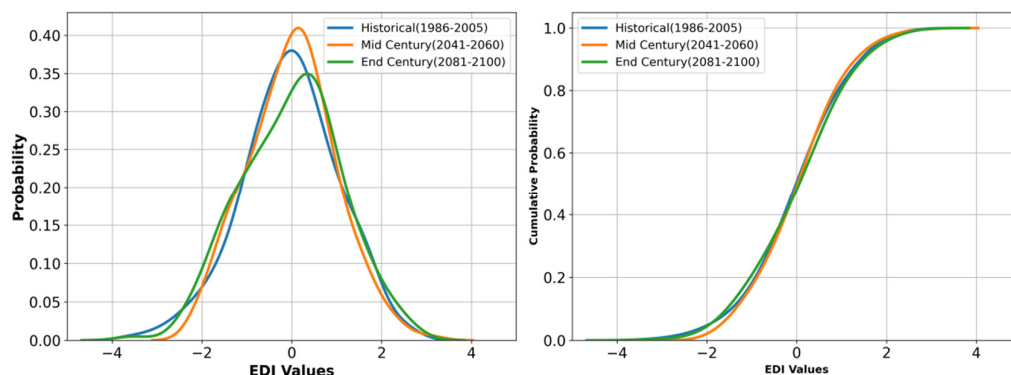


Figure 4-67: Probability of drought occurrence during mid and end-century (RCP 8.5)

Figure 4-66 and Figure 4-67 show the probability of zero EDI value (i.e., the wet conditions) is highest for the mid-century period for RCP 4.5 and RCP 8.5.

The probability distribution of drought occurrence is skewed towards the negative EDI values during the end-century period under RCP 4.5 and RCP 8.5. Under RCP 4.5, the end-century is projected to have a higher drought risk (40%) than historical (35%) and mid-century (35%) periods. The end-century time periods is projected to have the highest drought probability (40%), and frequency (70) under RCP 4.5 and RCP 8.5 scenarios, respectively.

4.6 Lumped HEC-HMS Model

Lumped HEC-HMS model was developed for the Padiyathalawa watershed to assess how the Maduru Oya River basin's streamflow will change in the future. There were no reach and junction components since river routing is not considered within the lumped model. The continuous streamflow was calculated using this model. The period of calibration was selected from 01-October-2004 to 30-September-2008, and the period of validation was selected from 01-October-2008 to 30-December-2012. The Coefficient of determination, RMSE standard deviation and Nash-Sutcliffe objective functions were evaluated to determine the model performances. The model's performance is evaluated using the criteria mentioned in Table 2-3.

There would be significant differences between the simulated and observed streamflow for validation due to the non-stationary precipitation conditions. As a result, only the changes in the baseflow model was considered in this study.

4.6.1 Initial Parameters Statistical Goodness of Fit Measures

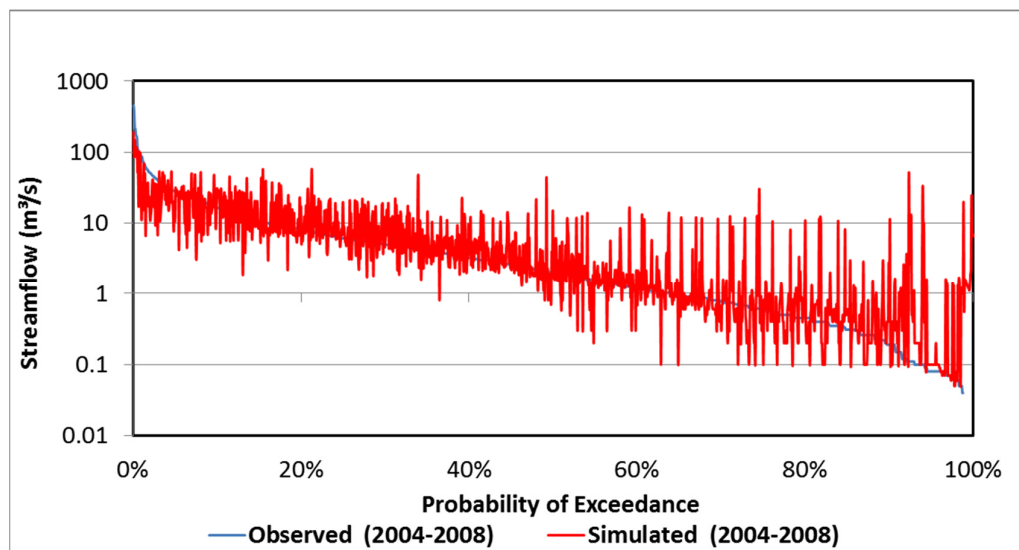


Figure 4-68: Flow duration curve for initial parameters

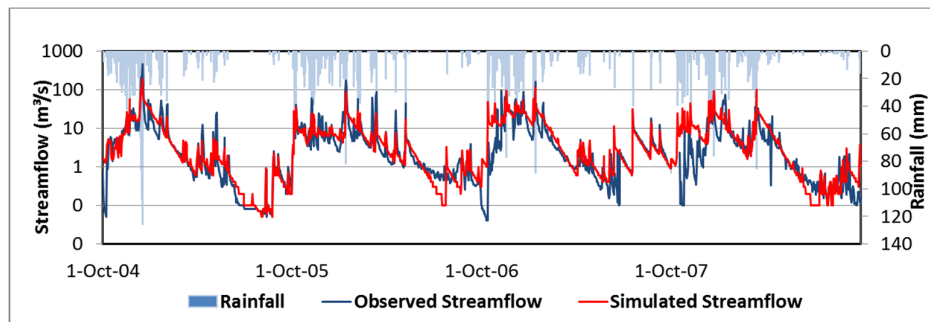


Figure 4-69: Hydrograph for the simulation run over four continuous years (2004-2008)

According to Figure 4-68, the model slightly overestimated the low flows and somewhat underestimated high flows. As shown in Figure 4-69, the model does not produce satisfactory results for the four year run. The model performance for the one and four-year simulations are summarized in Table 4-2.

Table 4-2: HEC-HMS model performance for simulation run

Simulation Run	NSE	R ²	RMSE Std. Dev.	PBIAS (%)
2004-2005	0.53	0.74	0.63	-23.81
2005-2006	0.50	0.73	0.68	-25.55
2006-2007	0.51	0.71	0.72	16.03
2007-2008	0.44	0.73	0.7	25.46
2004-2008	0.48	0.71	0.64	34.03

Except for the 2007-2008 and four-year simulations, the results show satisfactory performance when the respective hydrograph are compared (Figure 4-71) matching except for the year 2007-2008. The flow duration curve for the one-year simulation (2004-2008) for the calibration period is shown in Figure 4-70. The hydrograph resulting from the initial calibration parameters is shown in Figure 4-71. The model parameters were optimized to obtain satisfactory results for the calibration period.

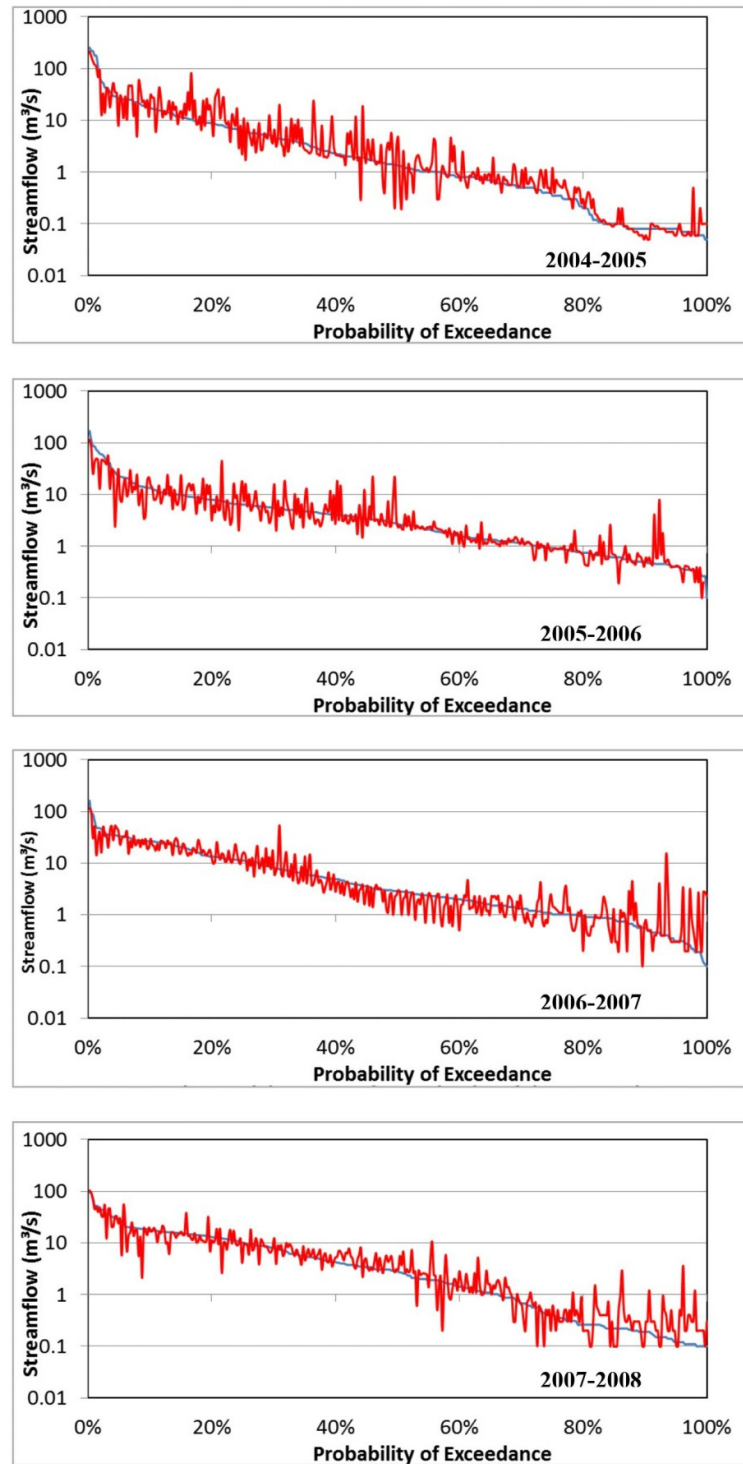


Figure 4-70: Flow duration curves of the simulations with initial parameters of the calibration period

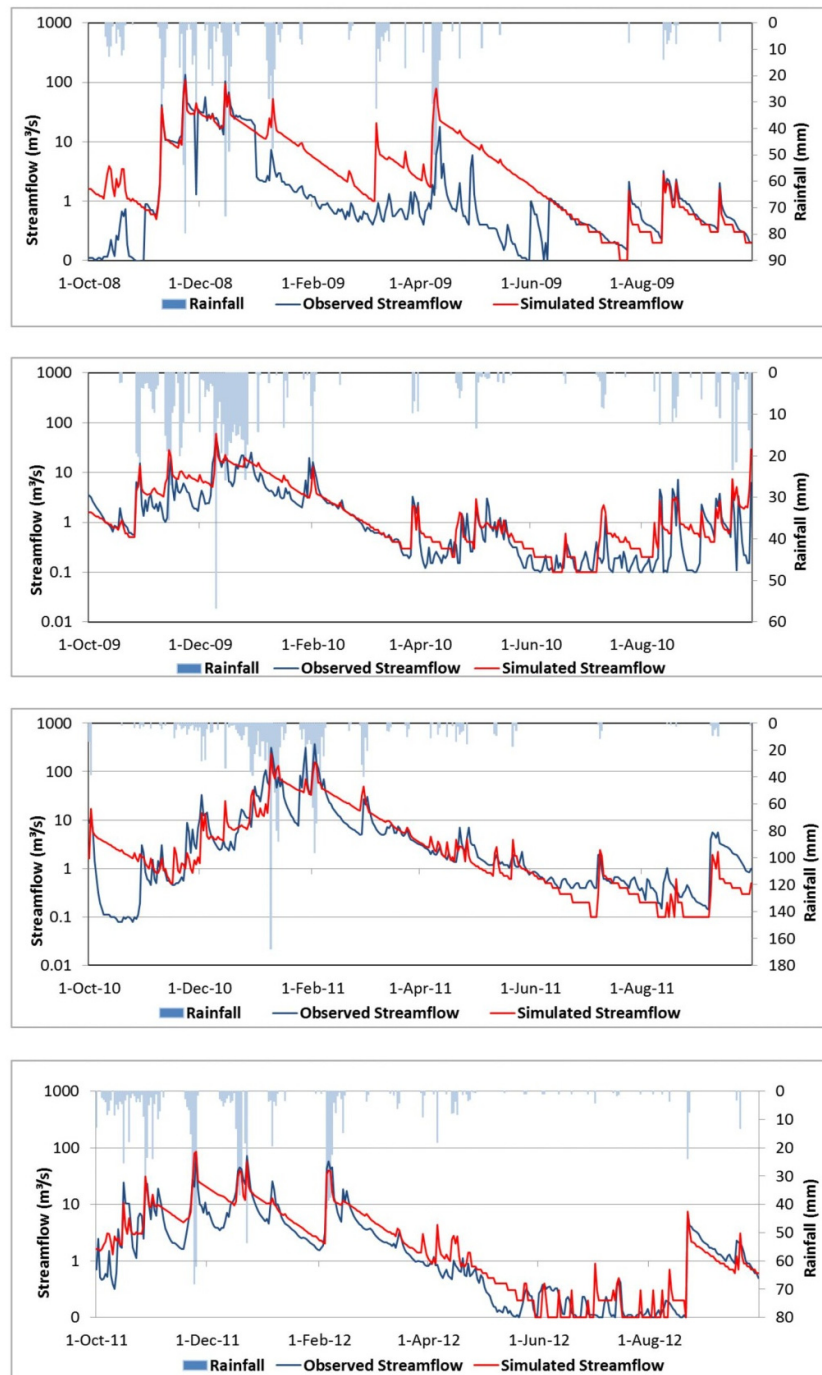


Figure 4-71: Hydrographs resulting from the initial parameters for the calibration period

4.6.2 Optimization of Parameters

The initial storage (%), initial discharge (m^3/s), recession constant, and threshold ratio are the selected optimized parameters during the model calibration. The optimized model parameters are summarized in Table 4-3.

Table 4-3: Optimization results of HEC-HMS parameters

Method	Input	Initial Value	Optimized Value
Canopy	Initial storage (%)	0	0.18
	Maximum storage (%)	1.37	1.37
	Impervious (%)	11.2	11.2
Loss	Constant rate (mm/hr)	1.27	1.29
	Maximum deficit (mm)	109.33	109.33
	Initial deficit (mm)	21.87	21.87
Transform	Lag time (min)	148	148
	Initial discharge (m^3/s)	4.65	10.7
Recession	Recession constant	0.95	0.94
	Threshold ratio	0.2	0.15

4.6.3 Optimum Parameters in Calibration Period for the Lumped Model

The flow duration curve in the calibration period and hydrograph generated after parameter optimization is shown in Figure 4-72 and Figure 4-73, respectively. Figure 4-72 shows that the model slightly underestimated the high flow and somewhat overestimated the low flow conditions. The model produces good results for the four-year simulation. The model performances for one and four-year simulations run are summarized in Table 4-4.

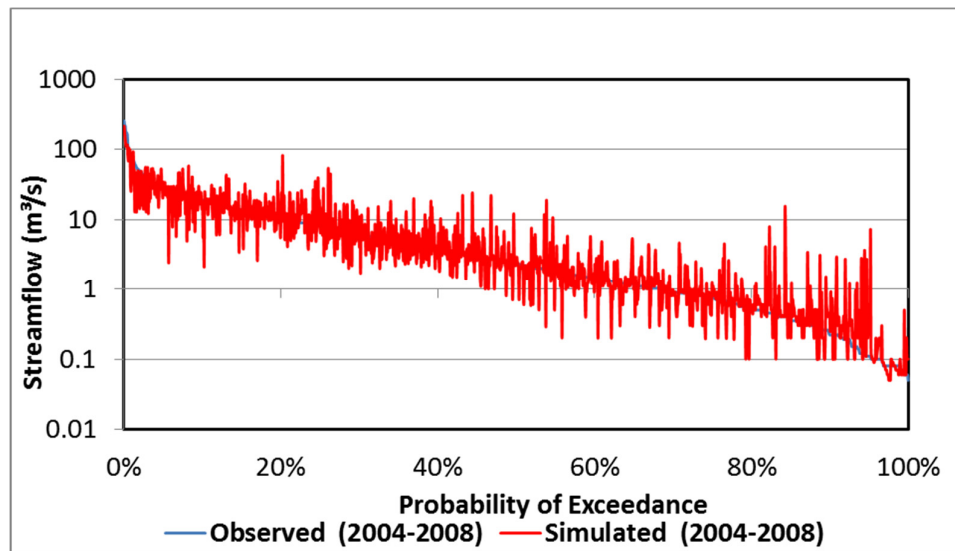


Figure 4-72: Flow duration curve for the calibration period for Padiyathalawa watershed

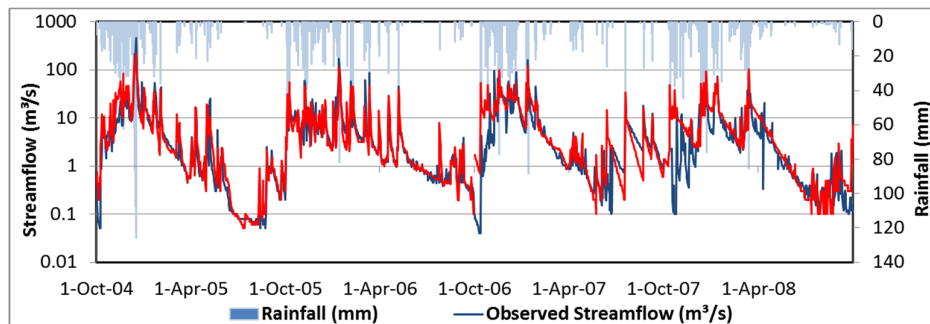


Figure 4-73: Hydrograph resulting from the optimised simulation of four continuous years

Table 4-4: HEC-HMS model performance after parameter optimization

Simulation Run	NSE	R ²	RMSE Std. Dev.	PBIAS (%)
2004-2005	0.68	0.81	0.58	-6.02
2005-2006	0.63	0.73	0.50	-9.16
2006-2007	0.63	0.79	0.61	8.15
2007-2008	0.58	0.81	0.7	11.81
2004-2008	0.68	0.81	0.57	4.55

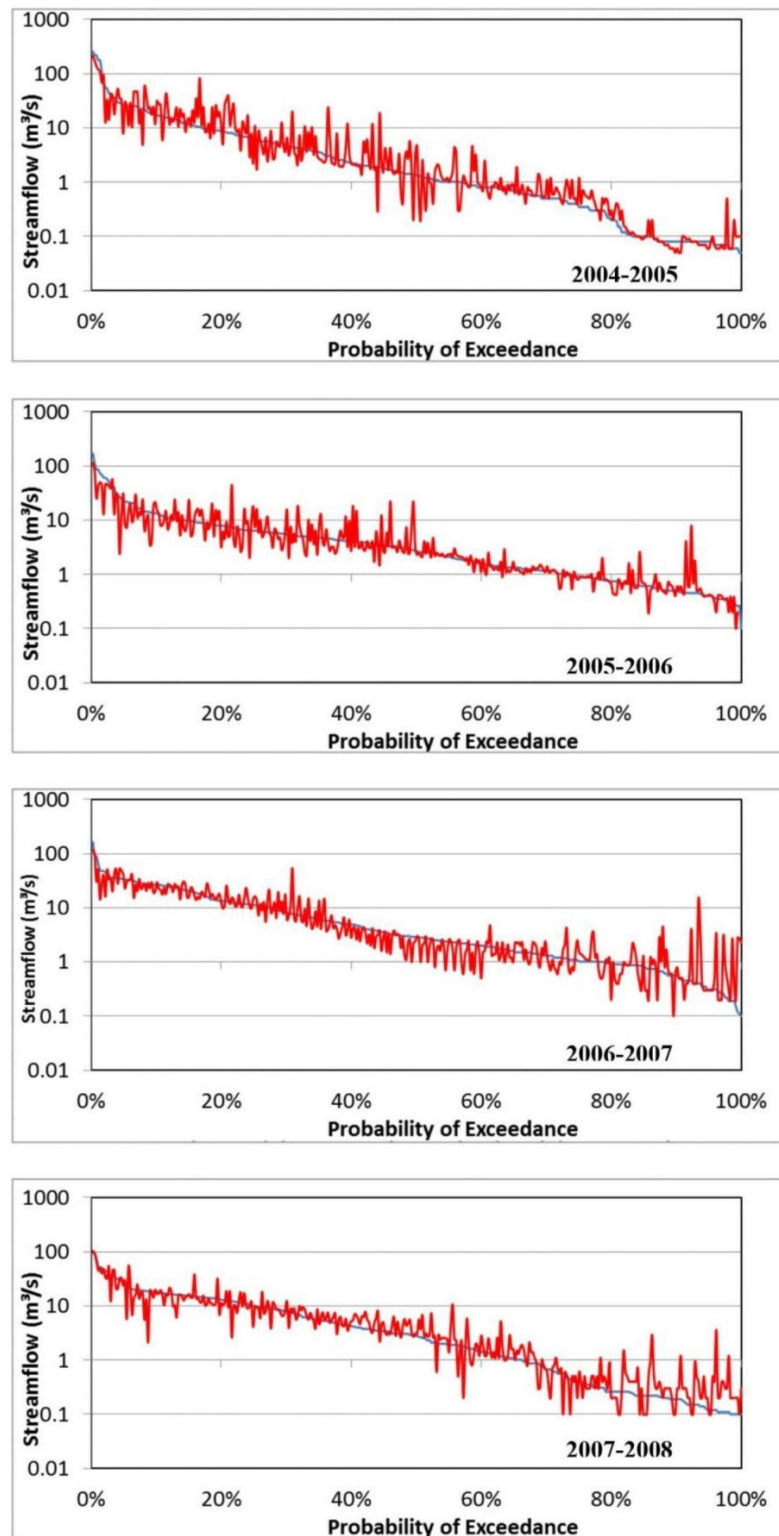


Figure 4-74: Flow duration curve for each year in the calibration period

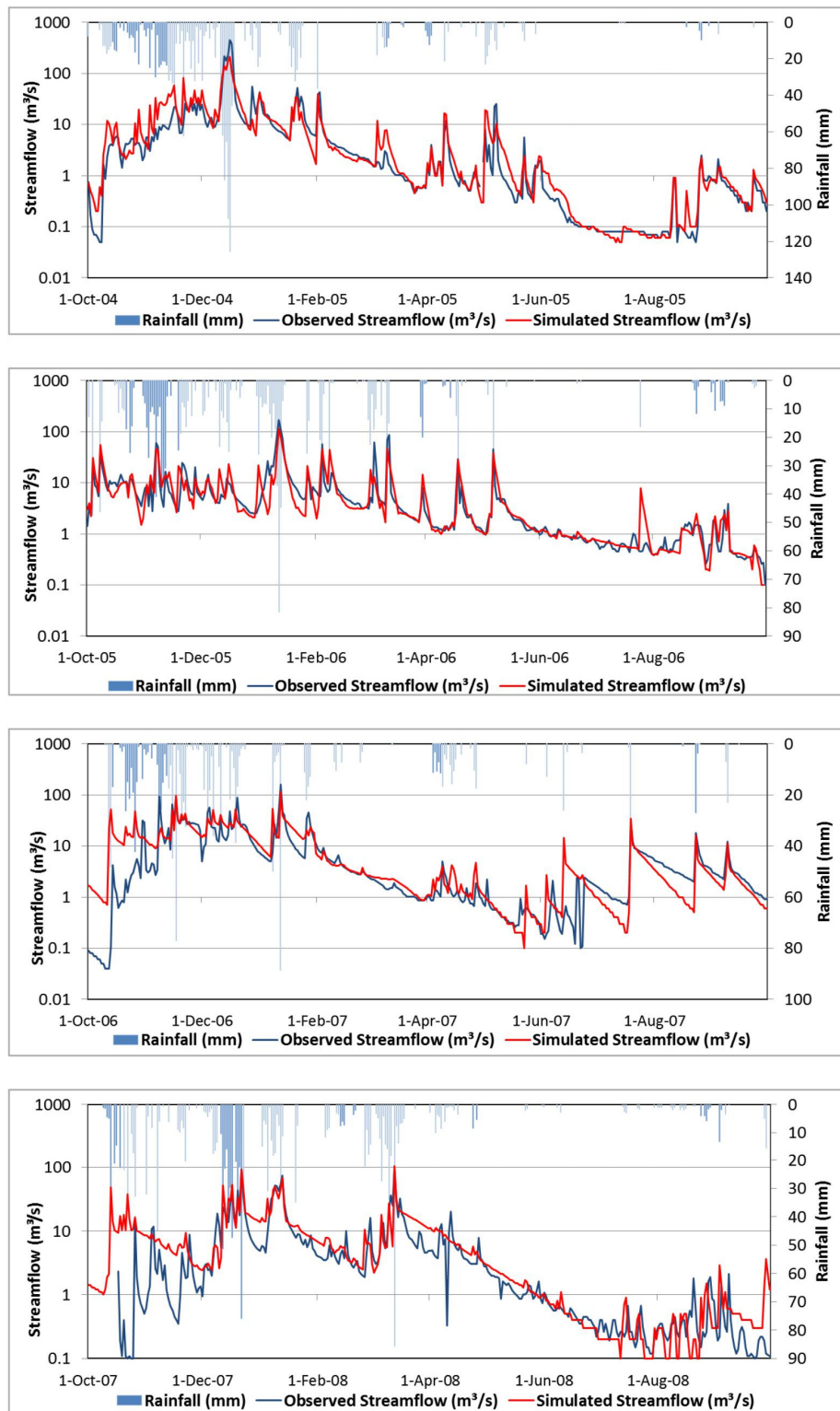


Figure 4-75: Hydrograph of optimized parameters in the calibration period

4.6.4 Lumped Model Result for Validation Period

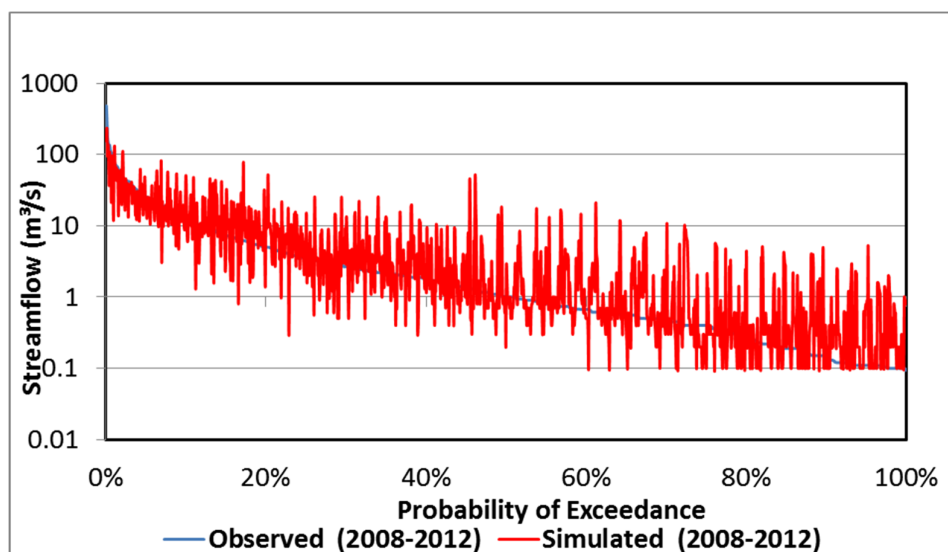


Figure 4-76: Flow duration curve of the lumped model for validation period

Table 4-5: HEC-HMS model performance for validation run

Simulation Run	NSE	R ²	RMSE Std. Dev.	PBIAS (%)
2008-2009	0.59	0.72	0.61	18.44
2009-2010	0.60	0.75	0.61	20.44
2010-2011	0.57	0.71	0.61	-13.27
2011-2012	0.57	0.76	0.55	13.62
2008-2012	0.59	0.72	0.60	9.83

The flow duration curve for the validation period is shown in Figure 4-76. The model produces satisfactory results for four year run. The model performance for the four-year simulation ($R^2=0.72$) is summarized in Table 4-5, and the flow duration curves for one year validation periods is shown in Figure 4-77.

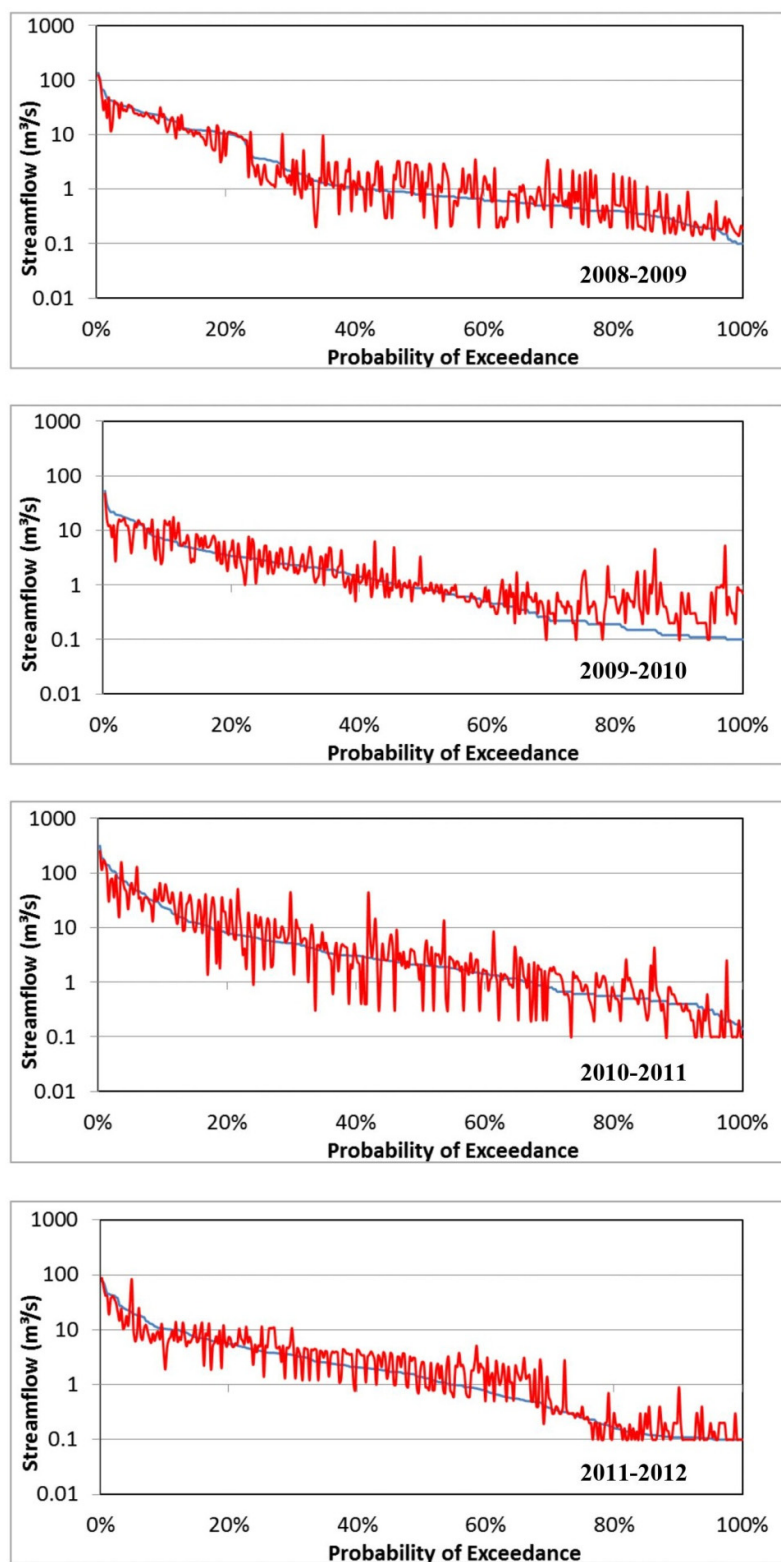


Figure 4-77: Flow duration curve for each year of the validation period

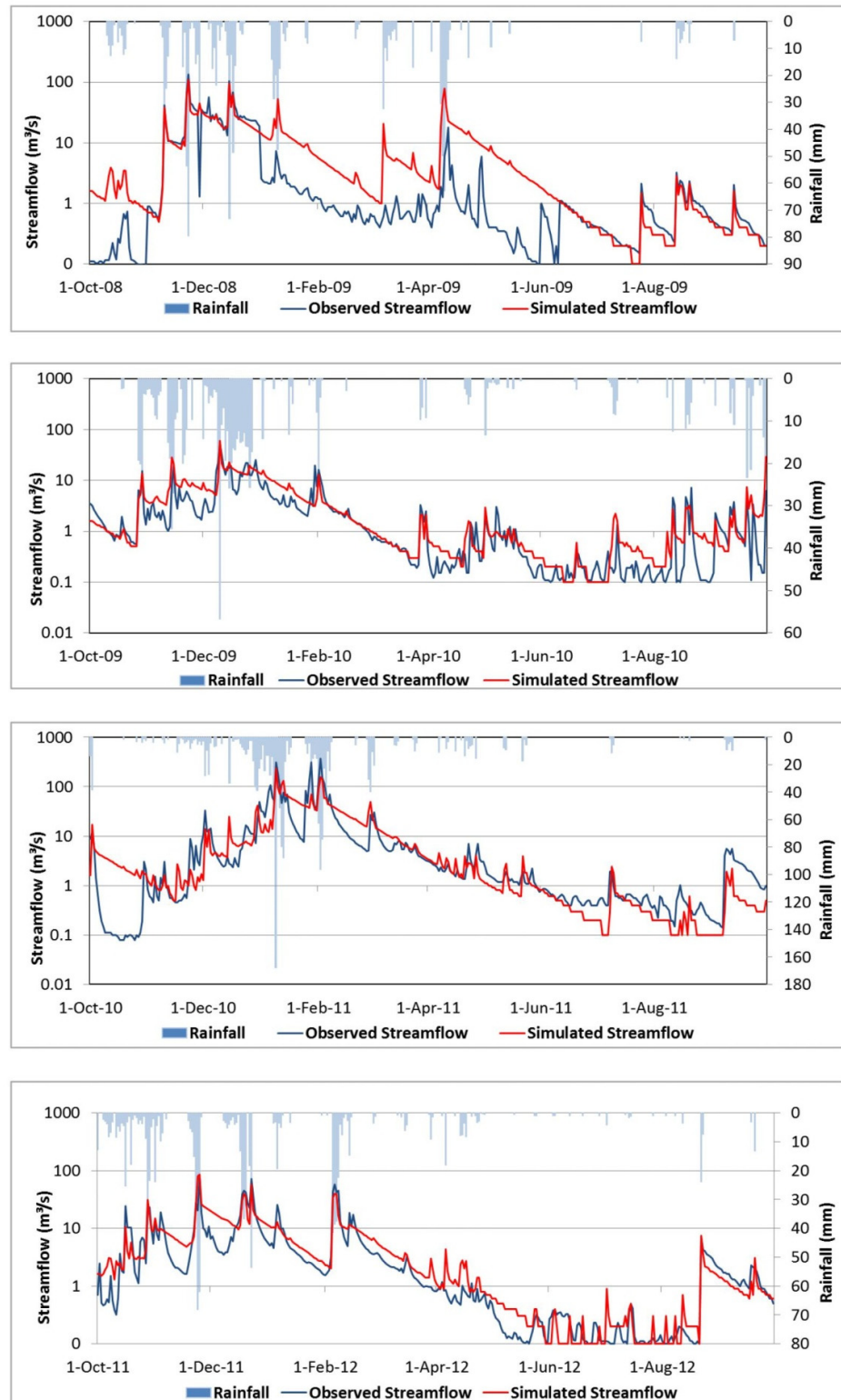


Figure 4-78: Simulated hydrograph for the validation period (2008-2012)

4.6.5 Future Streamflow Variation in Padiyathalawa Watershed

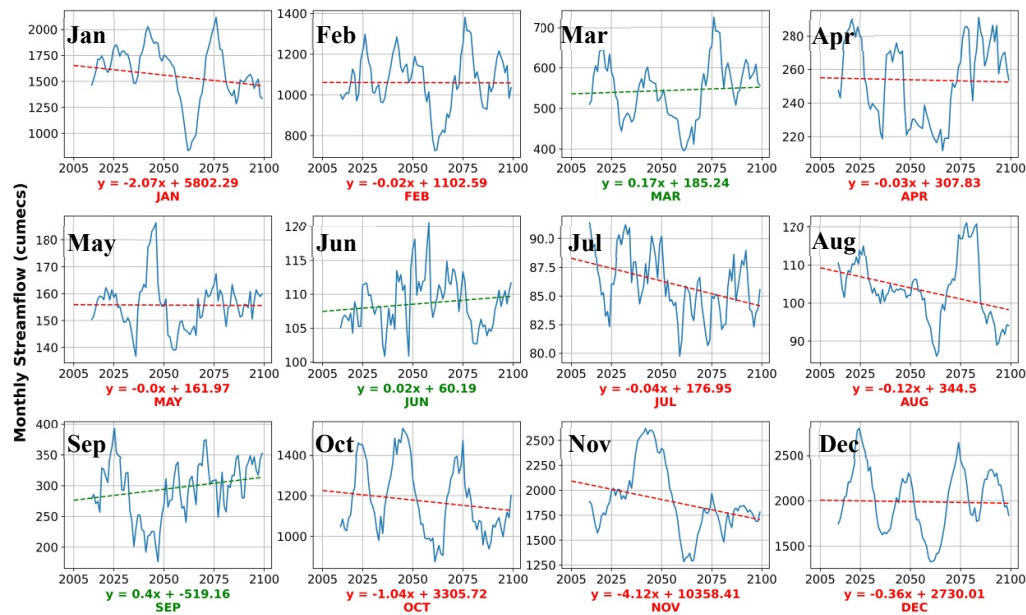


Figure 4-79: Projected streamflow trend over the 21st-century under RCP 4.5

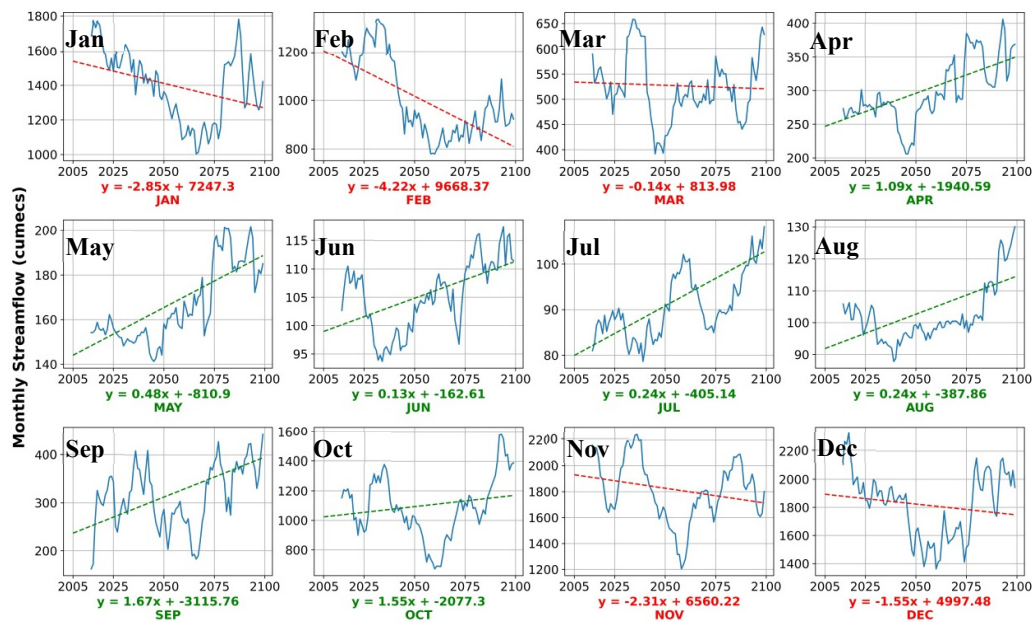


Figure 4-80: Projected streamflow trend over the 21st-century under RCP 8.5

4.7 Standardized Runoff Index (SRI)

SRI is calculated using streamflow values obtained from the calibrated HEC-HMS model. The SRI time series at monthly and seasonal timescales for the Maduru Oya River Basin concerning the recent and future drought risks are presented in the following sub-sections. The future drought risk time series are obtained using the generated streamflow from projected precipitation of RCM for RCP 4.5 and RCP 8.5.

4.7.1 SRI for Monthly Timescale

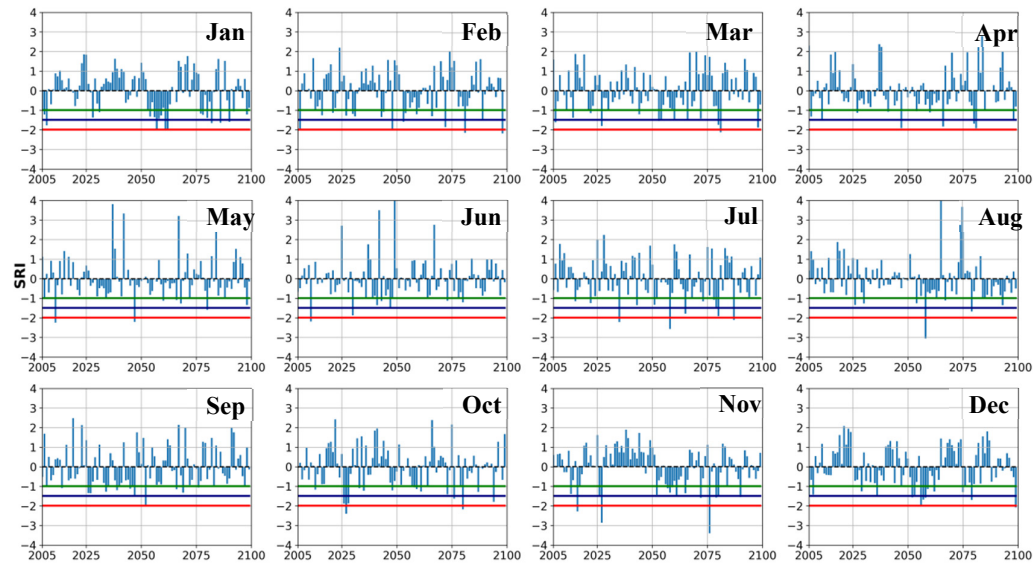


Figure 4-81: SRI values of monthly timescale for historical and future periods under RCP 4.5



Figure 4-82: SRI values of monthly timescale for historical and future periods under RCP 8.5

Figure 4-81 and Figure 4-82 show the monthly scale SRI for the recent (2006-2021) and future (2022-2099) conditions. These are mild and moderate droughts projected for every month under RCP 4.5 and RCP 8.5. For the future period, the frequency of negative SRI values is projected to increase with a high number of severe (15) and extreme (5) drought conditions for RCP 4.5 (compared to the recent period of 2006-2021 and end-century period of 2022-2099).

The trend analysis for SRI values depicting the future drought risks under RCP 4.5 and RCP 8.5 are summarized in

Annexure 8 - 15 and Annexure 8 - 16, respectively.

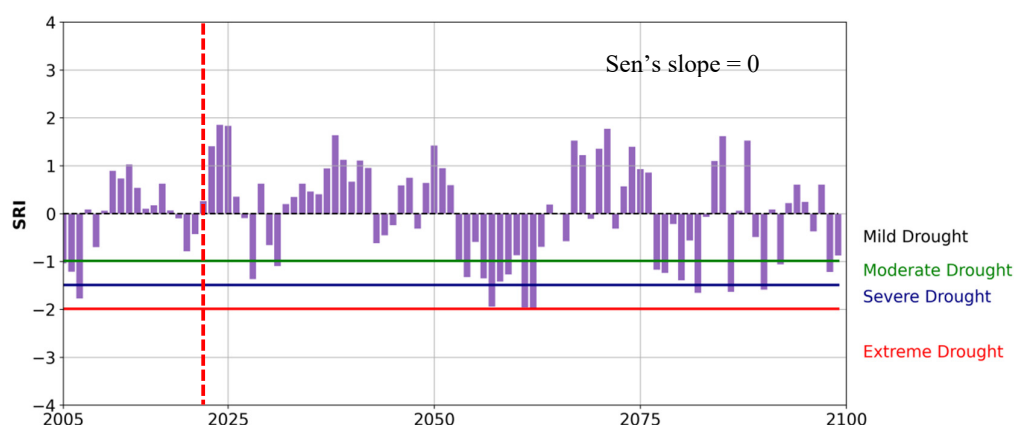


Figure 4-83: SRI values of January for the recent period (2005-2021) and future period (2022-2100) under RCP 4.5

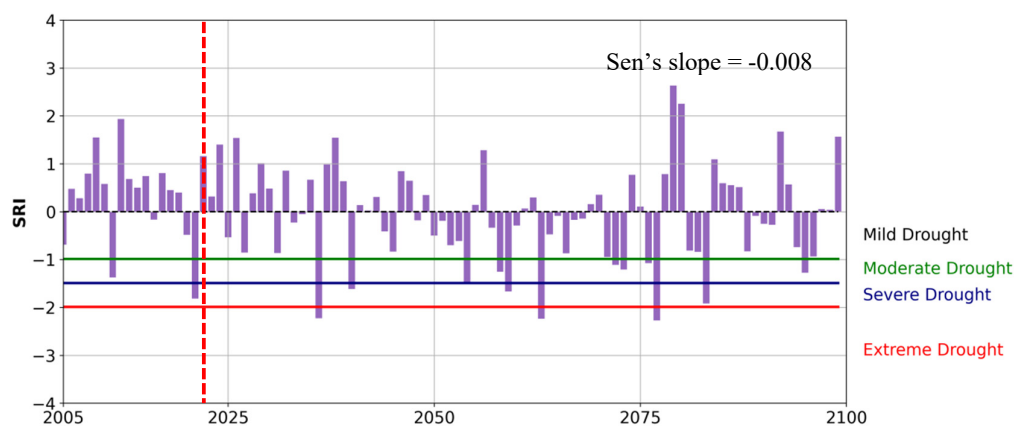


Figure 4-84: SRI values of January for the recent period (2005-2021) and future period (2022-2100) under RCP 8.5

The SRI time series for January is shown in Figure 4-83 (RCP 4.5) and Figure 4-84 (RCP 8.5). The recent period (2006- 2021) mostly has positive SRI values. For the future period (2022-2099), SRI values are projected to decrease under RCP 8.5 as depicted by Sen's slope values. The frequencies of severe (15) and extreme (5) droughts are projected to increase for mid-century scenarios (with respect to the recent period). The SRI time series of all months are shown in Annexure 7 - 1 to Annexure 7 - 24 for RCP 4.5 and RCP 8.5 scenarios.

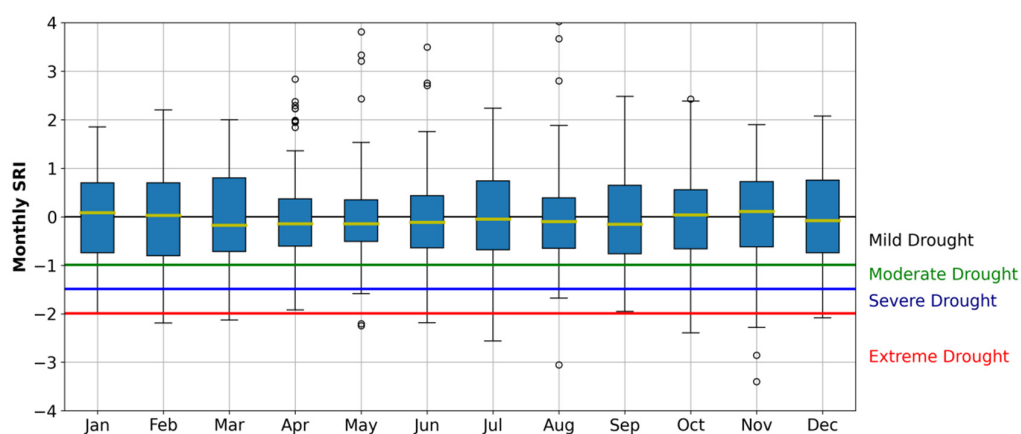


Figure 4-85: Monthly variation of SRI for RCP 4.5 scenario over 2022-2100 period

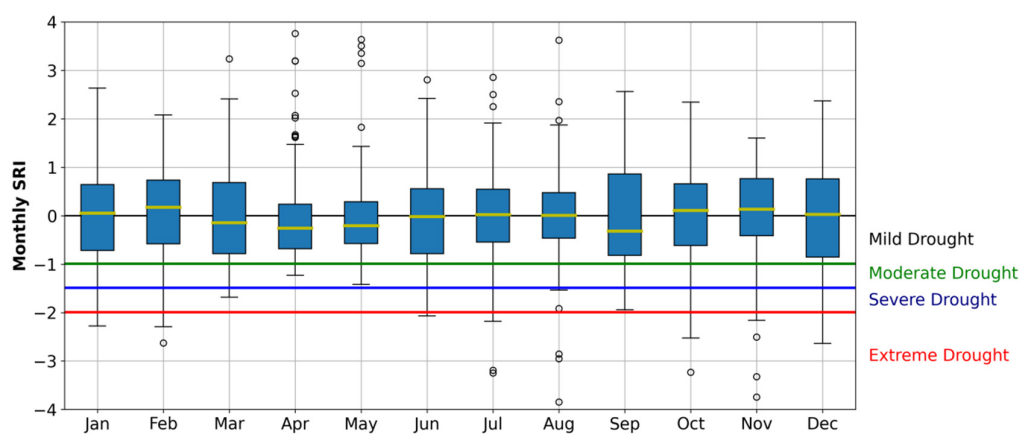


Figure 4-86: Monthly variation of SRI for RCP 8.5 scenario over 2022-2100 period

According to Figure 4-85 and Figure 4-86, the number of extreme drought events is projected to be high during July (4), August (3), October (5), and November (5) for RCP 8.5.

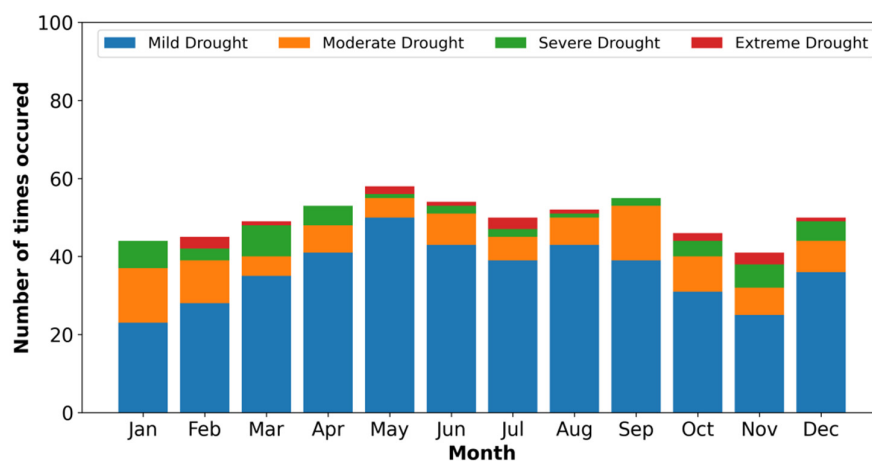


Figure 4-87: Projected frequency and severity of drought events under RCP 4.5 for 2022-2100 period

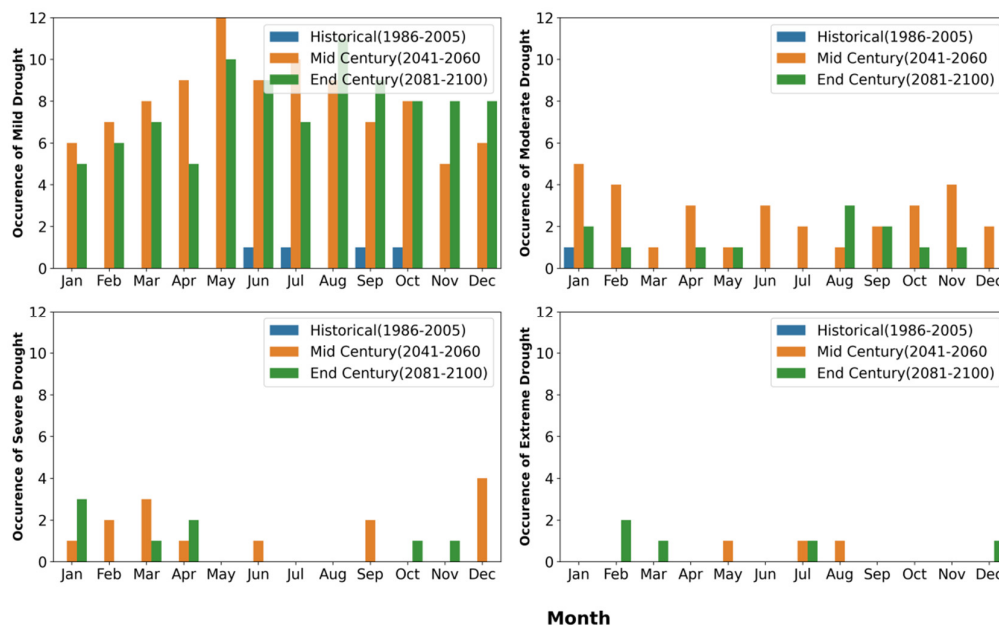


Figure 4-88: Occurrence of mild (top-left), moderate (top-right), severe (bottom-left), and extreme (bottom-right) droughts over the historical (1986-2005) and future periods (2022-2100) under RCP 4.5

Figure 4-87 shows that, under RCP 4.5, May has the highest projected frequency of droughts (20) within the Maduru Oya River Basin. The comparison of historical drought events with mid-century and end-century projections under RCP 4.5 (Figure 4-88) indicates the occurrence of mild (90), moderate (30), severe (15) and extreme

(3) droughts during mid-century periods (compared to the historical period (5)). The frequency analysis for the projections under RCP 8.5 is shown in Annexure 7 - 26 and Annexure 7 - 28.

4.7.2 SRI for Seasonal Timescale

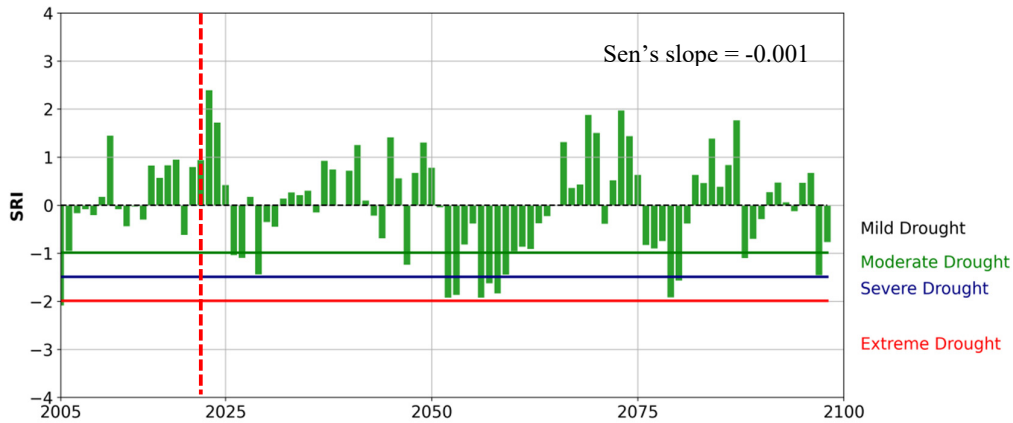


Figure 4-89: SRI for the recent and Northeast Monsoonal period (Dec-Mar) under RCP 4.5

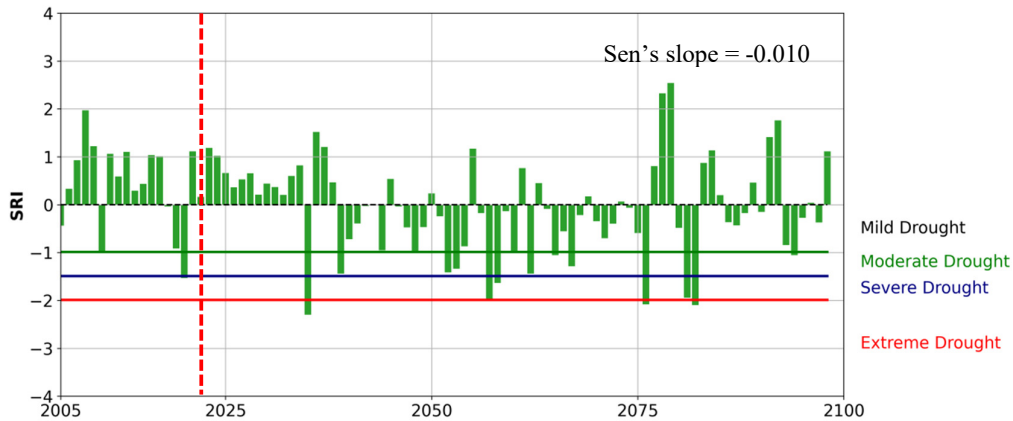


Figure 4-90: SRI for the recent and Northeast Monsoonal period (Dec-Mar) under RCP 8.5

The SRI values of the Northeast Monsoon period are positive for the recent period (2005-2021) with less frequency of drought events (5). For the future period, the trend of SRI is decreasing, which means an increase of projected drought events, especially over the mid-century for both RCP 4.5 and RCP 8.5 (Figure 4-89 and Figure 4-90). It is observed that SRI values are negative for the Southwest Monsoon season of the recent period with a high frequency of mild (8) and moderate (5) drought events. The

SRI trend is projected to increase, indicating a decrease of drought events (compared to the recent period) for both RCP 4.5 and RCP 8.5, as shown in Figure 4-91 and Figure 4-92. The seasonal time series plots of SRI for all seasons, projected under RCP 4.5 and RCP 8.5, are presented in Annexure 7 - 29 to Annexure 7 - 36, respectively.

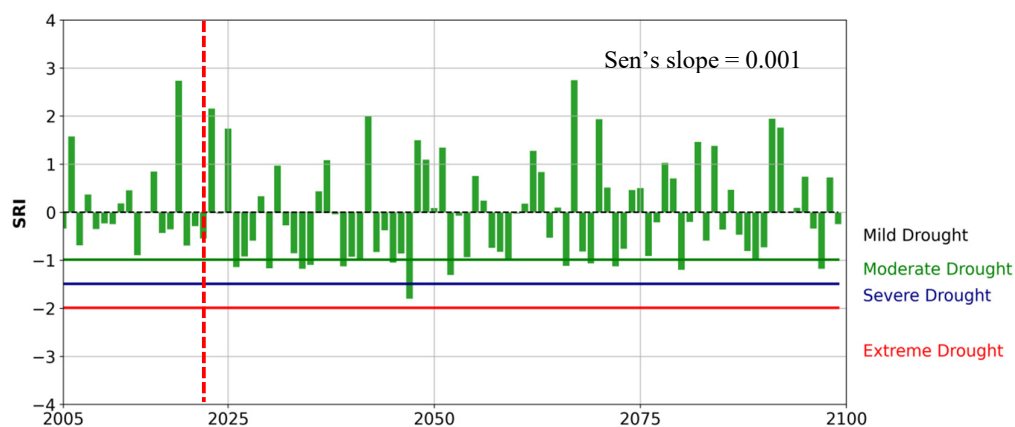


Figure 4-91: SRI for the recent and Southwest Monsoonal period (Dec-Mar) under RCP 4.5

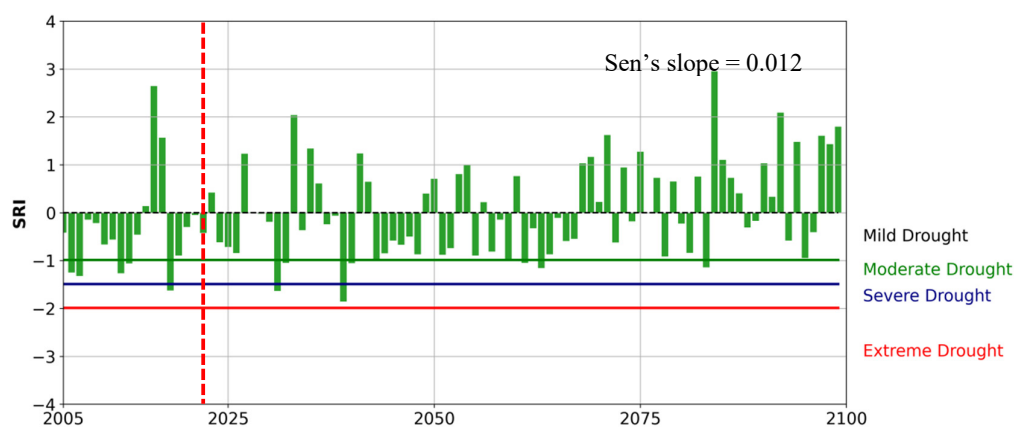


Figure 4-92: SRI for the recent and Southwest Monsoonal period (Dec-Mar) under RCP 8.5

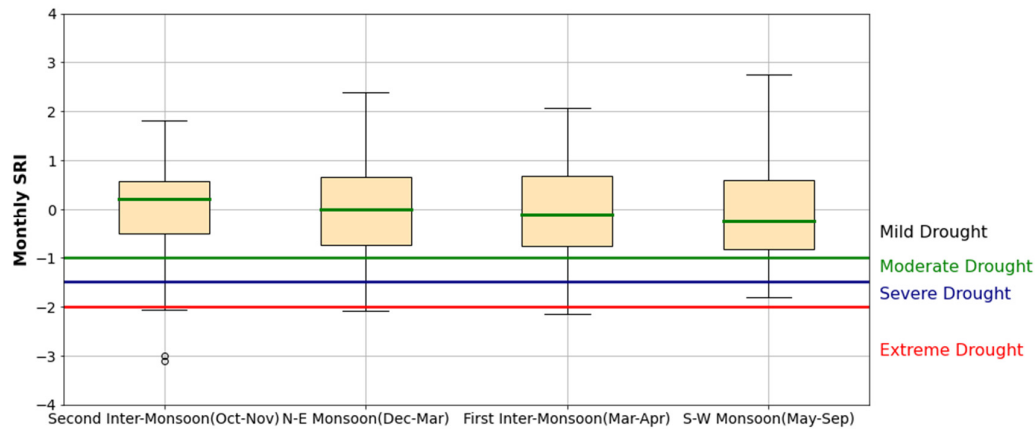


Figure 4-93: Seasonal variation of SRI for RCP 4.5 (2022-2100)

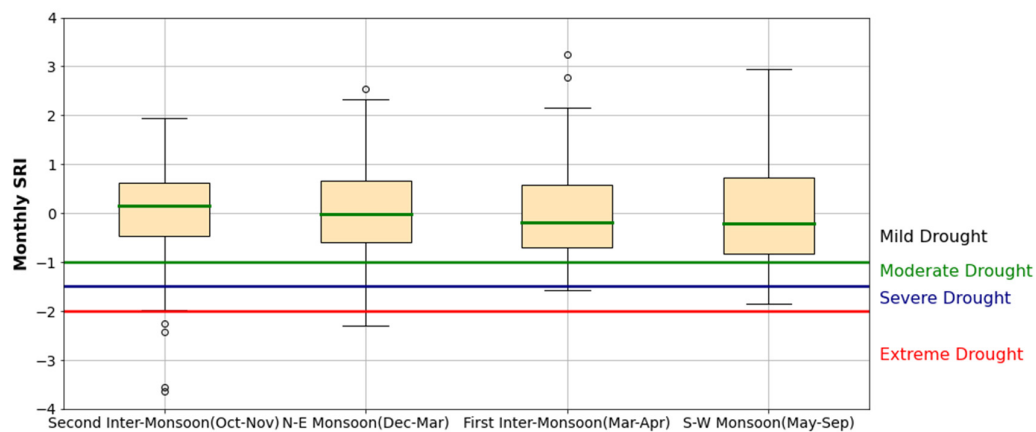


Figure 4-94: Seasonal variation of SRI for RCP 8.5 (2022-2100)

The boxplot of seasonal variation of SRI values indicates extreme drought events in in the Second inter-monsoon season for both RCP 4.5 and RCP 8.5, as shown in Figure 4-93 and Figure 4-94. The seasonal trend analysis of SRI using the M-K test and Sen Slope estimator is presented in

Annexure 8 - 17 and Annexure 8 - 18.

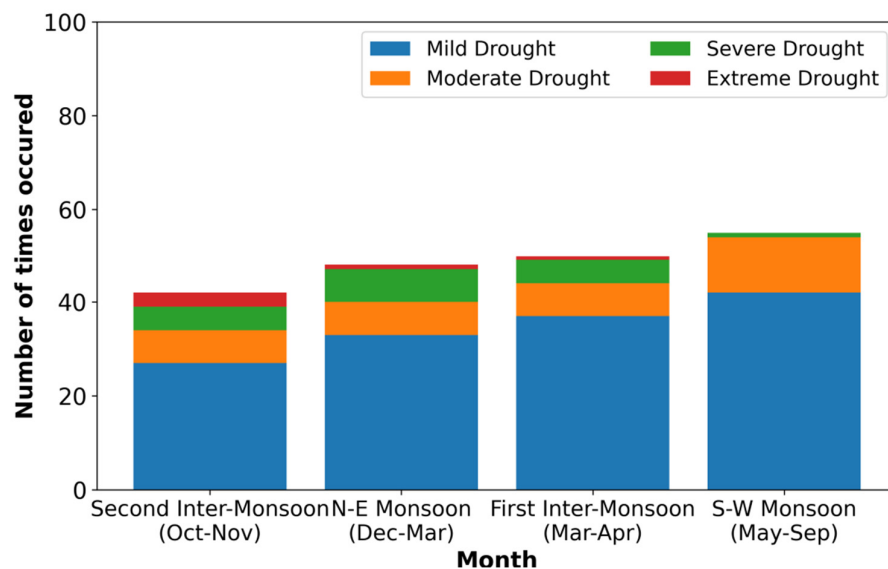


Figure 4-95: Projected frequency and severity of the projected seasonal drought events under RCP 4.5 for the 2022-2100 period

The projections shown in the above figure indicates that the Southwest monsoon season has the highest frequency of drought events (60) under RCP 4.5 scenario over the 21st-century. The frequency analysis of the projections made under RCP 8.5 is depicted in Annexure 7 - 38.

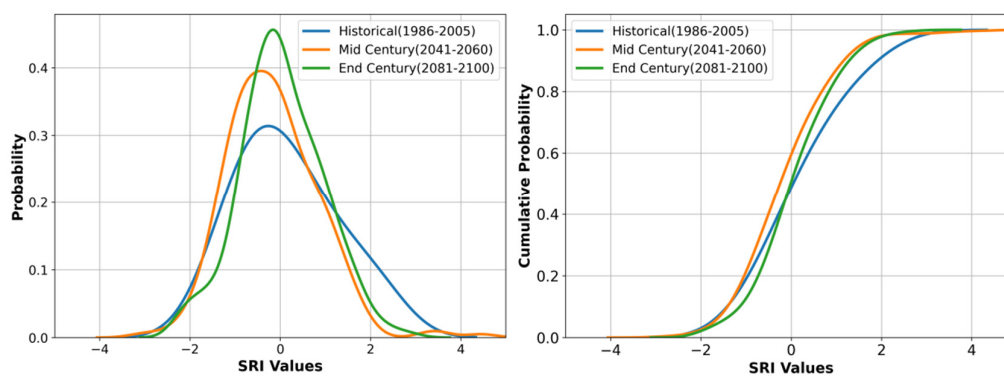


Figure 4-96: Probability of occurrence of droughts during the mid-century (left) and end-century (right) periods under RCP 4.5

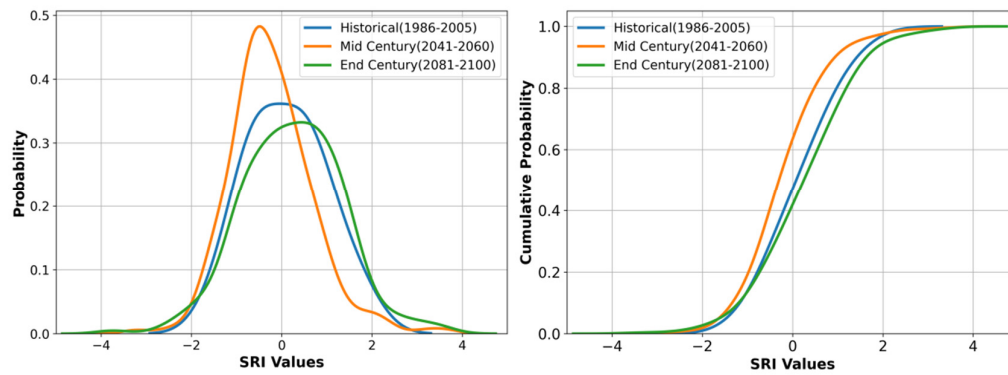


Figure 4-97: Probability of occurrence of droughts during the mid-century (left) and end-century (right) periods under RCP 8.5

The probability of zero SRI value (i.e., wet conditions) is highest for the end-century RCP 4.5 and mid-century under RCP 8.5 (Figure 4-96 and Figure 4-97).

The probability distribution of drought occurrence is skewed towards negative SRI values for mid and end-century periods under RCP 4.5 and RCP 8.5. The end- and mid-century periods are projected to be under higher drought risk than the historical period. The end-century period is projected to have the highest drought probability (50 %), and frequency (10) under both RCP 8.5 scenario and mid-century period for RCP 4.5 scenario.

CHAPTER 5

5 DISCUSSION

5.1 Data and Data Period

The data availability of 34 years at the Maduru Oya River Basin gauging stations was considered when selecting the observed data period. The available five rainfall stations in the Maduru Oya River Basin provide a longer data record up to 2018, with just minor errors from 1981. WMO and IPCC suggested at least 30 years of data in daily resolution for climate change research pertaining to RCM projections. For the hydrological modelling component, the period of calibration was selected from 01-October-2005 to 30-September -2008, and the period of validation was selected from 01-October-2008 to 30-September-2012. Because this data set covers both dry and rainy periods in a representative manner, it was assumed that the resulting runoff data were unaffected by the data period.

5.2 Meteorological Drought Indices

For the present study, droughts within the Maduru Oya River Basin were quantified using four meteorological drought indices: SPI, SPEI, RDI and EDI at monthly and seasonal time scales. Droughts' time series were obtained for the historical (1951-2005), recent (2005-2021), and future (2022-2100) periods. The bias-corrected RCM projections of precipitation and potential evapotranspiration under RCP 4.5 and RCP 8.5 were used to calculate the meteorological drought indices.

5.2.1 Standardized Precipitation Index (SPI)

The meteorological drought index SPI is commonly used for drought quantification in many countries of the South Asian region (Chandrasekara et al., 2021). The SPI is calculated according to the method presented in Section 2.6.1.

The projected results show four months of decreasing trend, four months with no significant trends, and four months of an increasing trend of SPI under RCP 4.5 at monthly time scales over the 2022-2100 period with the highest (17) drought events in the January. Under RCP 8.5, four months are projected with decreasing SPI trends and three months with no significant trends. For monthly timescale, 110 and 104 drought events are projected under RCP 4.5 and RCP 8.5, respectively. Under both RCPs, high frequency (11,10) and severity (severe, extreme) droughts are projected for the Northeast Monsoon season (i.e., December-February).

The results in the study are consistent with Kumar et al. (2012), in which a time series of the monthly SPI values was developed using daily rainfall of monsoon season (June-September) for 1951–2007 over India. The findings revealed that in India, the extent of the regions prone to moderate drought frequency has increased since the beginning of the 21st-century. In contrast to the present findings, Manesha et al. (2015) used the same timescale to examine severe drought events in Sri Lanka between 1976 and 2001. The study indicated that the SPI index on a monthly scale is insufficient to characterize the severity of drought conditions, whereas SPI-3 is capable of monitoring the beginning of droughts and SPI-6 is capable of describing the severity and duration of droughts in Sri Lanka.

5.2.2 Standardized Precipitation Evapotranspiration Index (SPEI)

The SPI is based on a probabilistic approach of precipitation, it overlooks the impact of warming on drought conditions. The SPEI, on the other hand, incorporates different drought-related variables such as precipitation and temperature, and the final index combines a simplified formula, a flexible time scale, and a range of meteorological variables (Jia et al., 2018b). The method to calculate SPEI is described in Section 2.6.2.

The results indicate that three months would have decreasing trends of SPEI values, five months with no significant trends, and four months of increasing trends of the projected SPEI values under RCP 4.5 over the 2022-2100 period with the highest (17) drought events in the March and August. Under RCP 8.5, four months are projected with decreasing trends and four months with no significant trends. For monthly timescale, 128 and 122 drought events are projected under RCP 4.5 and RCP 8.5,

respectively. Under both RCPs, high frequency (33,31) and severity (severe, extreme) droughts are projected during the Northeast Monsoon season (i.e., December-February).

The SPEI includes the effect of temperature via evaporative demand, and it is highly sensitive to PET computation (Krishnan et al., 2020). Kumar et al. (2021) showed SPEI as a robust, multi-scalar drought index via the study conducted in Sindh, Pakistan. They concluded similarly to the results generated by the present study, where a decrease in precipitation amounts and increase of temperature leading to high evapotranspiration in the region ultimately generate an immense threat to available water resources. The results in the present study are consistent with the findings presented by Muangthong et al. (2020), in which more frequent drought events are predicted in the near future than over the rest of the 21st-century. The same study also concluded that the consistency of drought occurrence projected by SPEI is higher than the SPI based projections.

5.2.3 Reconnaissance Drought Index (RDI)

The RDI index considers the input and output of the water system and provides a robust approach to drought indices classification (Tigkas, 2015). The most common reference period for RDI calculation is 3, 6, 9 and 12 months. The computation procedure of RDI calculation is described in Section 2.6.3.

Results indicate that there would be four months of decreasing trends, four months with no significant trends, and four months with increasing trends for the projected RDI values under RCP 4.5 over the 2022-2100 period with the highest (17) drought events in the January. Under the RCPs, droughts with high frequency (33,33) and severity (severe, extreme) are projected during the Northeast Monsoon season of the 21st century.

RDI is more capable of predicting drought years when compared to SPI (Chandrasekara et al., 2021). Khan et al. (2021) used RDI in the Songhua River Basin of China and revealed that more severe droughts are expected to occur during the late 21st century (2050–2099), which is consistent with the findings of the present study.

Their results predicted a larger number of droughts under RCP 4.5 than RCP 8.5, in contrast to the present study results.

In Sri Lanka, only a few studies on RDI have been conducted. Zarch et al. (2011) studied RDI for forty meteorological stations in Iran, and their results revealed that SPI and RDI produced nearly identical results in several locations, contrary to the present study's findings. Their study further described that additional meteorological characteristics, such as evapotranspiration, were addressed by RDI, which plays an important role in the basins for water losses. As a result, RDI should be considered in drought monitoring.

5.2.4 Effective Drought Index (EDI)

EDI is an effective, non-parametric test, initially developed to be applied at daily temporal resolutions and works at monthly scales (Smakhtin & Hughes, 2004). The concept of available water as a function of precipitation and time is used in EDI. It is easy to calculate EDI for any region where precipitation is recorded with only a single input required for computations. The outputs of all climate regimes may be compared using EDI because it is standardized. It effectively identifies the onset, ending and persistence of drought events. The major drawback of this method is the non-consideration of temperature related impacts on droughts. EDI is calculated according to the method described in Section 2.6.4. The results did not show any trend of monthly EDI values in the historical period, and future period under both RCPs.

Results indicate that under RCP 8.5 over the 2022-2100 period, the highest (13) drought events are projected in the April. Under the RCPs, droughts with high frequency (92,121) and severity (severe, extreme) are projected at monthly timescale over the 21st century.

Jain et al. (2015b) studied the Ken River Basin in Central India and revealed that detecting long- and short-term monthly rainfall deficiency is more robustly achieved via EDI than other drought indices, which is according to the present work.

Pandey et al. (2008) studied drought characterisation in Orissa, India and revealed that EDI better represents the droughts in that area than any other index. This drought study was event based on daily time-steps, which could be the possible reason for the

difference of results with the present study. The study also concluded that SPI and EDI, reflect drought severity similar trends.

5.3 Model Development and Evaluation of Model Performance

The streamflow evaluation at the Padiyathalawa sub-watershed was carried out using the HEC-HMS model. The parameters included in the HEC-HMS model were for continuous runoff modeling in the Maduru Oya River Basin for one year and four years. For the current study, simulations concerning the four years, the NSE (0.48) and RMSE (0.64) objective functions yielded satisfactory results. Further, the coefficient of determination value (R^2) is 0.71, indicating an agreeable correlation. The calibrated model may have produced a different result for the future period due to the non-stationary precipitation series with changes in climate forcing.

The newly optimized parameters for the calibration of the baseflow are 10.7 m³/s as Initial Discharge, 0.94 as Recession Constant, and 0.15 as Ratio to Peak flow, which were optimized. The Initial storage of the canopy model was optimized to 0.18. The model performance for simulation (2004-2008), calibration (2004-2008) and validation (2008-2012) period is summarized in Table 5-1.

Table 5-1: HEC-HMS Model Performance for 4-year continuous modelling

4-year run	NSE	R^2	RMSE Std. Dev.	PBIAS (%)
Simulation	0.48	0.71	0.64	34.03
Calibration	0.68	0.81	0.57	4.55
Validation	0.59	0.72	0.60	9.83

Climate change impact on streamflow was analysed as monthly variations. Under RCP 4.5, nine months are projected to have decreasing streamflow over the 21st century, with Northeast monsoon depicting the highest decrease. Under RCP 8.5, model projections indicate reductions in streamflow five months (January, February, April, November and December), included the entire Northeast monsoon period. The possible reason for decreasing streamflow is the decreasing trend of rainfall projected

by RCPs. Changes in streamflow will have an impact on future water availability in the Maduru Oya River Basin.

5.4 Standardized Runoff Index (SRI)

Climate change is likely to affect the Maduru Oya River basins' hydrological characteristics explicitly. The hydrological drought, which includes streamflow changes, is the most representative when the drought conditions within the entire region are considered. The Standardized Runoff Index (SRI) has been widely used because of its simple computation and comparability in varied spatial and temporal scales (Xiang et al., 2020).

The SRI is a extensively used for its simplicity and data requirement for assessing hydrologic drought conditions. SRI has a number of time scales that characterize hydrological droughts at various time scales represented as SRI-m, where m is month (Xiang et al., 2020). SRI is calculated by the process described in Section 2.6.5.

According to the model projections, there is no trend of SRI values under RCP 4.5 over the 2022-2100 period. Under RCP 8.5, two months are projected with decreasing SRI trends and seven months with no significant trend. Under the RCPs, droughts with high frequency (65,62) and severity (severe, extreme) are projected at monthly timescale over the 21st-century Further, droughts with high frequency (9,7) and severity (severe,extreme) are projected under the same projection scenario during the Northeast Monsoon season.

There are hardly any studies related to the SRI drought index computations in Sri Lanka. The study conducted by Vu et al. (2017) over Vu Gia-Thu Bon in Central Vietnam used SRI for drought assessment. Although a warmer and wetter future climate is consistent with the current study results, the results suggest that the study area will be subjected to more severe and extreme droughts.

5.5 Climate Change Impact on Drought in Maduru Oya River Basin

- Based on long-term SPI, SPEI and RDI monthly time series, it is projected that the occurrence of severe and extreme droughts may increase during the mid

(30)- and end (20)-century periods under RCP 4.5 and RCP 8.5 (compared to the historical period (10)).

- The historical SPI, SPEI and RDI values depicted the Northeast Monsoon as the season with the least drought frequency (3), whereas the Southwest Monsoon as the season with the highest frequency (8) of droughts.
- The seasonal analysis of SPI, SPEI and RDI projects the increasing frequency (14,14) of drought for Northeast Monsoon season and decreasing frequency (6,4) for Southwest Monsoon season for both scenarios over the 21st-century.
- The EDI values at the monthly time scale show no trend (Sen's slope=0) under both the RCP scenarios for mid- and end-century periods, with more droughts occurring over the mid-century period.
- The projected values of the hydrological drought index, SRI, show no trend (Sen's slope=0) under RCP 4.5 at monthly and seasonal time scales. The Northeast Monsoon season is projected to be drier (9 drought events), and the Southwest Monsoon is wetter (1 drought event) compared to the historical period.
- The projected values of SRI show an increase in drought frequency and severity under RCP 8.5 at monthly (65,62) and seasonal (26,19) time scales under RCP 4.5 and RCP 8.5, respectively.
- EDI and SRI trend values are similar for RCP 4.5 at monthly and seasonal scale.
- SRI trend values are similar with SPI, SPEI and RDI for RCP 8.5 at monthly and seasonal time scales.
- Meteorological and hydrological drought frequency, severity and intensity are projected to increase in the Maduru Oya river basin over the 21st-century for SPI, SPEI, RDI, EDI and SRI under RCP 4.5 and RCP 8.5 (compared to historical period).

CHAPTER 6

6 CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

1. SPI, SPEI and RDI projected that the occurrence of severe and extreme droughts may increase during the mid (30)- and end (20)-century periods under RCP 4.5 and RCP 8.5 (compared to the historical period (10)).
2. At monthly and seasonal timescales, the projected climate in the Maduru Oya River Basin indicates a declining trend of SPI, SPEI, RDI, and SRI values (Sen's slope=-0.005). Furthermore, the streamflow in the Padiyathalawa sub-watershed has a decreasing trend.
3. The projected variation in rainfall and streamflow in the Maduru Oya River Basin do not immediately reflect the rise in temperature in the future. However, increasing evapotranspiration would influence and lower the volume of surface water in the Maduru Oya River Basin. As indicated by SPEI, this could lead to drought events.
4. SPI, SPEI and RDI projected the increasing frequency (14,14) of drought for Northeast Monsoon season and decreasing frequency (6,4) for Southwest Monsoon season for both scenarios over the 21st-century (compared to the historical period (3,8)).
5. The calibrated model of streamflow used to project future changes in streamflow according to future changes in precipitation with respect to the base period well represented the regional scale climate parameters in Maduru Oya River Basin, while the RCM used to project future changes in climate well reflected the regional climate parameters in Maduru Oya River Basin.
6. According to the IPCC, future rainfall variations and possible evapotranspiration will result in extended droughts of high frequency, severity,

- and intensity, as confirmed by the current Maduru Oya River Basin study (SPI, SPEI, SRI, and RDI).
7. The results obtained from the HEC-HMS model are satisfactory (NSE=0.59, $R^2=0.72$, RMSE Std. Dev.=0.60) for validation to simulate hydrological parameters of the Maduru Oya River Basin. When the discharge of the drought years is compared against the discharge of the years having an average rainfall, it is observed to have a considerable decrease in the percentage of the basin's discharge. This validates the computation and characterization of drought based on drought indices for the basin.
 8. It can also be concluded that the climate change impact on meteorological drought will affect the discharge of the basin. In the Maduru Oya River Basin, this might result in a high frequency of extreme and severe droughts in the mid-century under RCP 8.5 and at the end-century under RCP 4.5.

6.2 Recommendations

1. Throughout the time period considered in this study, the land use pattern is assumed to be constant. It is recommended to include the land-use changes in future studies to better represent the catchment characteristic under anthropogenic impacts.
2. The study focuses on the effects of climate change on the drought of the Maduru Oya River's catchment area, which is located upstream of the Maduru Oya Reservoir. The spatial extent of the study area could be increased if the streamflow dataset is available for downstream areas.
3. This study has a further future scope of analysis of the basin by hydrological modelling using the energy balance approach to assess other hydrological parameters such as evapotranspiration while considering the discharge of the main outlet and along primary streams of the basin.
4. Since the area has a consistent mild drought minor irrigation and water conservation projects in the basin which can be upgraded to moderate drought conservation projects to efficiently overcome the drought, especially in the upper Maduru Oya River Basin region.

5. Increased flood/drought vulnerability downstream of the Maduru Oya River Basin would be caused by variation in temperature and rainfall. The direct and indirect effects of climate change should be thoroughly investigated in order to establish sustainable water resource development solutions.
6. It is recommended to further study on the agricultural drought index and possible climate change impacts on agriculture concerning other climate warming parameters using the same RCM.
7. It is recommended to bias correct Potential evapotranspiration data before applying for SPEI calculation.

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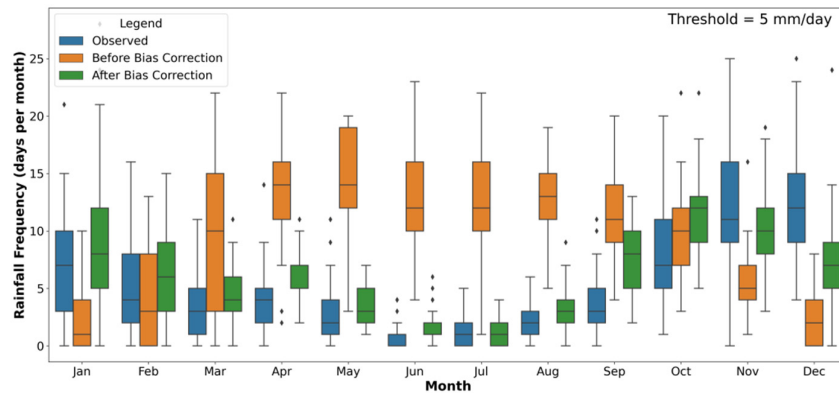
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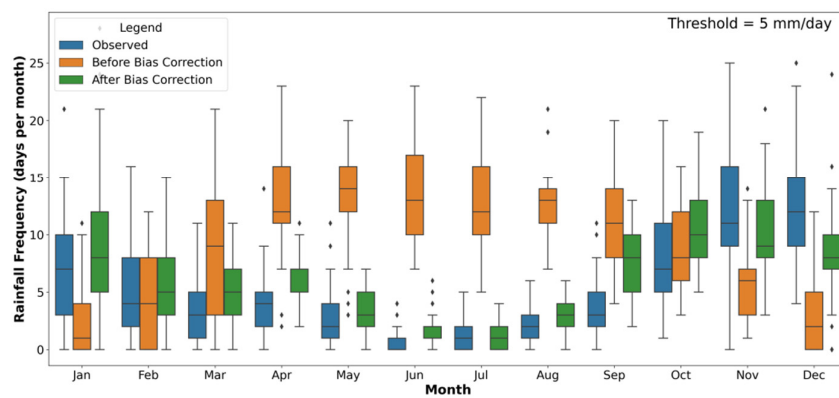
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ANNEXURE 1

BIAS CORRECTION



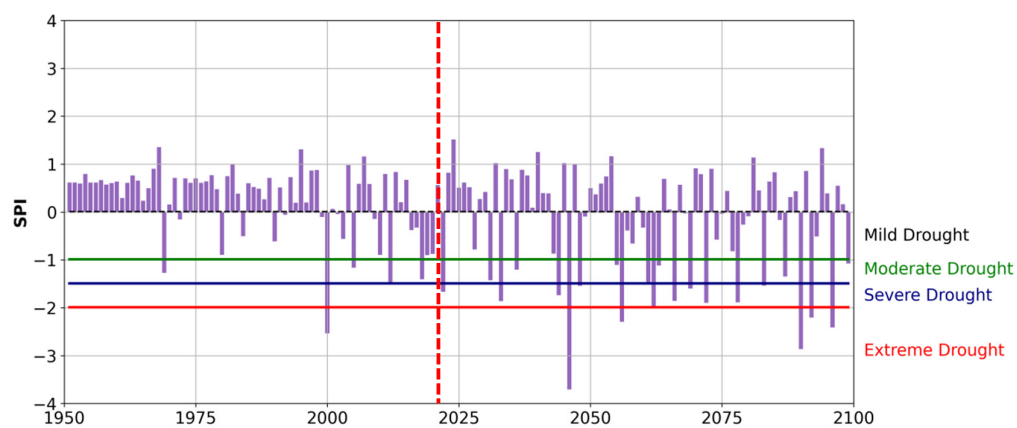
Annexure 1 - 1: Bias correction results of Rainfall frequency for historical time period and RCP 4.5 (1981-2018)



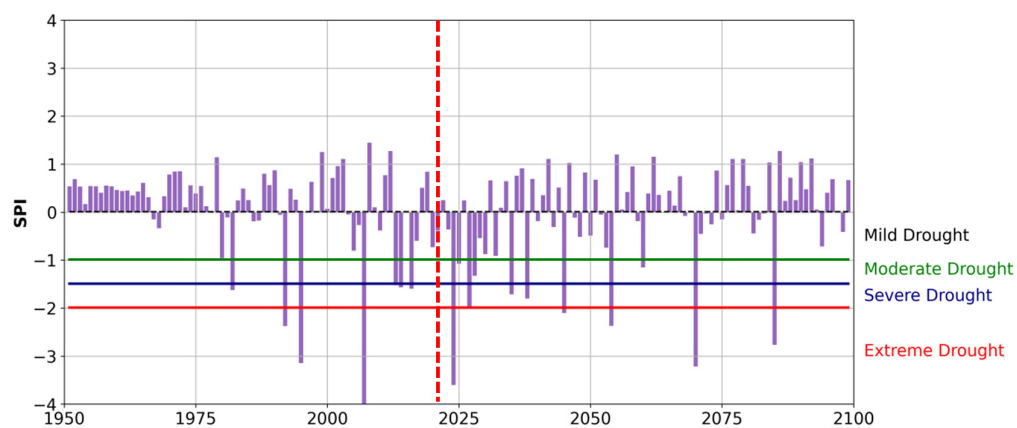
Annexure 1 - 2: Bias correction results of Rainfall frequency for historical time period and RCP 8.5 (1981-2018)

ANNEXURE 2

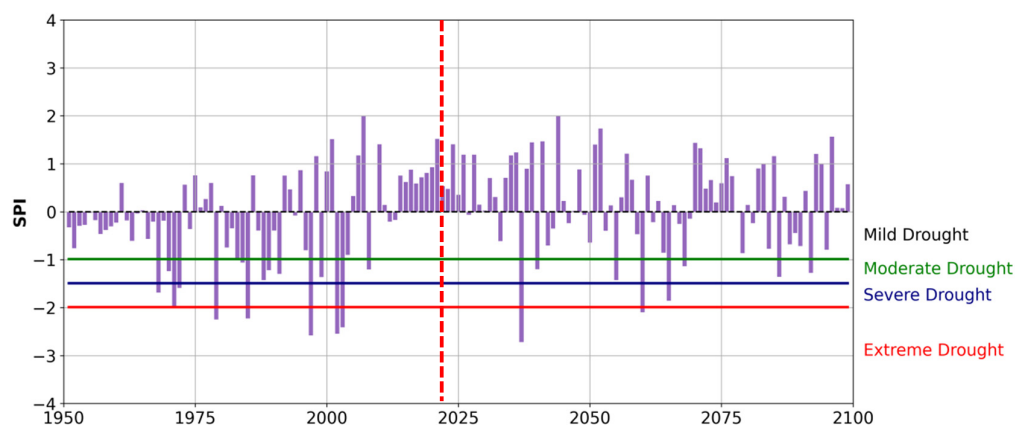
SPI



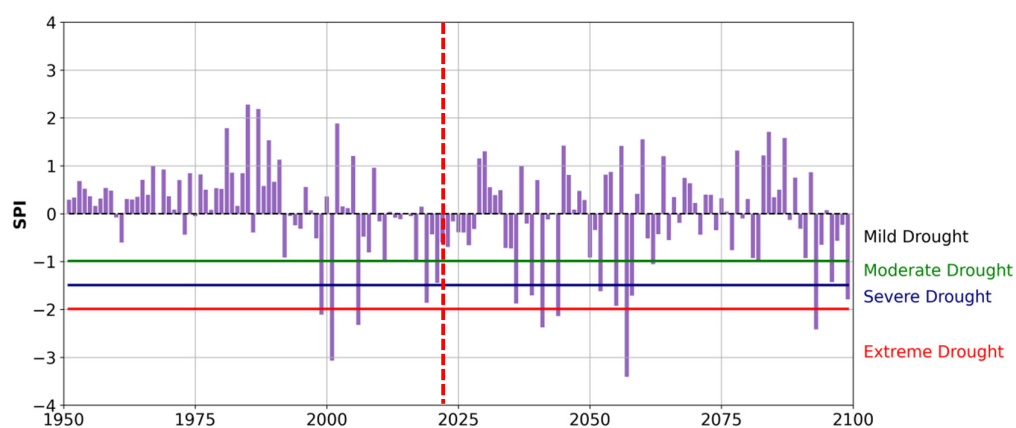
Annexure 2 - 1: SPI values of 1-month timescale for historical period and RCP 4.5 (Jan)



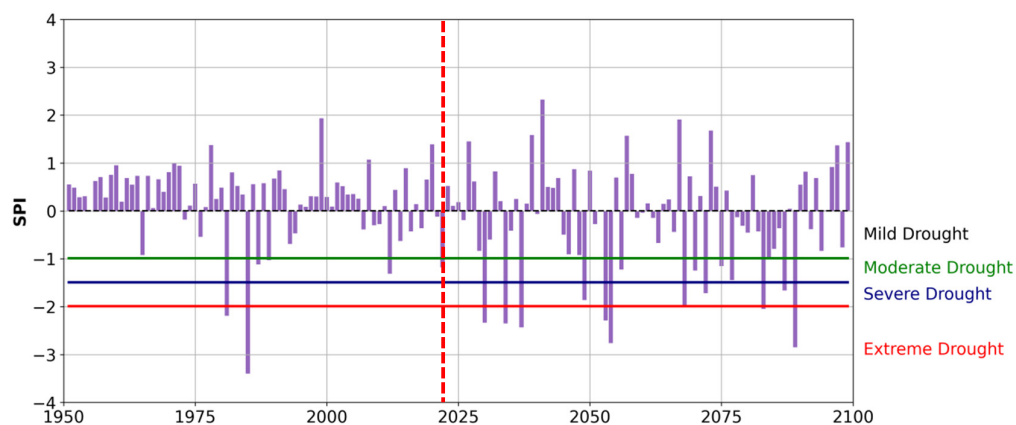
Annexure 2 - 2: SPI values of 1-month timescale for historical period and RCP 4.5 (Feb)



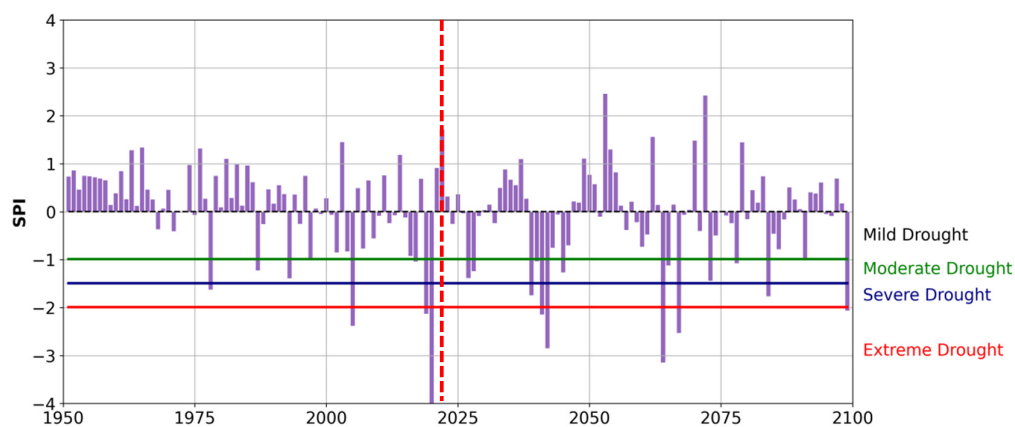
Annexure 2 - 3: SPI values of 1-month timescale for historical and RCP 4.5 (Mar)



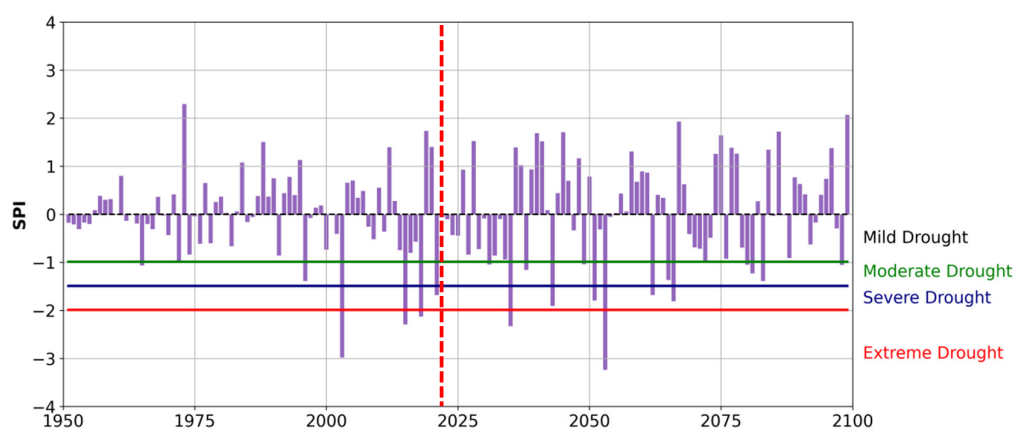
Annexure 2 - 4: SPI values of 1-month timescale for historical period and RCP 4.5 (Apr)



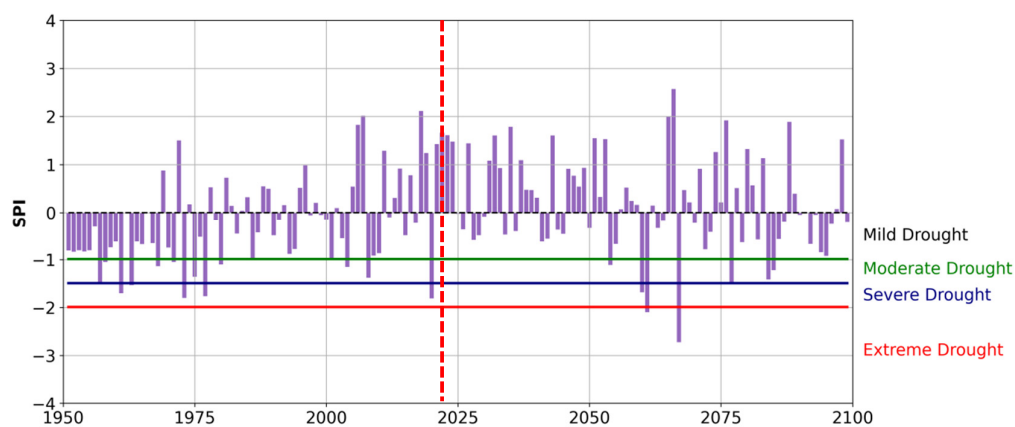
Annexure 2 - 5: SPI values of 1-month timescale for historical period and RCP 4.5 (May)



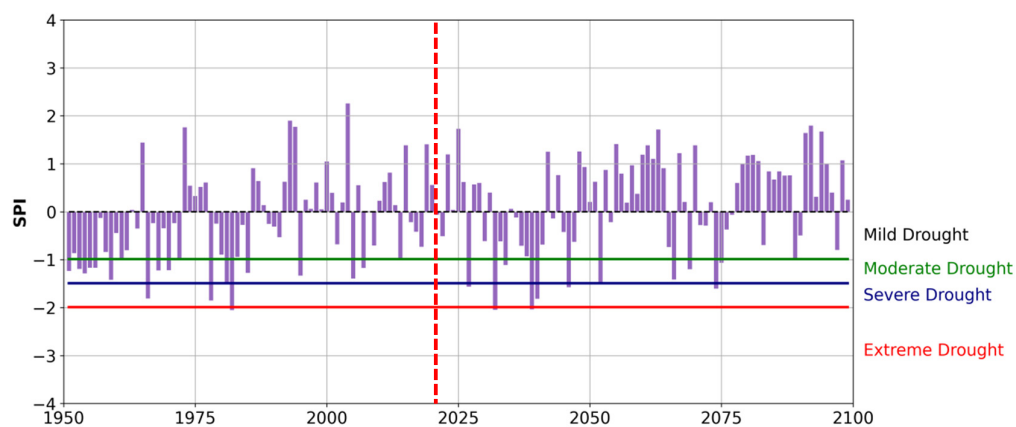
Annexure 2 - 6: SPI values of 1-month timescale for historical period and RCP 4.5 (Jun)



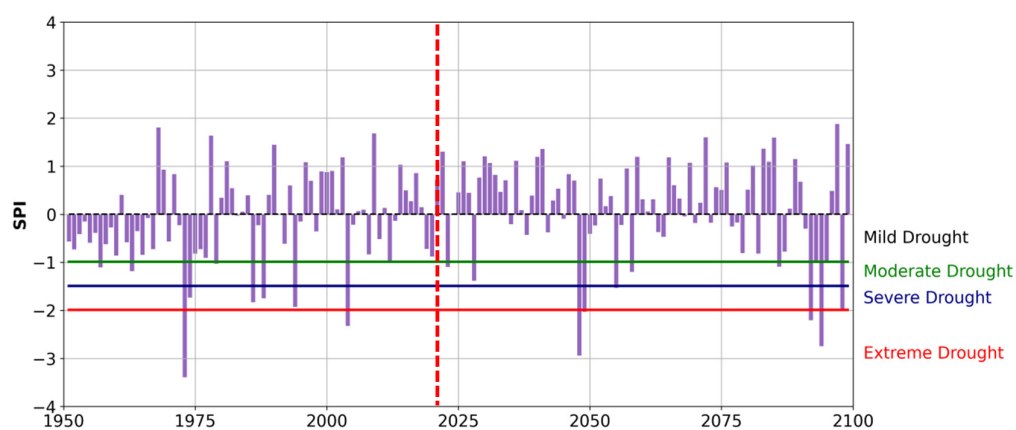
Annexure 2 - 7: SPI values of 1-month timescale for historical period and RCP 4.5 (Jul)



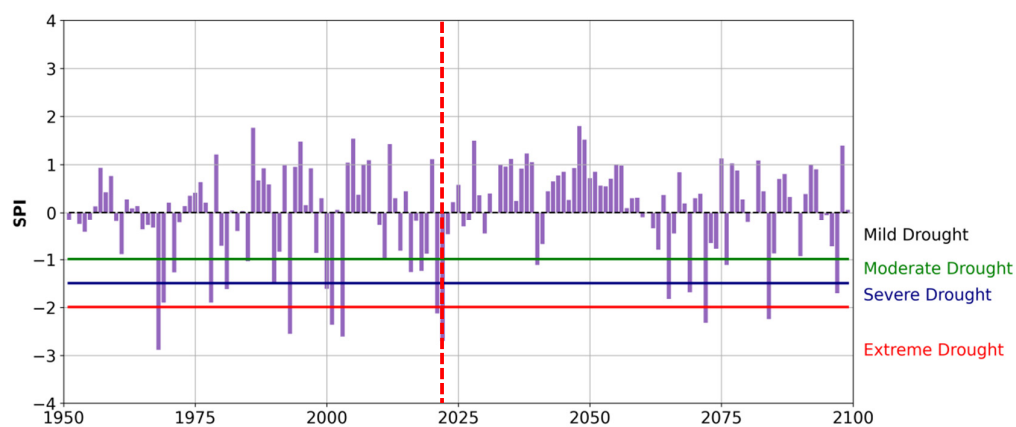
Annexure 2 - 8: SPI values of 1-month timescale for historical period and RCP 4.5 (Aug)



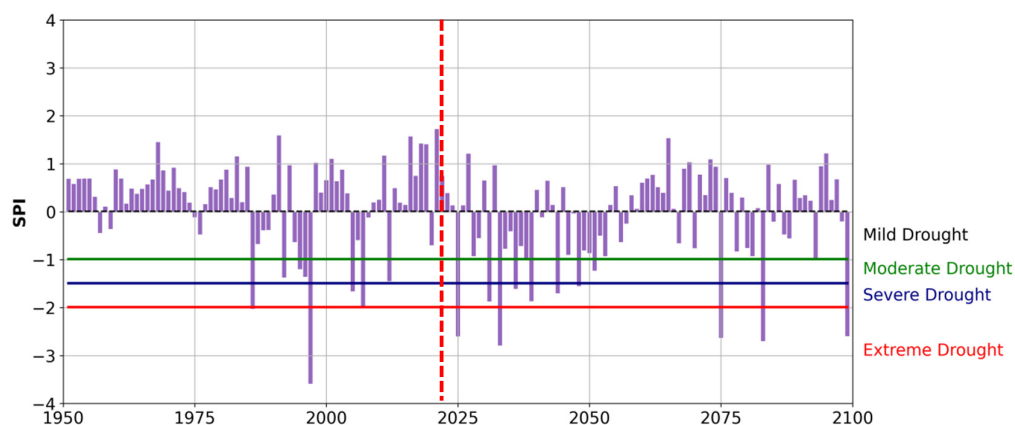
Annexure 2 - 9: SPI values of 1-month timescale for historical period and RCP 4.5 (Sep)



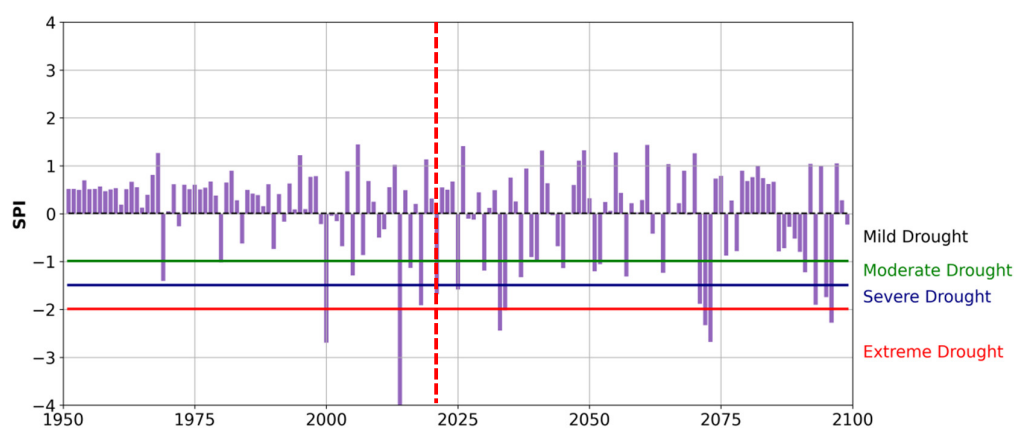
Annexure 2 - 10: SPI values of 1-month timescale for historical period and RCP 4.5 (Oct)



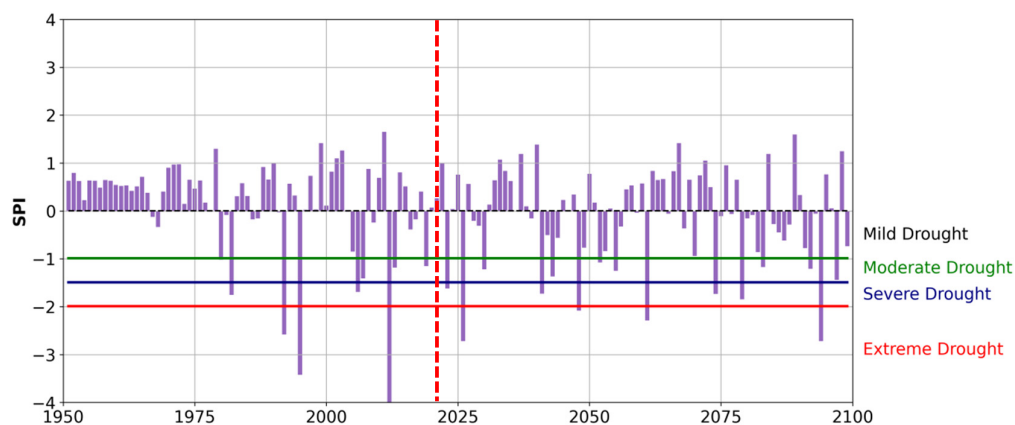
Annexure 2 - 11: SPI values of 1-month timescale for historical period and RCP 4.5 (Nov)



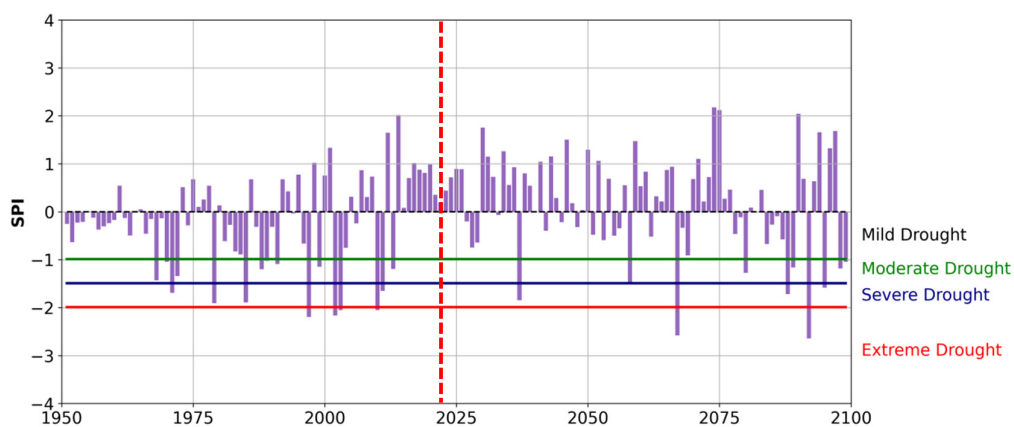
Annexure 2 - 12: SPI values of 1-month timescale for historical period and RCP 4.5 (Dec)



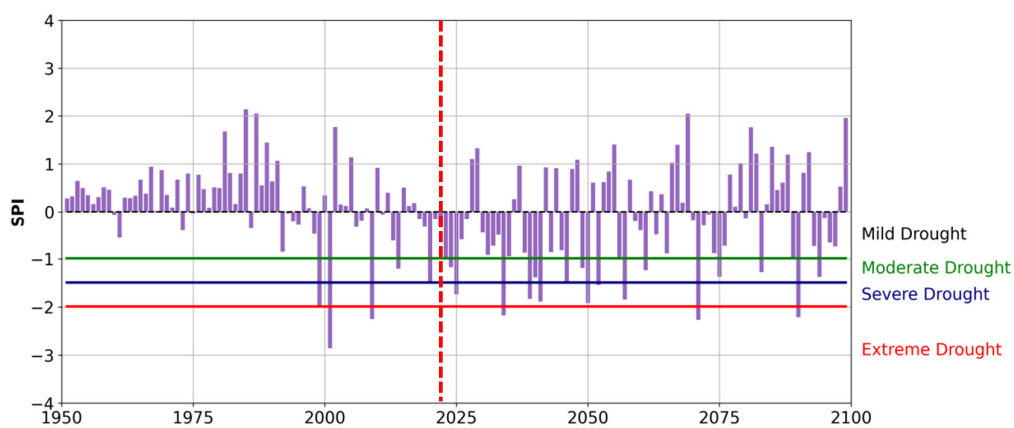
Annexure 2 - 13: SPI values of 1-month timescale for historical period and RCP 8.5 (Jan)



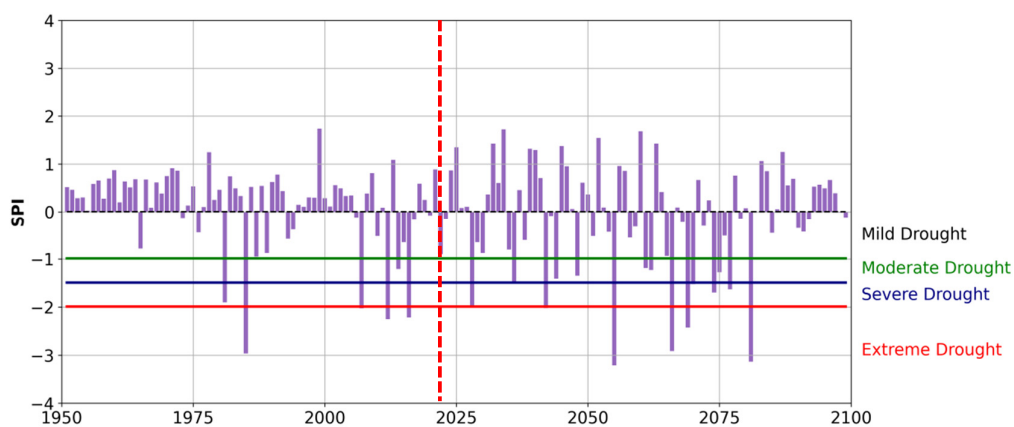
Annexure 2 - 14: SPI values of 1-month timescale for historical period and RCP 8.5 (Feb)



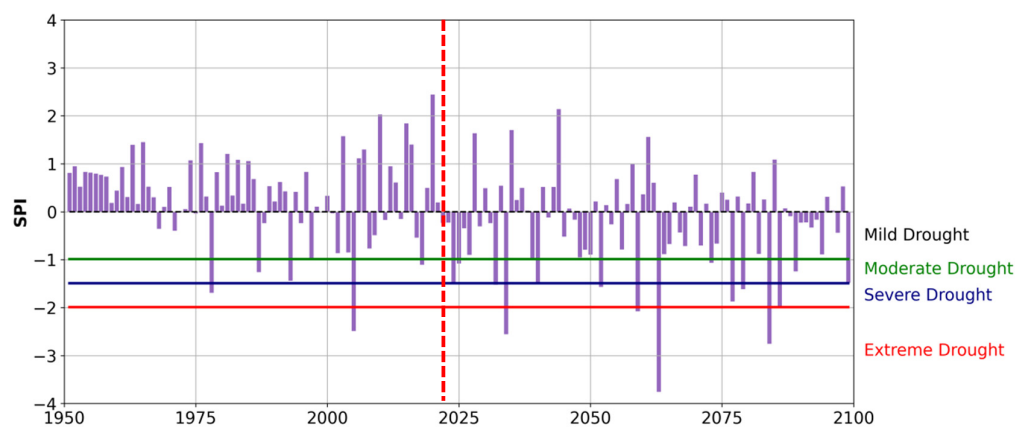
Annexure 2 - 15: SPI values of 1-month timescale for historical period and RCP 8.5 (Mar)



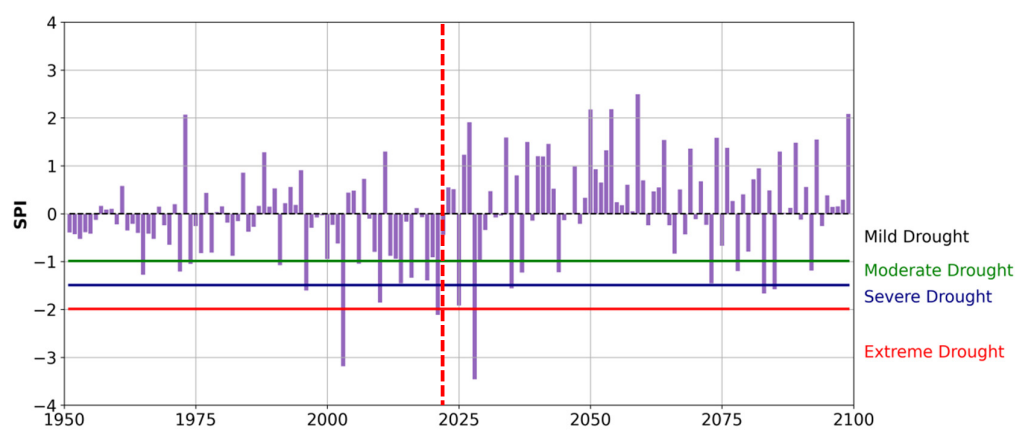
Annexure 2 - 16: SPI values of 1-month timescale for historical period and RCP 8.5 (Apr)



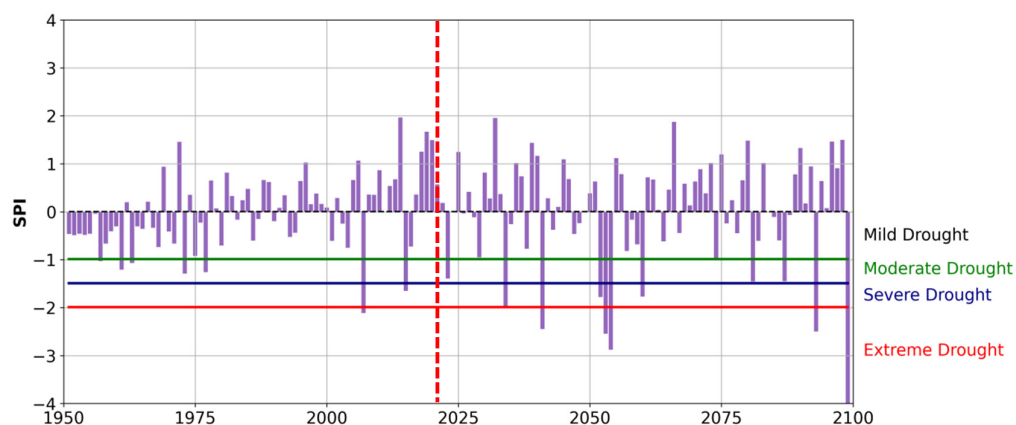
Annexure 2 - 17: SPI values of 1-month timescale for historical period and RCP 8.5 (May)



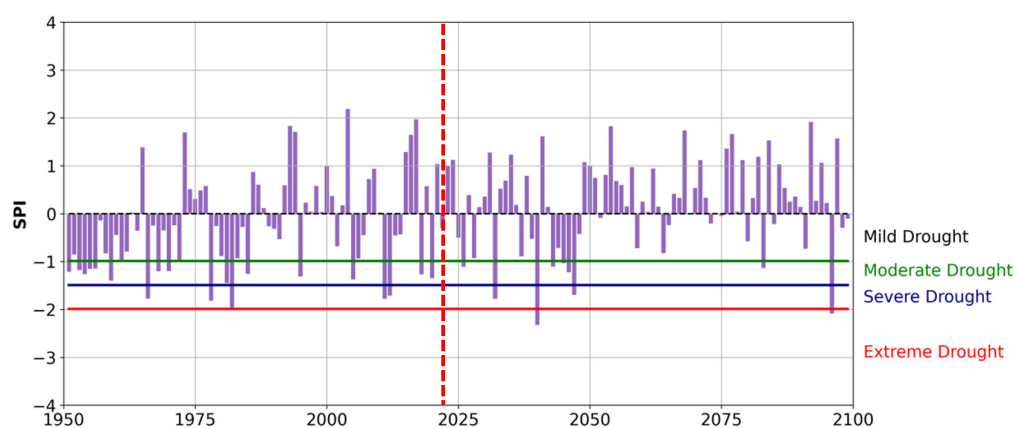
Annexure 2 - 18: SPI values of 1-month timescale for historical period and RCP 8.5 (Jun)



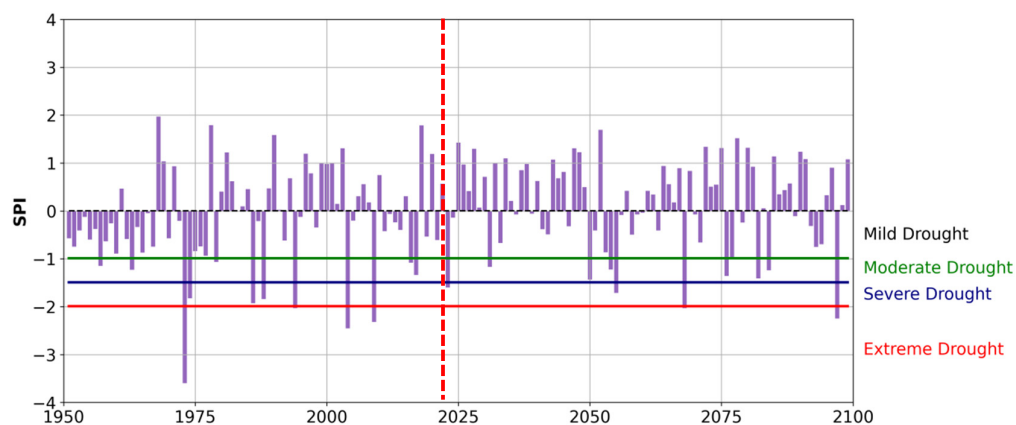
Annexure 2 - 19: SPI values of 1-month timescale for historical period and RCP 8.5 (Jul)



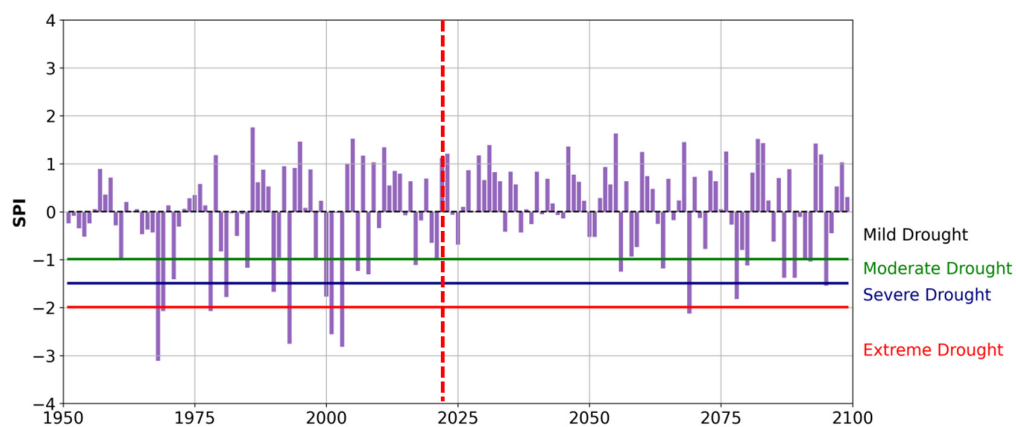
Annexure 2 - 20: SPI values of 1-month timescale for historical period and RCP 8.5 (Aug)



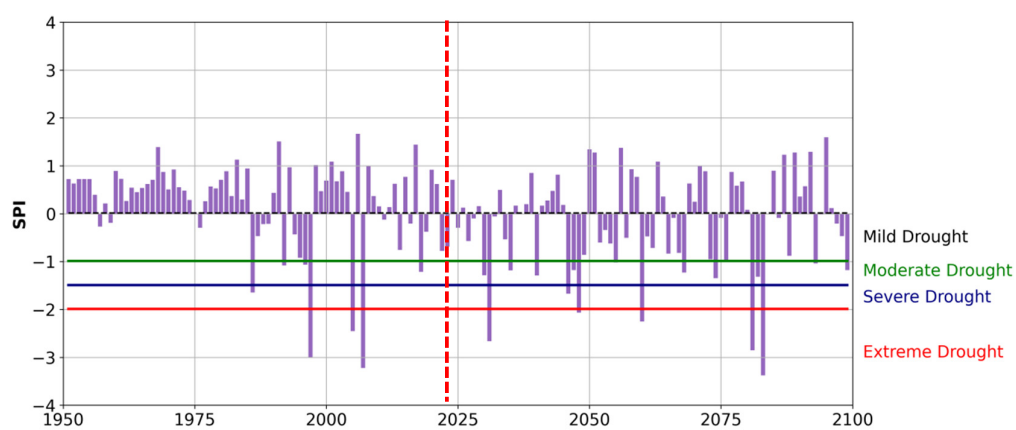
Annexure 2 - 21: SPI values of 1-month timescale for historical period and RCP 8.5 (Sep)



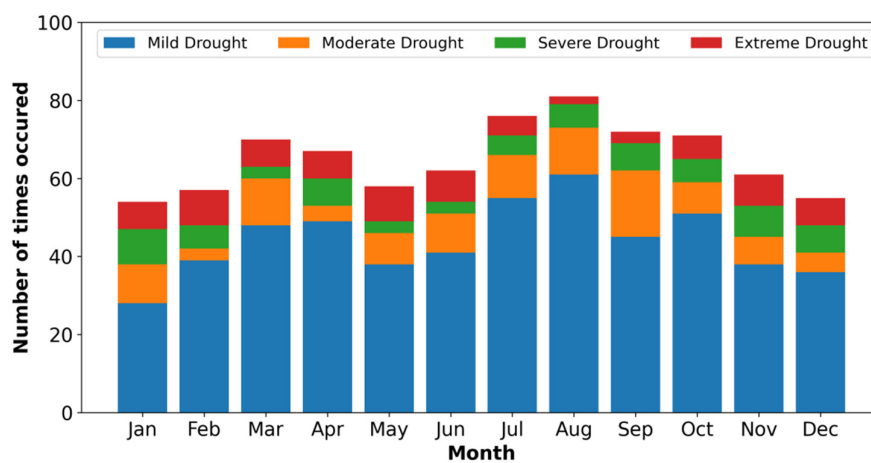
Annexure 2 - 22: SPI values of 1-month timescale for historical period and RCP 8.5 (Oct)



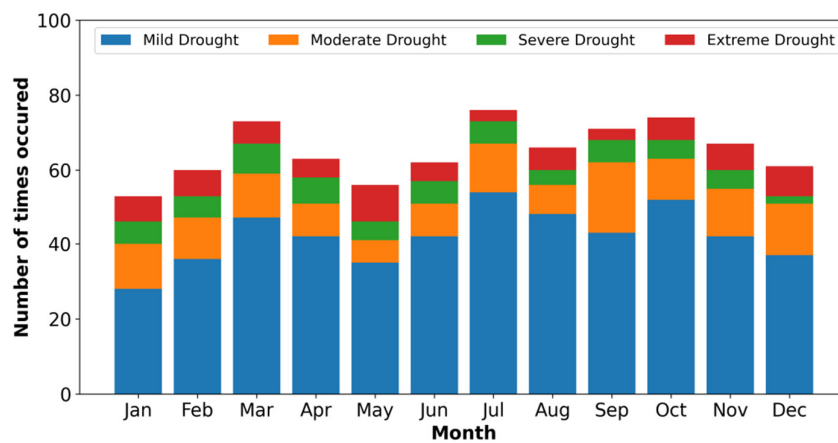
Annexure 2 - 23: SPI values of 1-month timescale for historical period and RCP 8.5 (Nov)



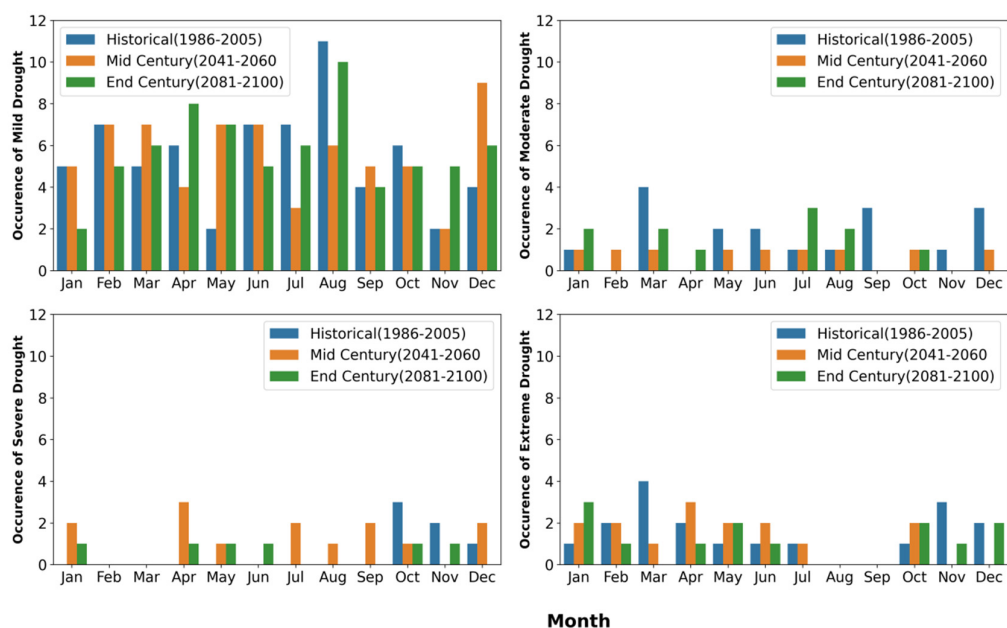
Annexure 2 - 24: SPI values of 1-month timescale for historical period and RCP 8.5 (Dec)



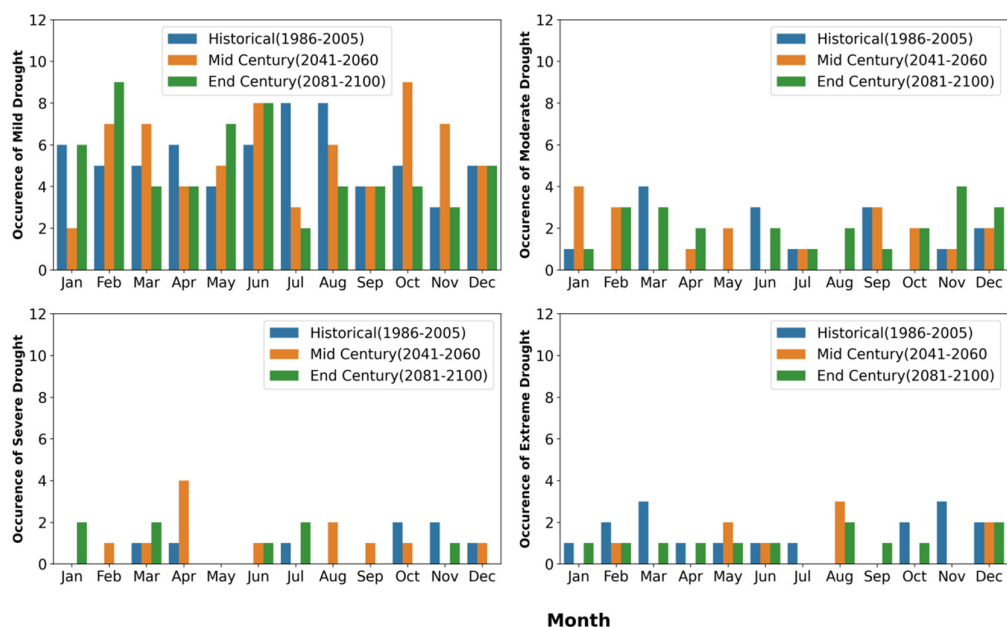
Annexure 2 - 25: Projected frequency and severity of drought events (RCP 4.5)



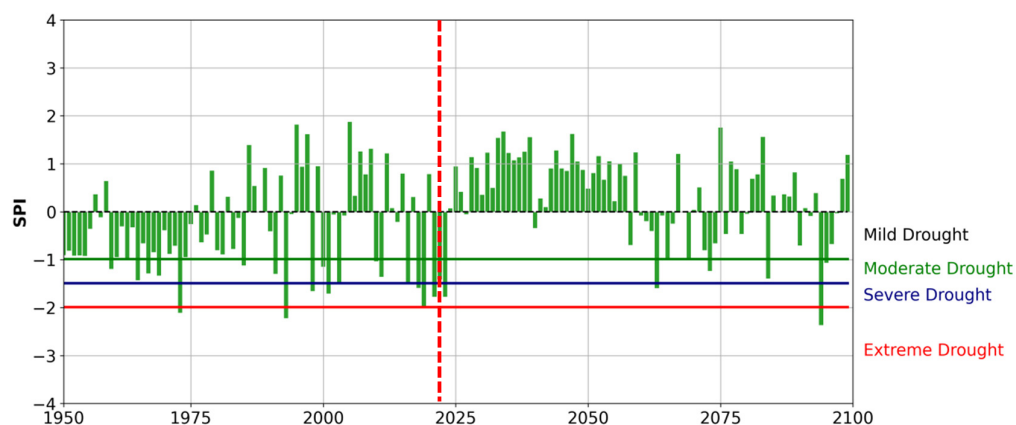
Annexure 2 - 26: Projected frequency and severity of drought events (RCP 8.5)



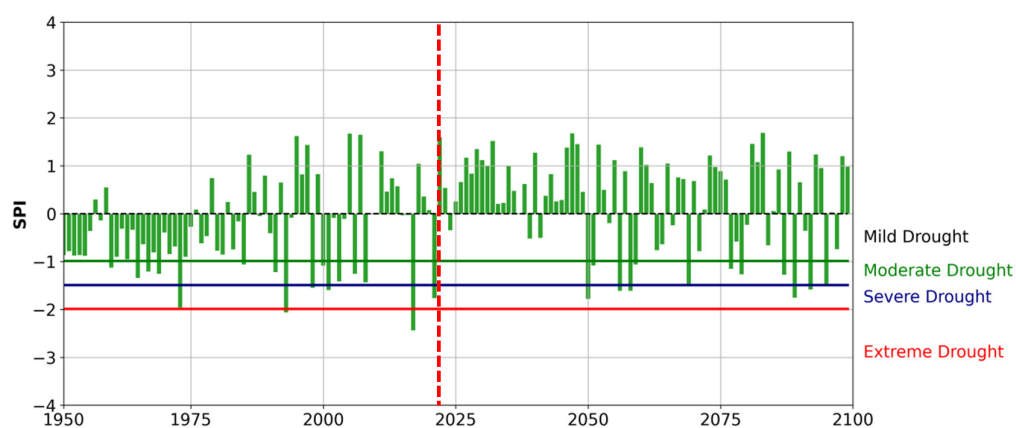
Annexure 2 - 27: Comparison of historical, mid-century and end-century RCP 4.5 drought events



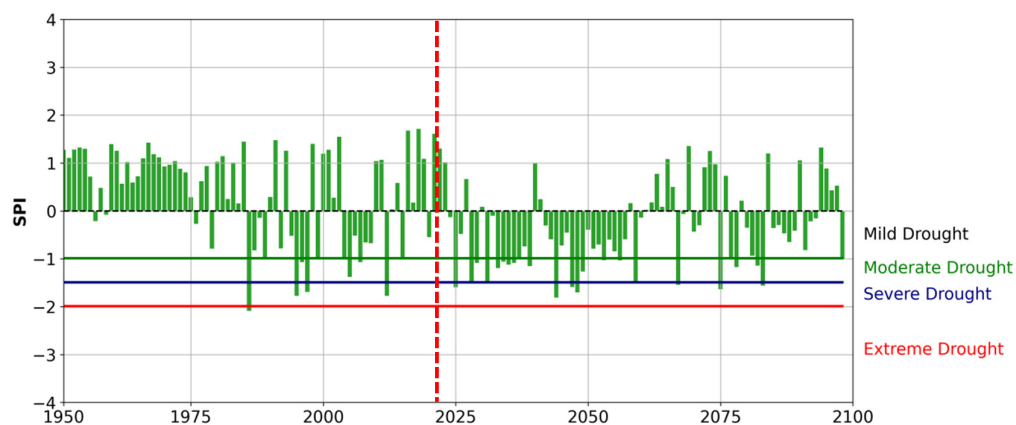
Annexure 2 - 28: Comparison of historical, mid-century and end-century RCP 8.5 drought events



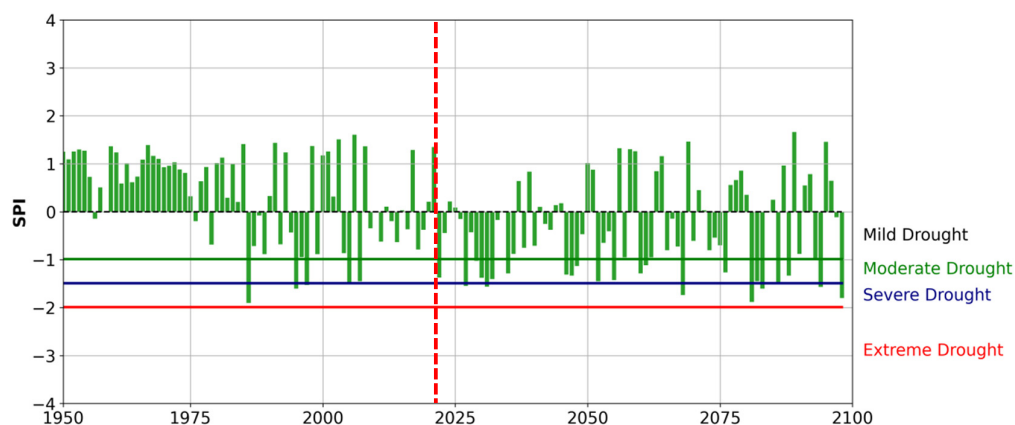
Annexure 2 - 29: SPI for historical period and RCP 4.5 (Second inter-monsoon (Oct-Nov))



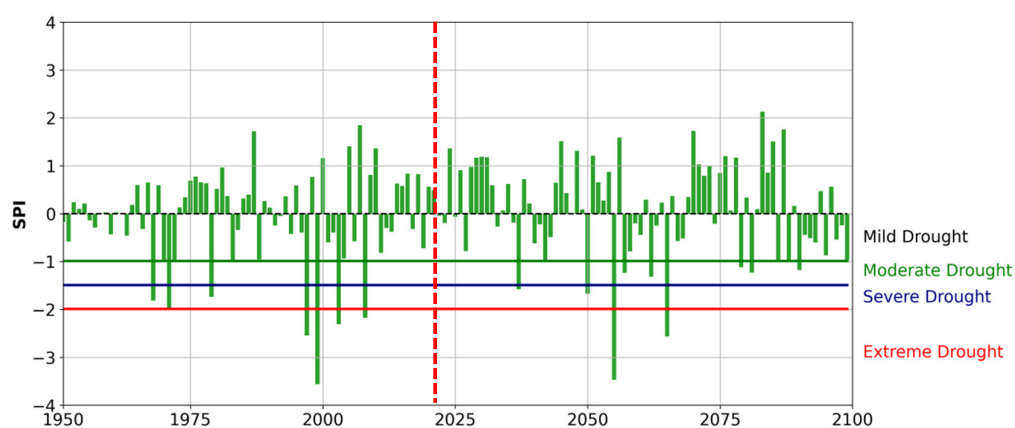
Annexure 2 - 30: SPI for historical period and RCP 8.5 (Second inter-monsoon (Oct-Nov))



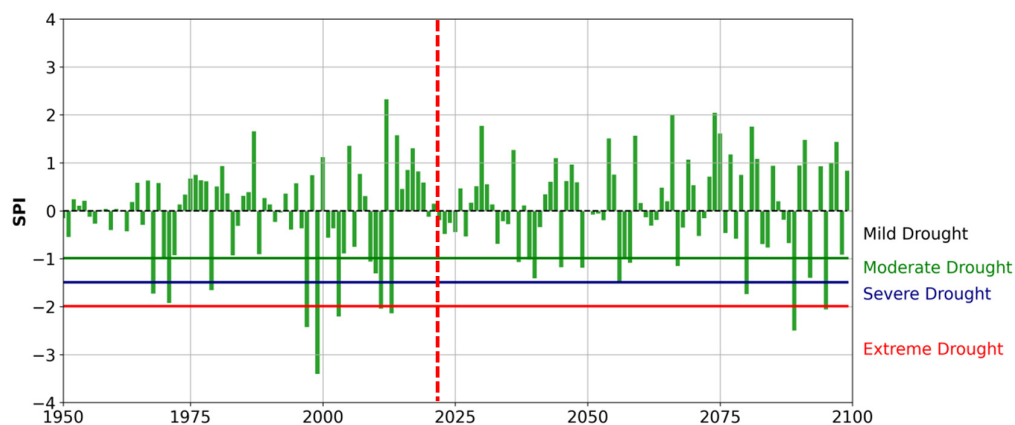
Annexure 2 - 31: SPI for historical period and RCP 4.5 (N-E Monsoon (Dec-Mar))



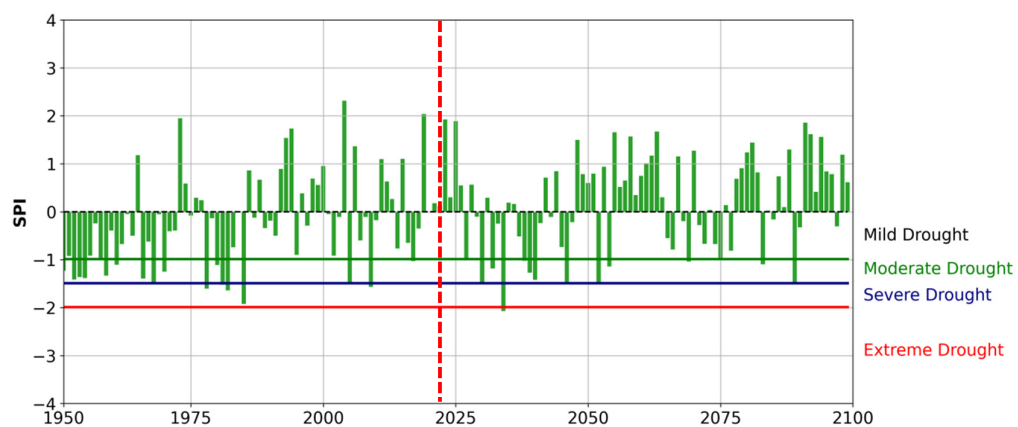
Annexure 2 - 32: SPI for historical period and RCP 8.5 (N-E Monsoon (Dec-Mar))



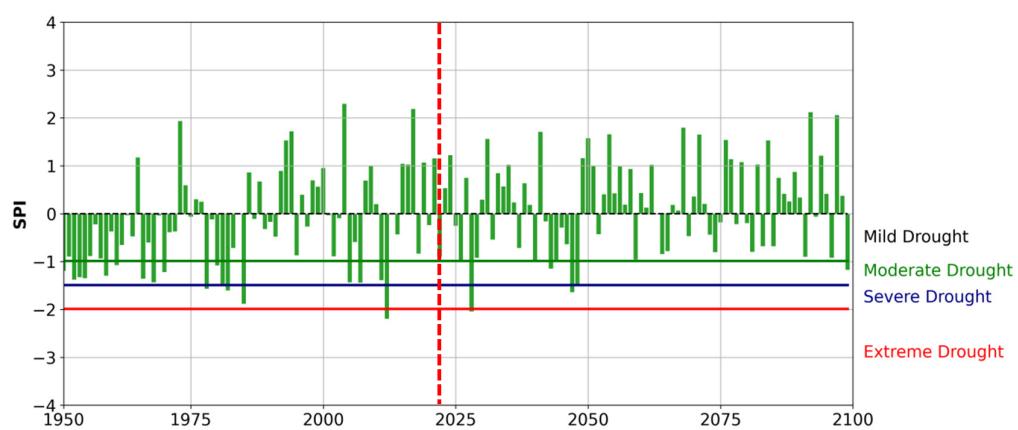
Annexure 2 - 33: SPI for historical period and RCP 4.5 (First inter-monsoon (Mar-Apr))



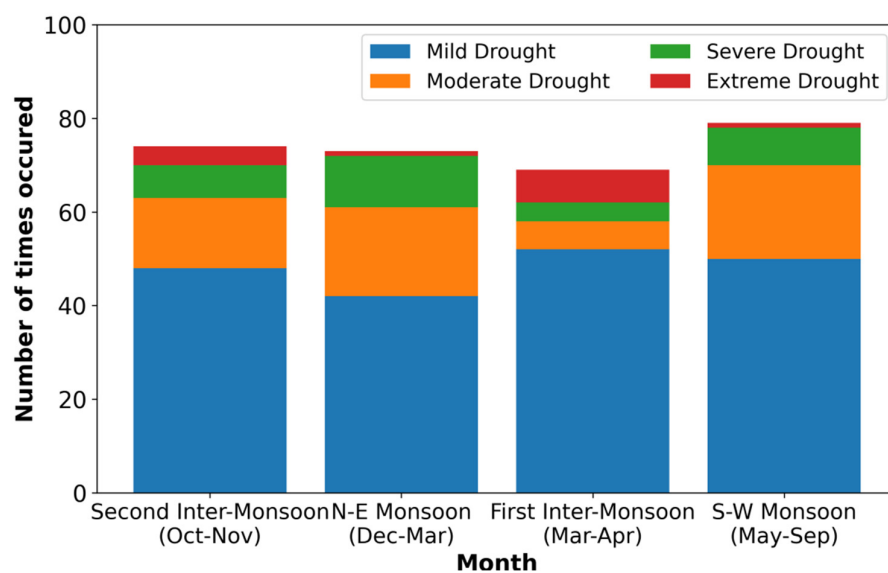
Annexure 2 - 34: SPI for historical period and RCP 8.5 (First inter-monsoon (Mar-Apr))



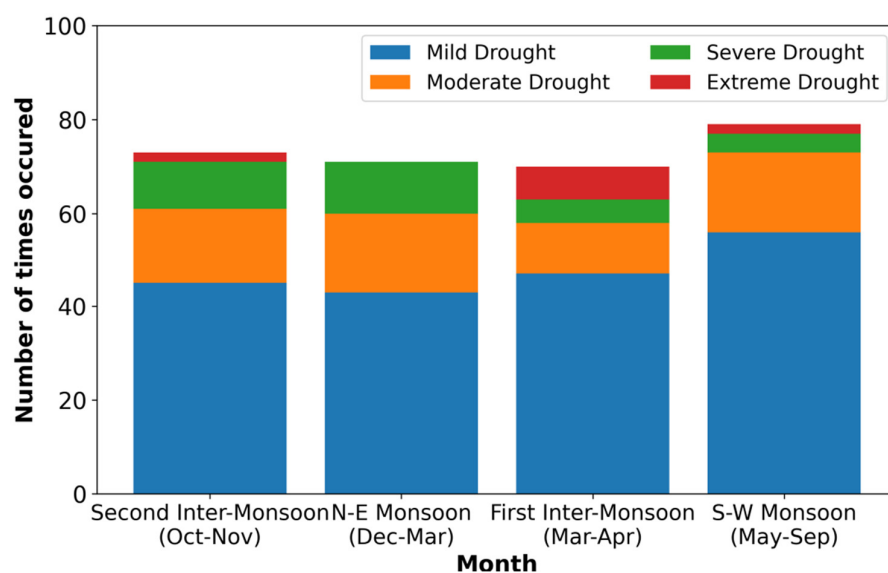
Annexure 2 - 35: SPI for historical period and RCP 4.5 (S-W Monsoon (May-Sep))



Annexure 2 - 36: SPI for historical period and RCP 8.5 (S-W Monsoon (May-Sep))



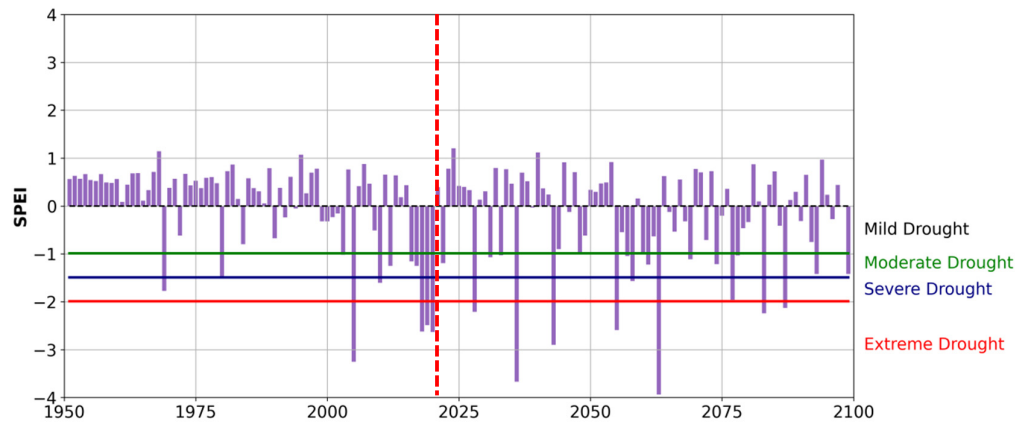
Annexure 2 - 37: Projected frequency and severity of seasonal drought events (RCP 4.5)



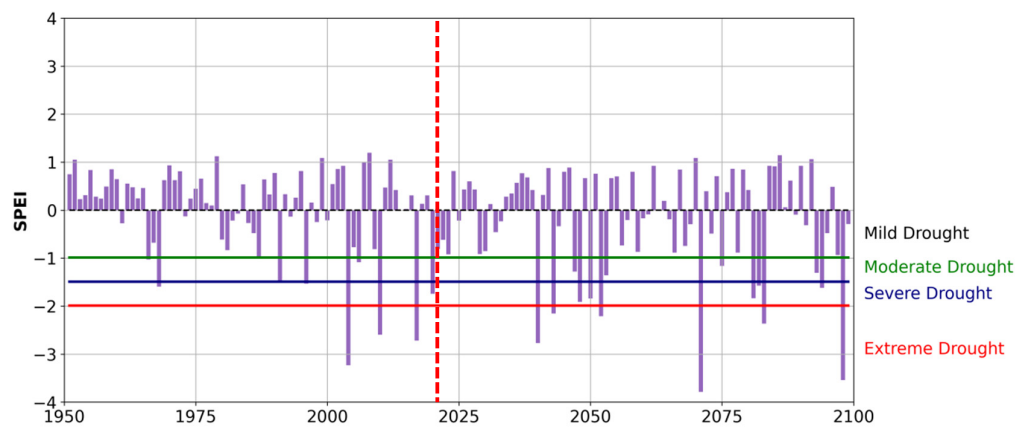
Annexure 2 - 38: Projected frequency and severity of seasonal drought events (RCP 8.5)

ANNEXURE 3

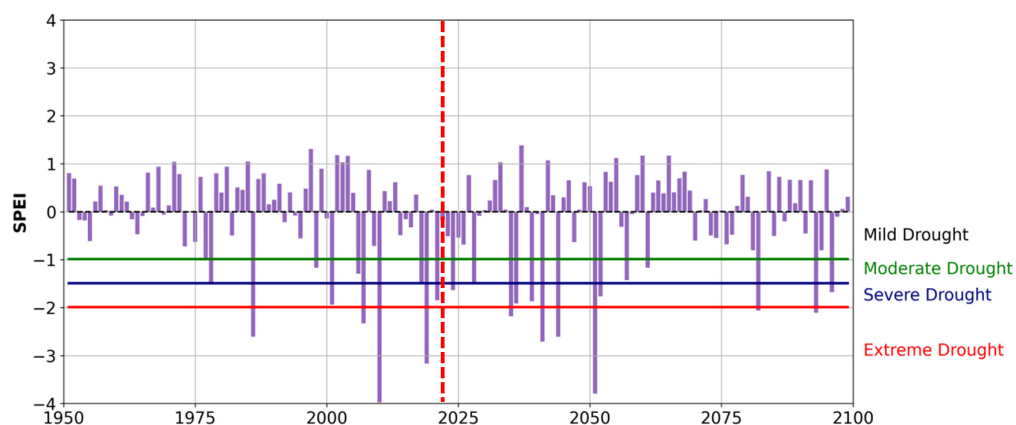
SPEI



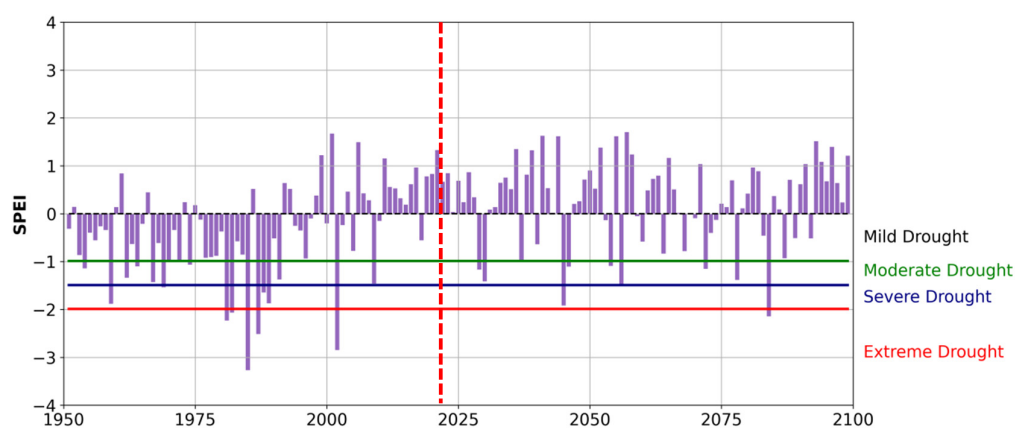
Annexure 3 - 1: SPEI values of 1-month timescale for historical period and RCP 4.5 (Jan)



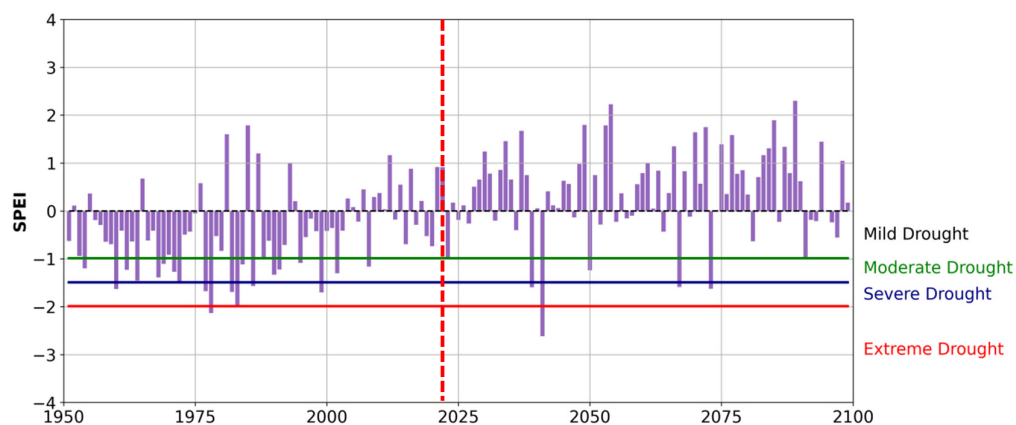
Annexure 3 - 2: SPEI values of 1-month timescale for historical period and RCP 4.5 (Feb)



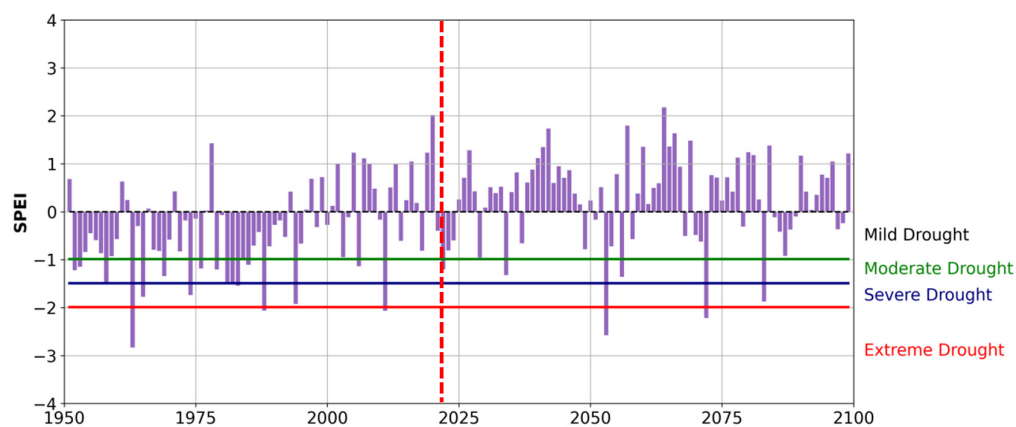
Annexure 3 - 3: SPEI values of 1-month timescale for historical period and RCP 4.5 (Mar)



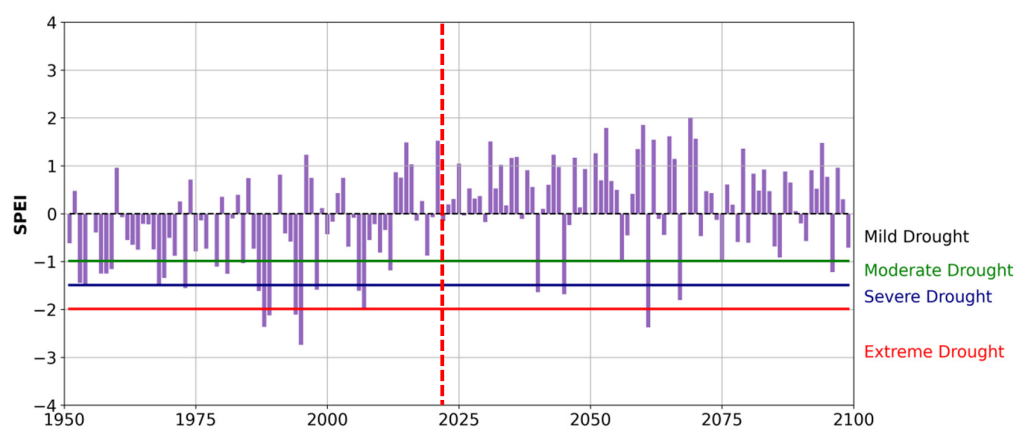
Annexure 3 - 4: SPEI values of 1-month timescale for historical period and RCP 4.5 (Apr)



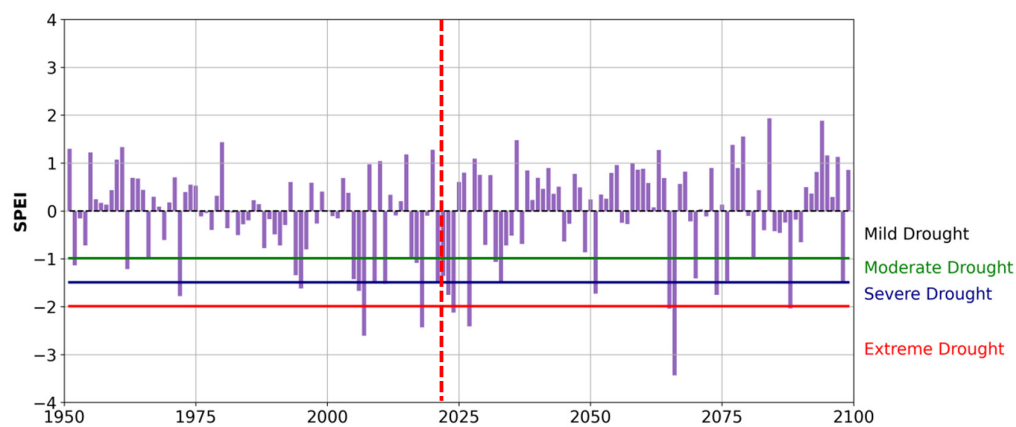
Annexure 3 - 5: SPEI values of 1-month timescale for historical period and RCP 4.5 (May)



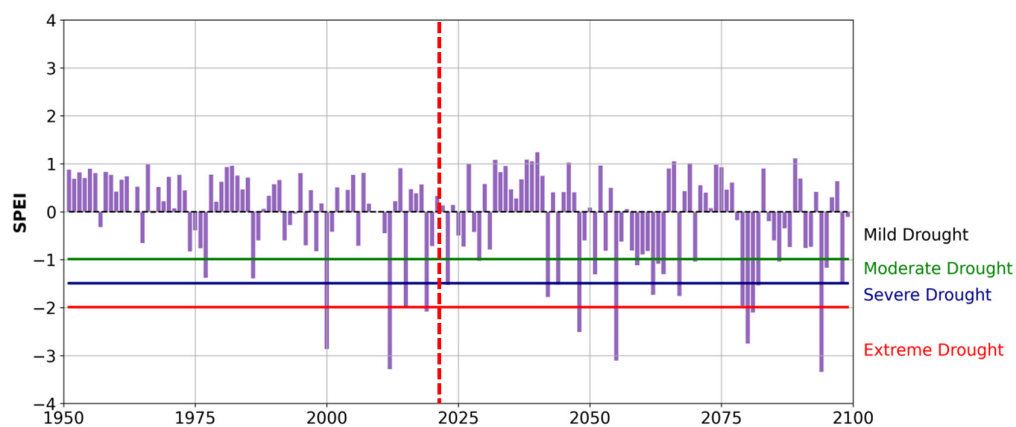
Annexure 3 - 6: SPEI values of 1-month timescale for historical period and RCP 4.5 (Jun)



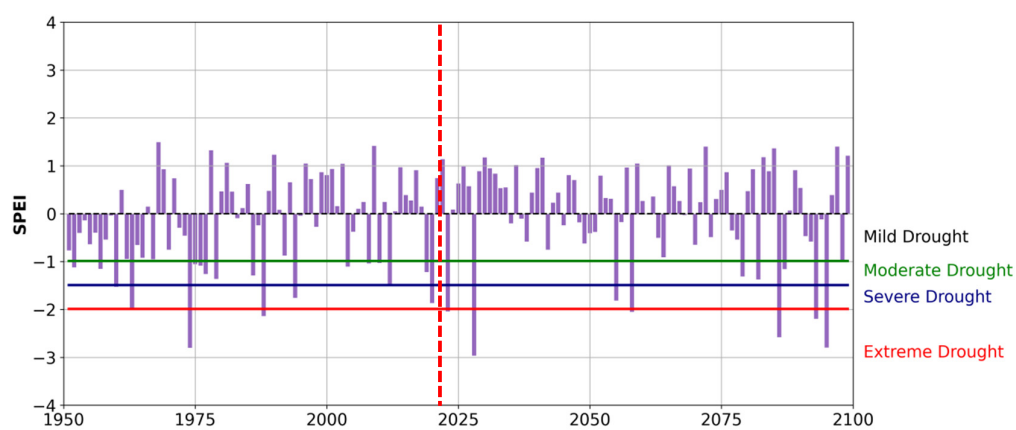
Annexure 3 - 7: SPEI values of 1-month timescale for historical period and RCP 4.5 (Jul)



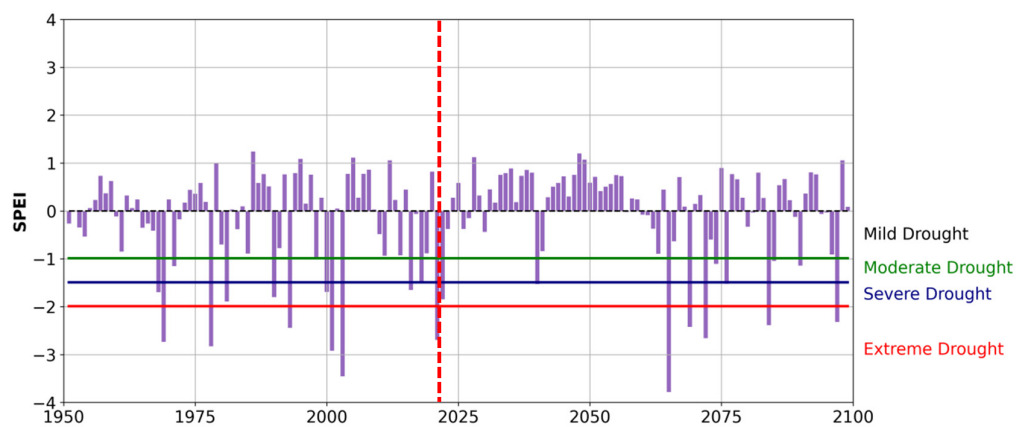
Annexure 3 - 8: SPEI values of 1-month timescale for historical period and RCP 4.5 (Aug)



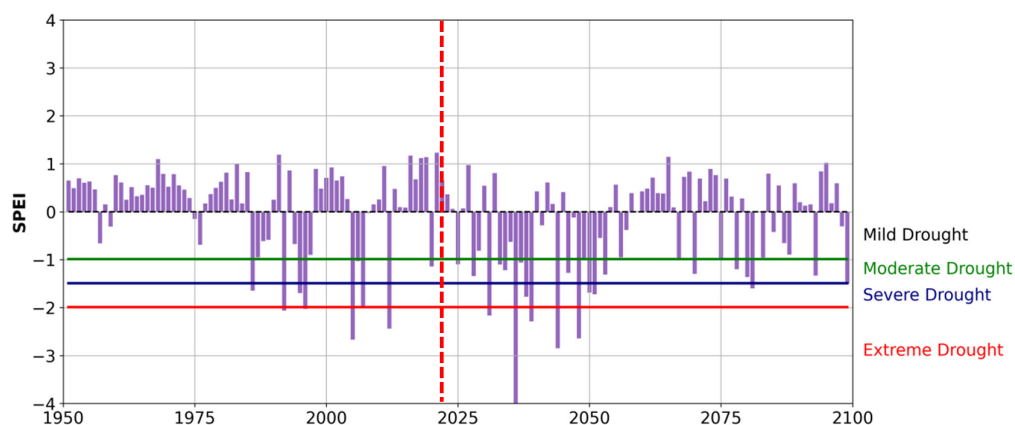
Annexure 3 - 9: SPEI values of 1-month timescale for historical period and RCP 4.5 (Sep)



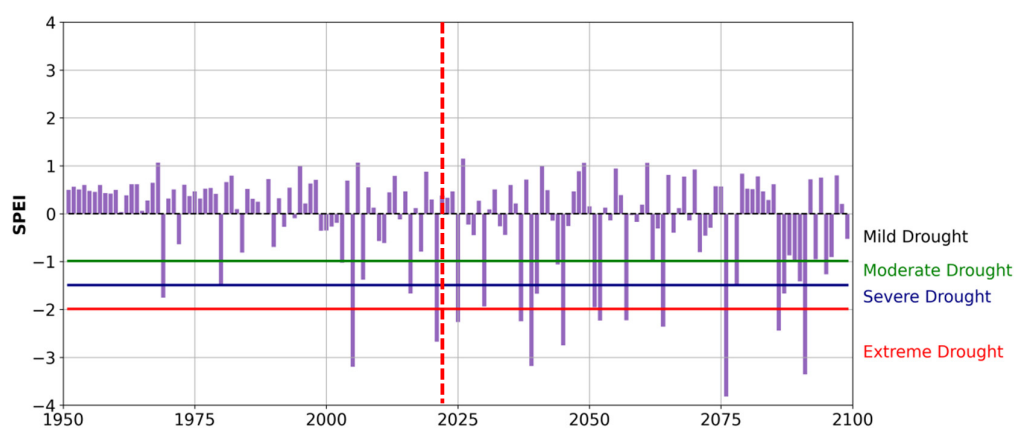
Annexure 3 - 10: SPEI values of 1-month timescale for historical period and RCP 4.5 (Oct)



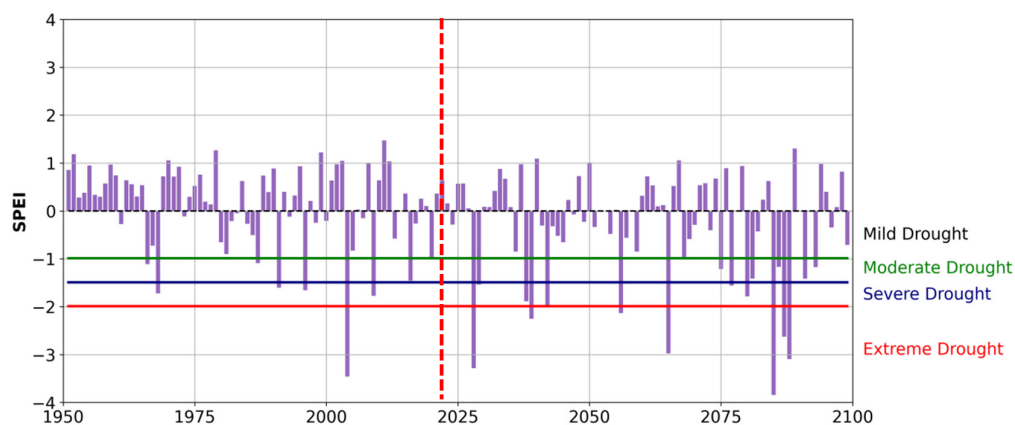
Annexure 3 - 11: SPEI values of 1-month timescale for historical period and RCP 4.5 (Nov)



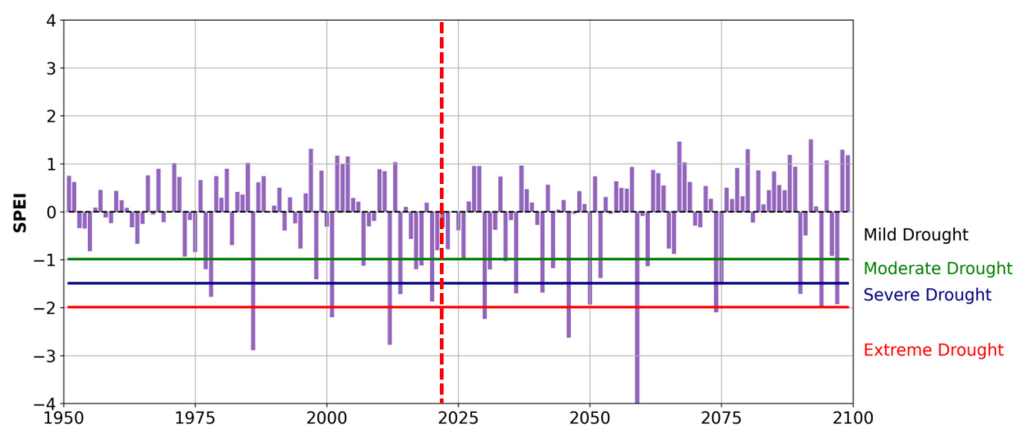
Annexure 3 - 12: SPEI values of 1-month timescale for historical period and RCP 4.5 (Dec)



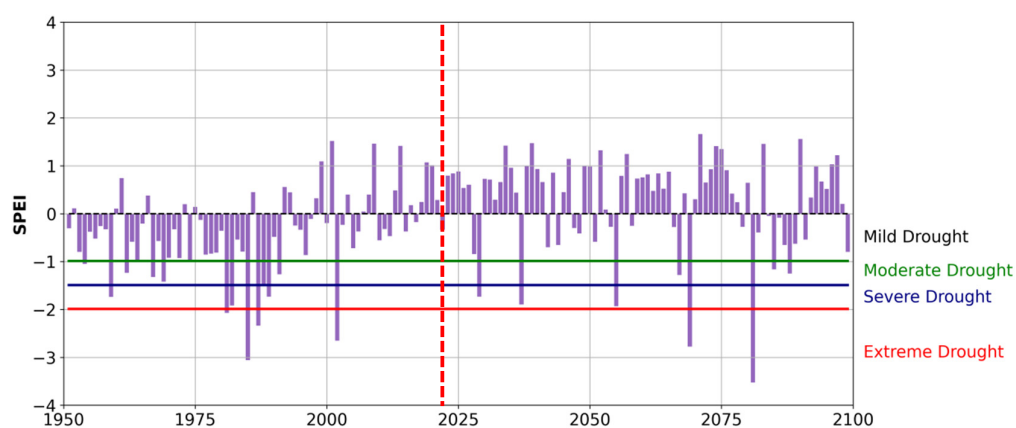
Annexure 3 - 13: SPEI values of 1-month timescale for historical period and RCP 8.5 (Jan)



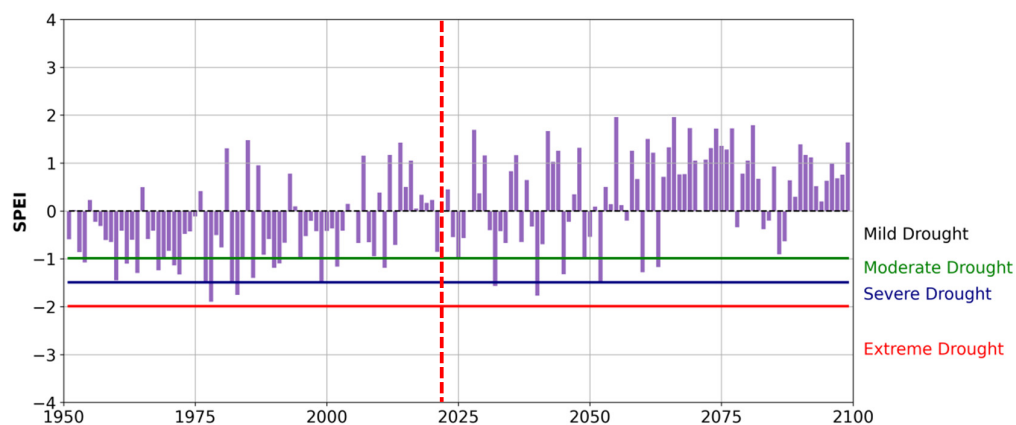
Annexure 3 - 14: SPEI values of 1-month timescale for historical period and RCP 8.5 (Feb)



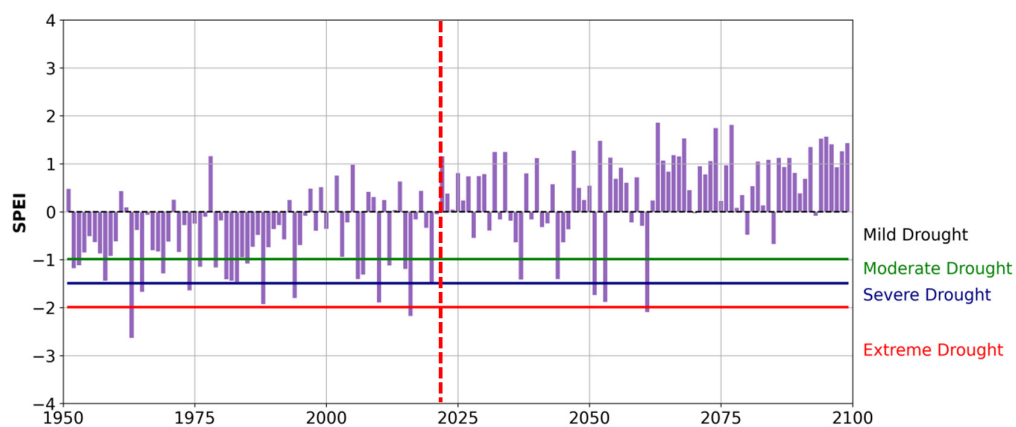
Annexure 3 - 15: SPEI values of 1-month timescale for historical period and RCP 8.5 (Mar)



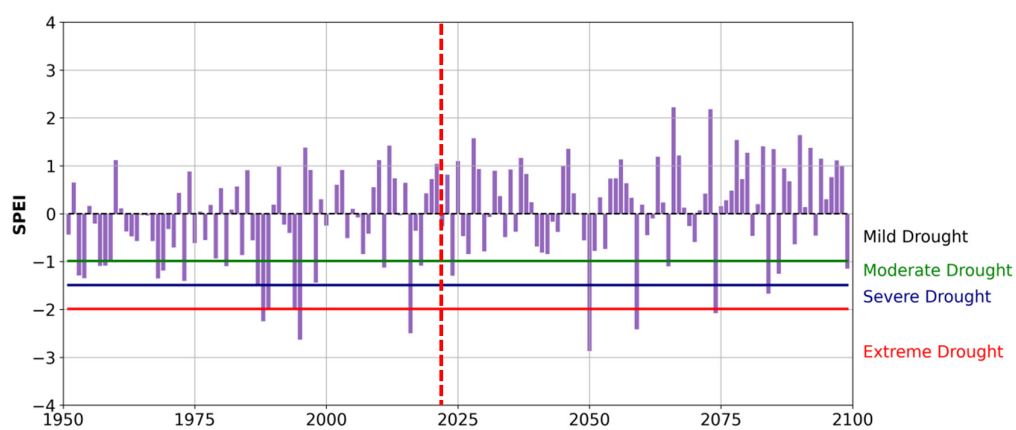
Annexure 3 - 16: SPEI values of 1-month timescale for historical period and RCP 8.5 (Apr)



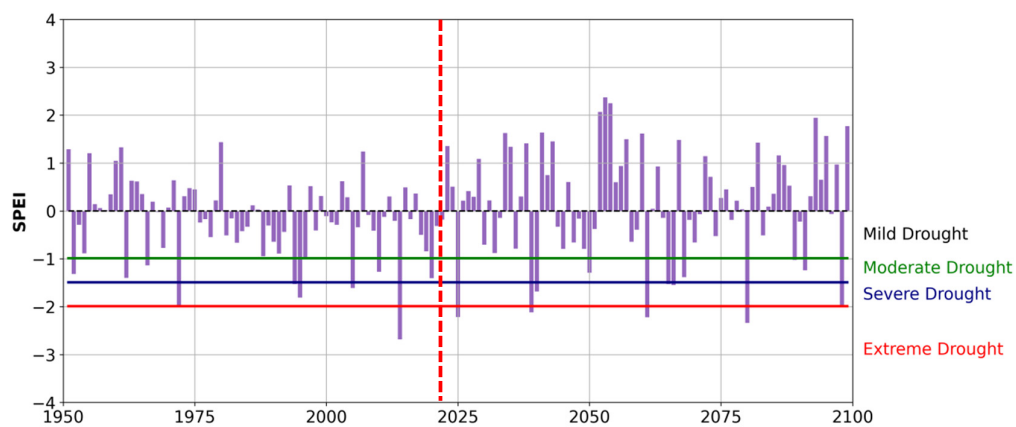
Annexure 3 - 17: SPEI values of 1-month timescale for historical period and RCP 8.5 (May)



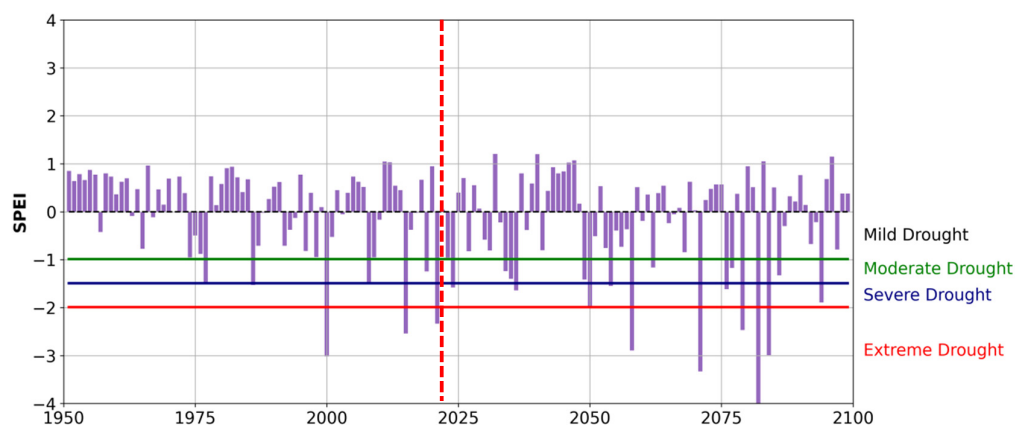
Annexure 3 - 18: SPEI values of 1-month timescale for historical period and RCP 8.5 (Jun)



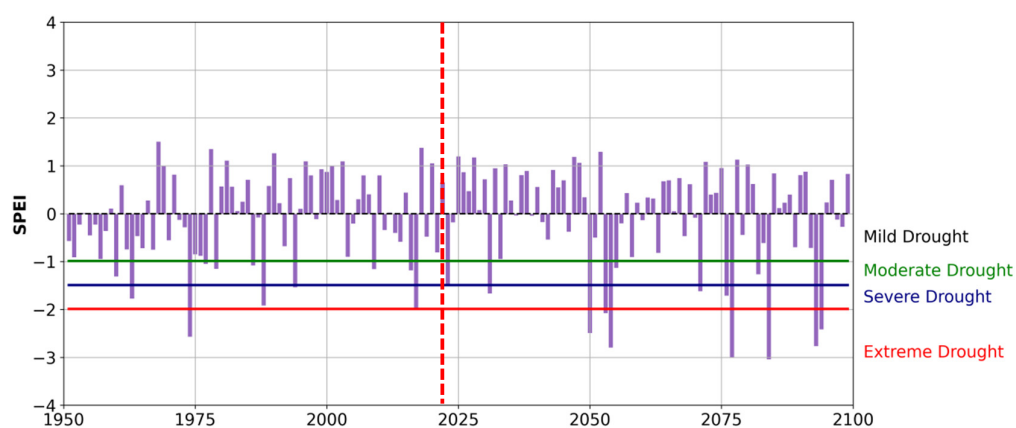
Annexure 3 - 19: SPEI values of 1-month timescale for historical period and RCP 8.5 (Jul)



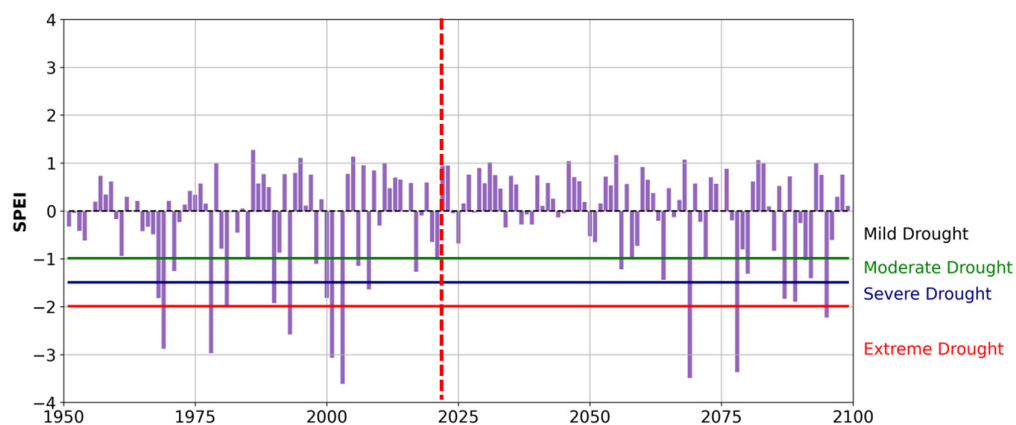
Annexure 3 - 20: SPEI values of 1-month timescale for historical period and RCP 8.5 (Aug)



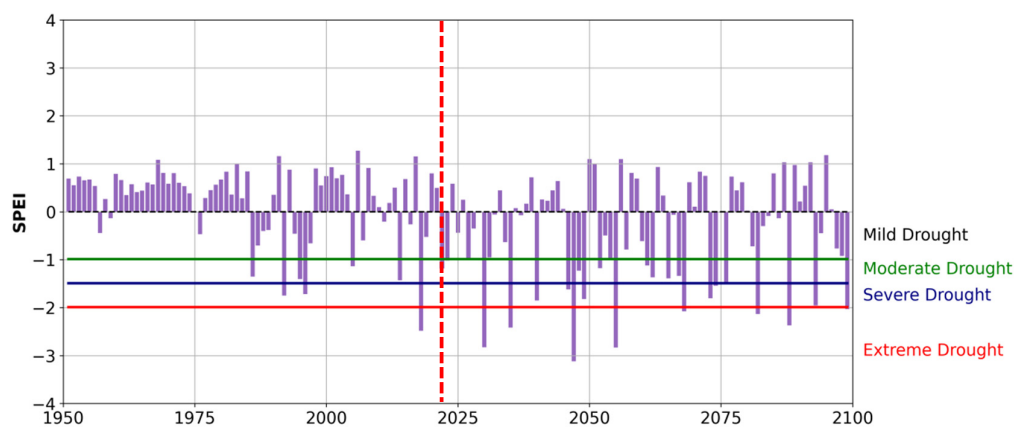
Annexure 3 - 21: SPEI values of 1-month timescale for historical period and RCP 8.5 (Sep)



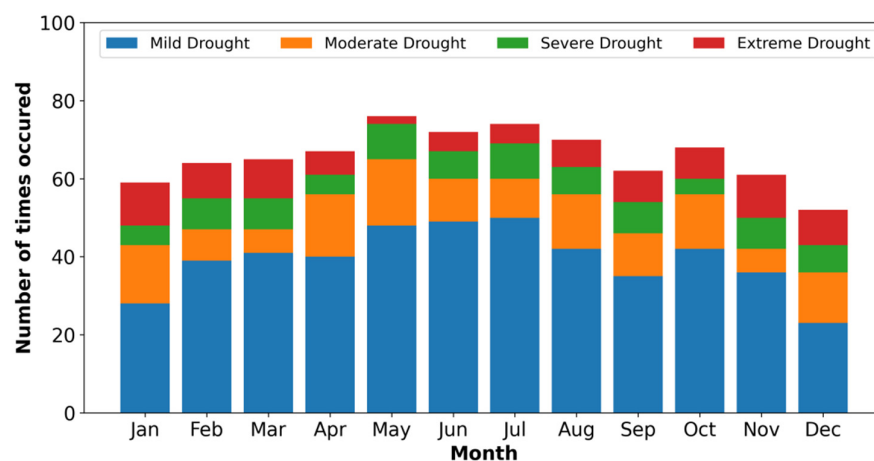
Annexure 3 - 22: SPEI values of 1-month timescale for historical period and RCP 8.5 (Oct)



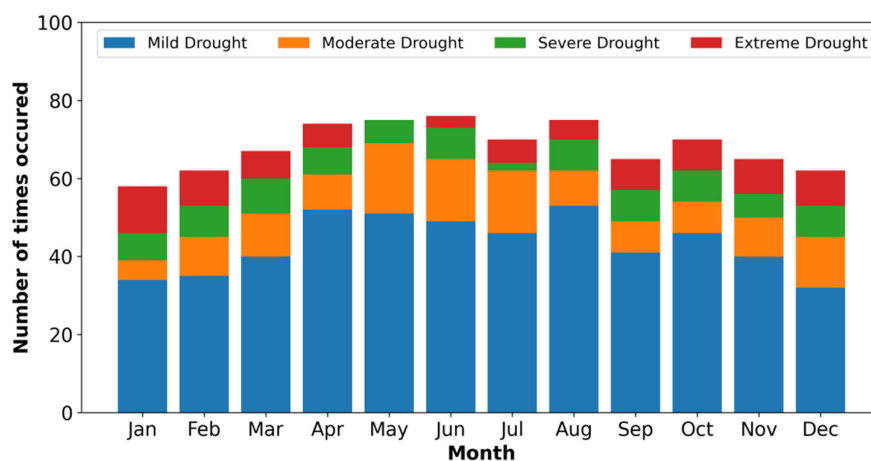
Annexure 3 - 23: SPEI values of 1-month timescale for historical period and RCP 8.5 (Nov)



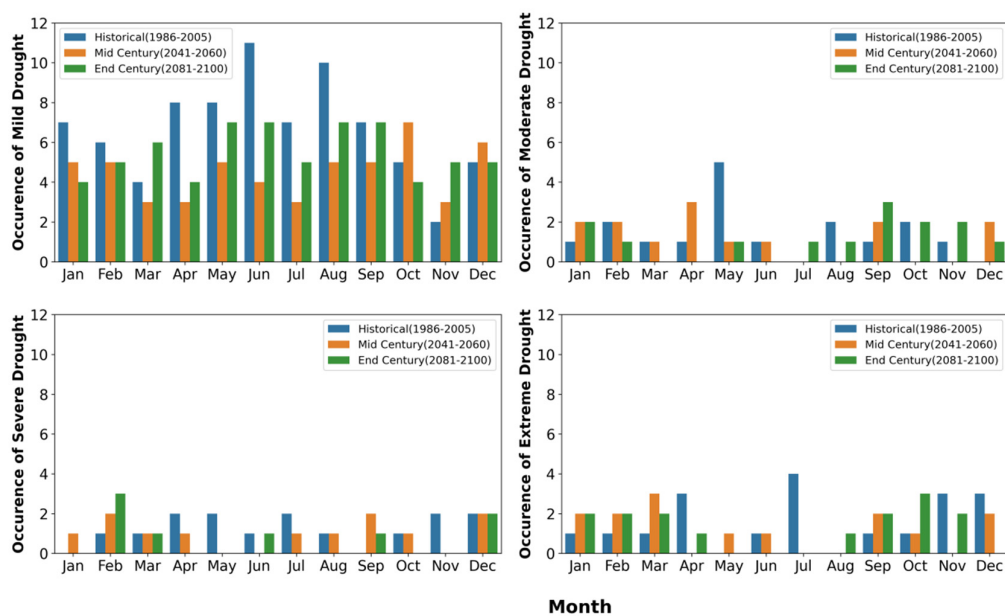
Annexure 3 - 24: SPEI values of 1-month timescale for historical period and RCP 8.5 (Dec)



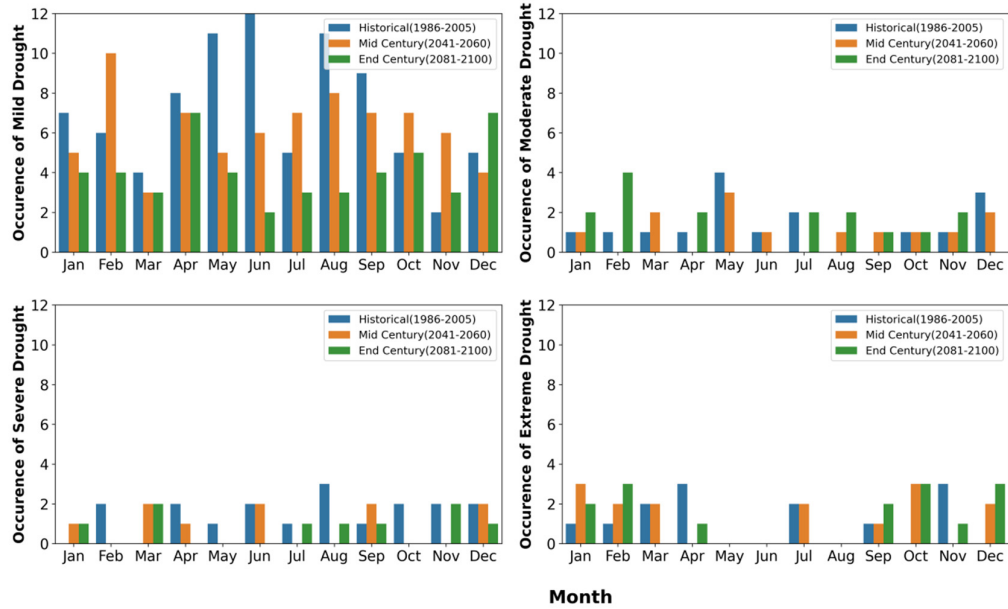
Annexure 3 - 25: Projected frequency and severity of drought events (RCP 4.5)



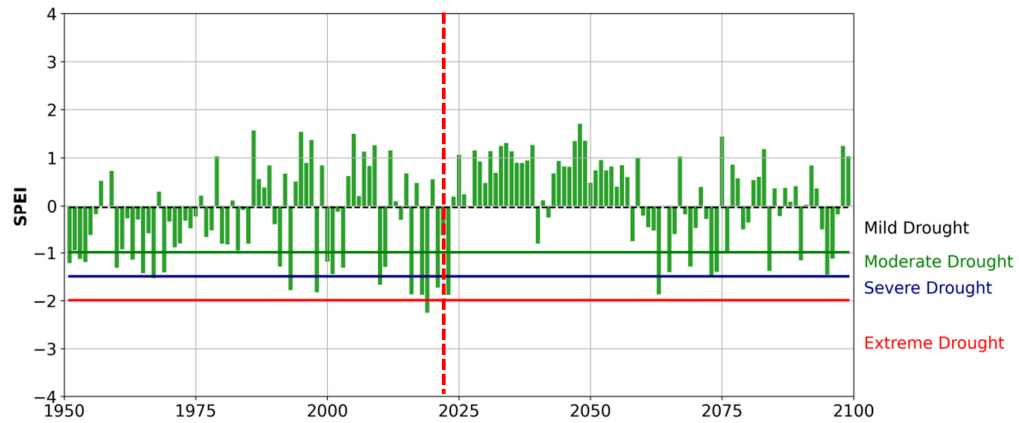
Annexure 3 - 26: Projected frequency and severity of drought events (RCP 8.5)



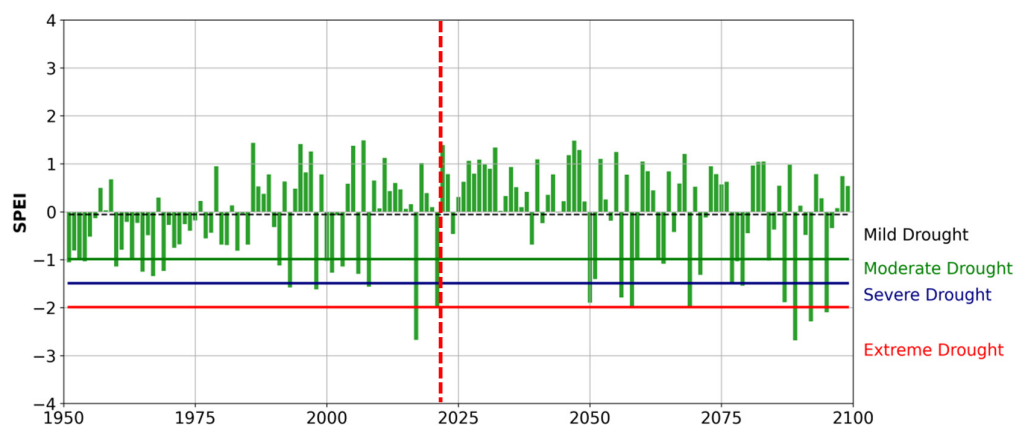
Annexure 3 - 27: Comparison of historical, mid-century and end-century RCP 4.5 drought events



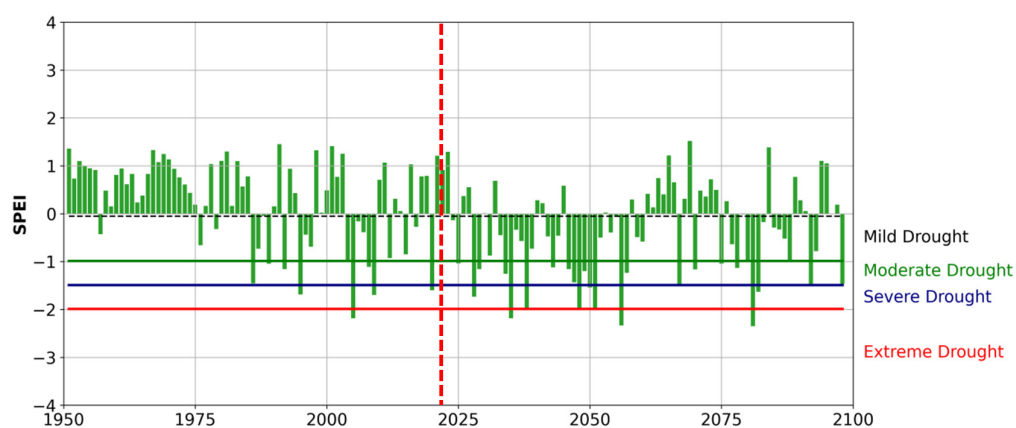
Annexure 3 - 28: Comparison of historical, mid-century and end-century RCP 8.5 drought events



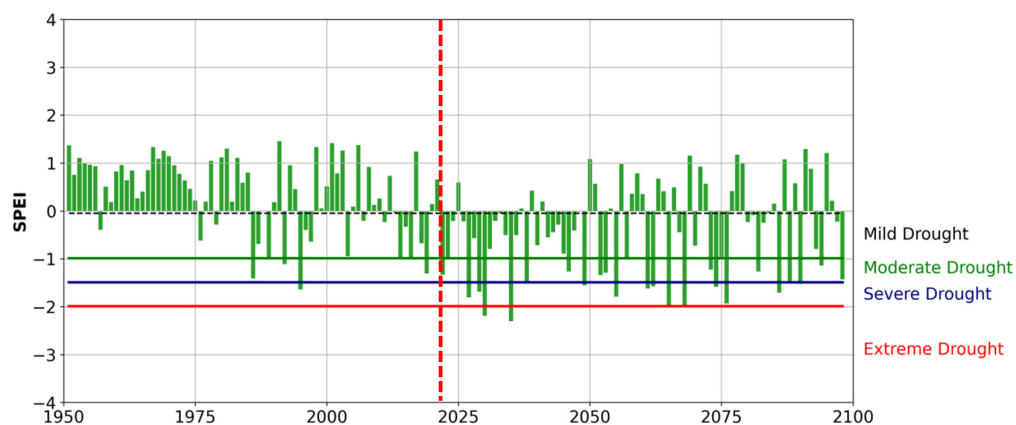
Annexure 3 - 29: SPEI for historical period and RCP 4.5 (Second inter-monsoon (Oct-Nov))



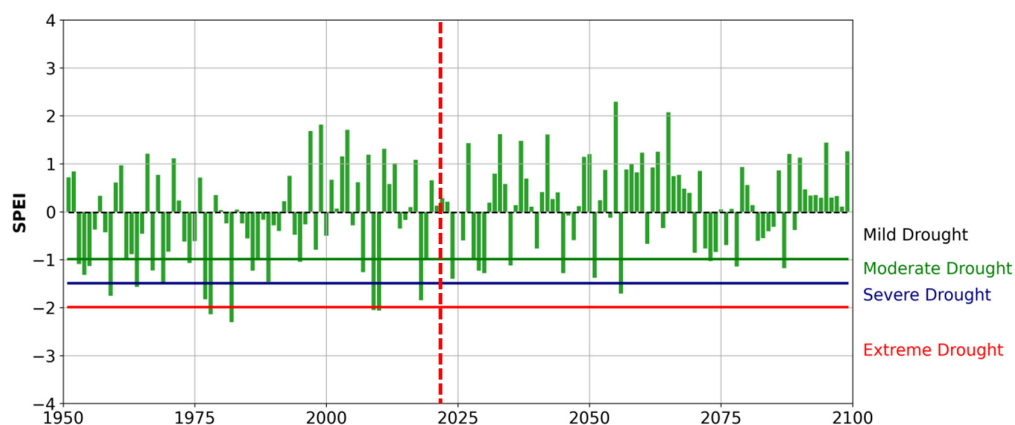
Annexure 3 - 30: SPEI for historical period and RCP 8.5 (Second inter-monsoon (Oct-Nov))



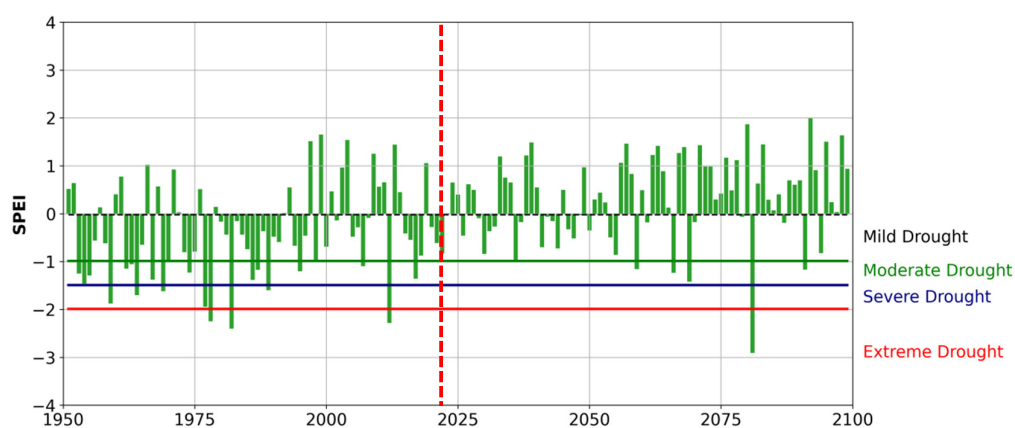
Annexure 3 - 31: SPEI for historical period and RCP 4.5 (N-E Monsoon (Dec-Mar))



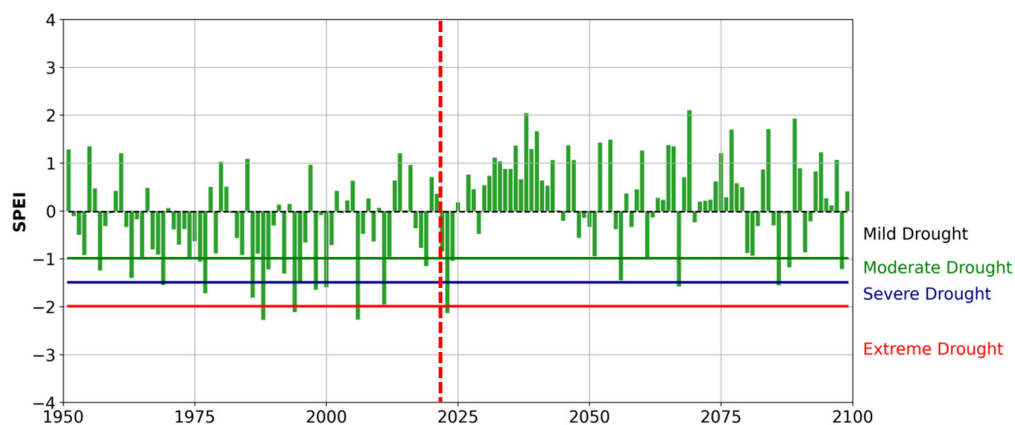
Annexure 3 - 32: SPEI for historical period and RCP 8.5 (N-E Monsoon (Dec-Mar))



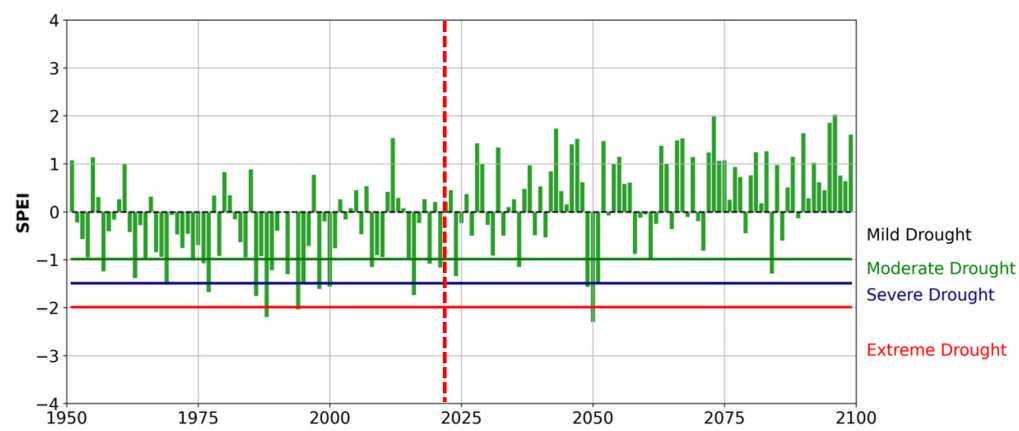
Annexure 3 - 33: SPEI for historical period and RCP 4.5 (First inter-monsoon (Mar-Apr))



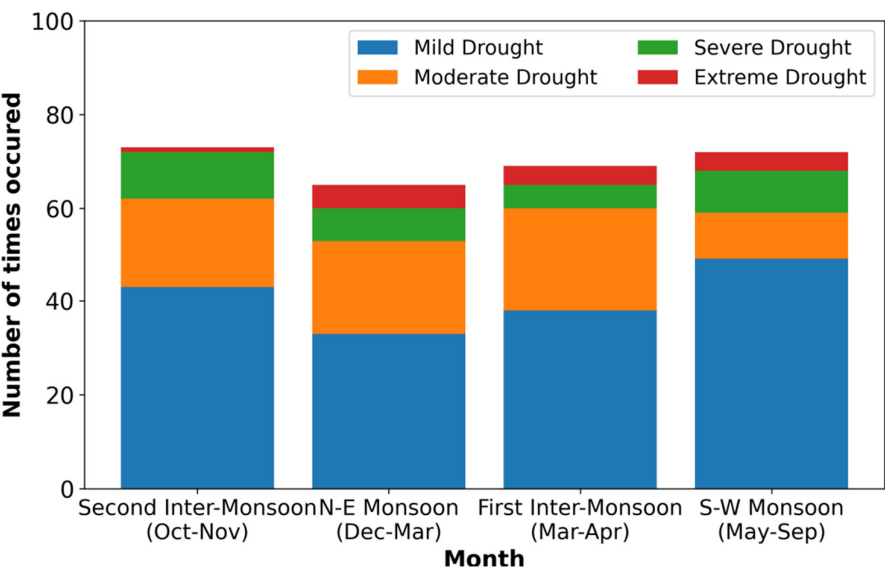
Annexure 3 - 34: SPEI for historical period and RCP 8.5 (First inter-monsoon (Mar-Apr))



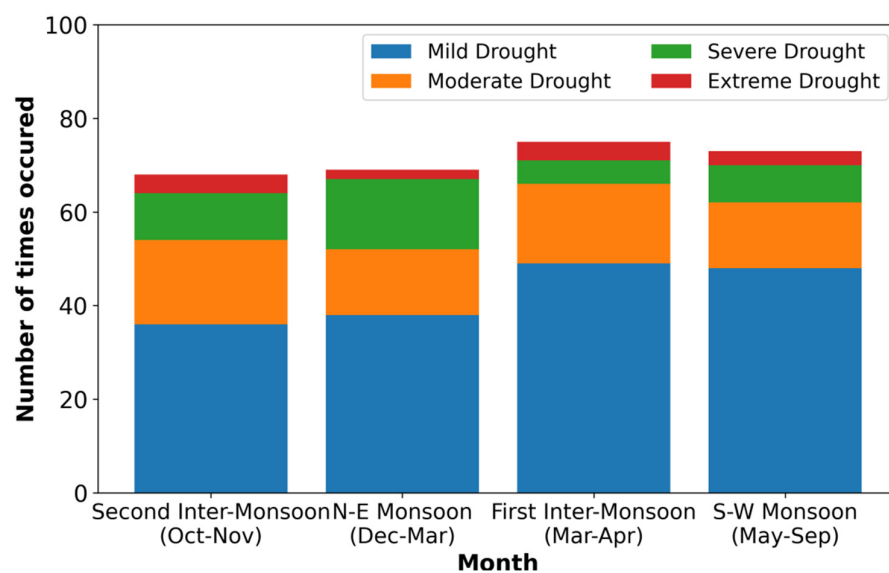
Annexure 3 - 35: SPEI for historical period and RCP 4.5 (S-W Monsoon (May-Sep))



Annexure 3 - 36: SPEI for historical period and RCP 8.5 (S-W Monsoon (May-Sep))



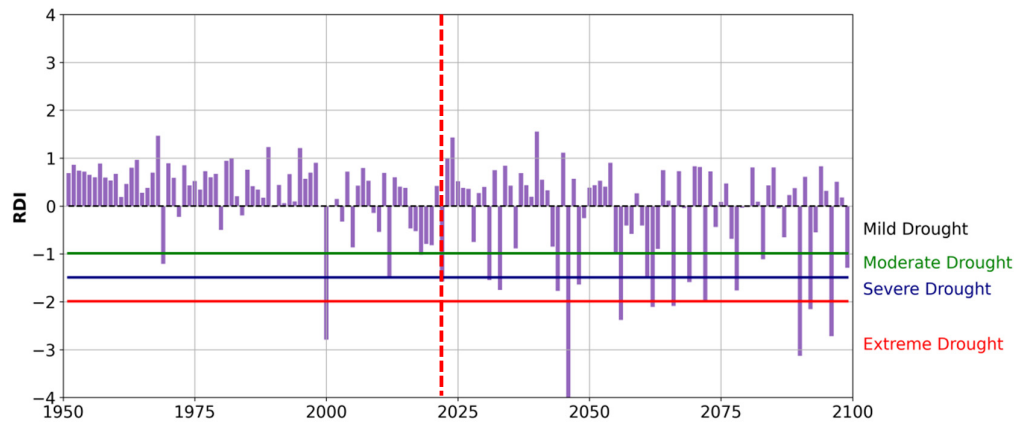
Annexure 3 - 37: Projected frequency and severity of seasonal drought events (RCP 4.5)



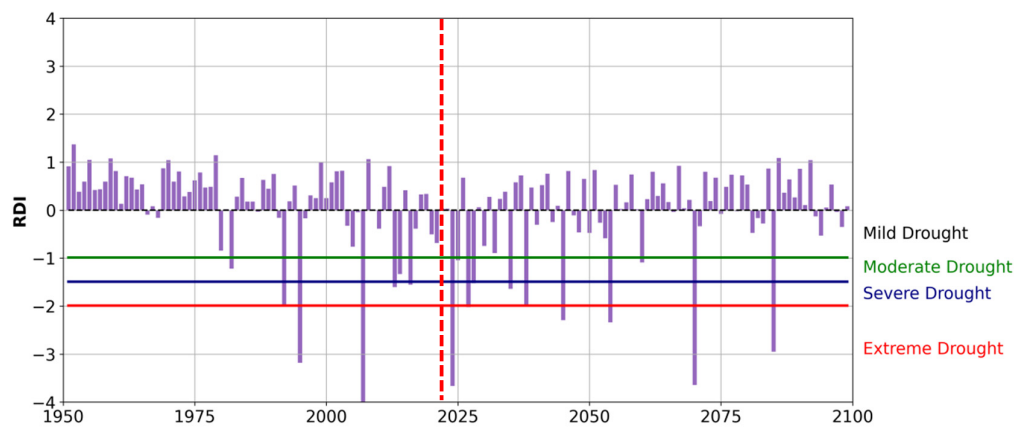
Annexure 3 - 38: Projected frequency and severity of seasonal drought events (RCP 8.5)

ANNEXURE 4

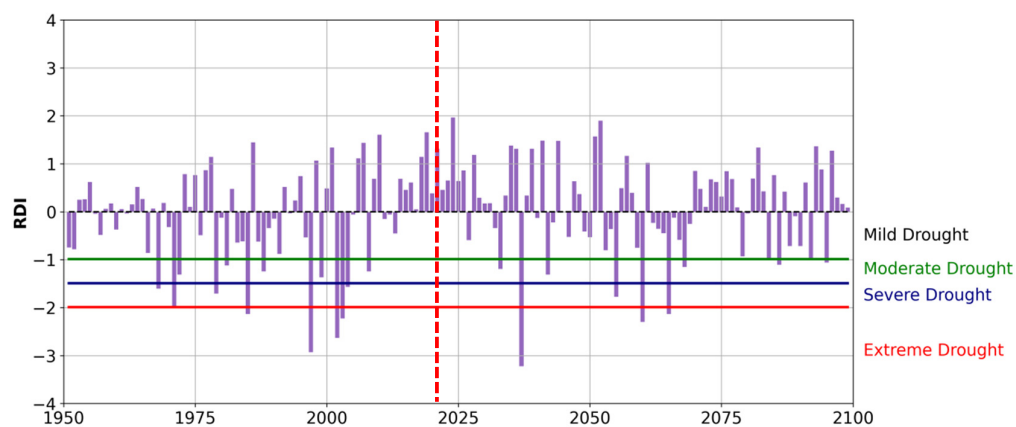
RDI



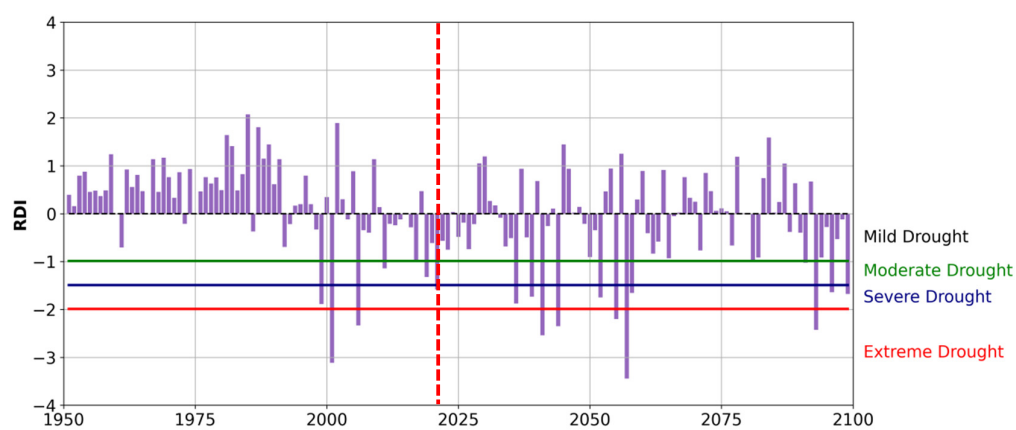
Annexure 4 - 1: RDI values of 1-month timescale for historical period and RCP 4.5 (Jan)



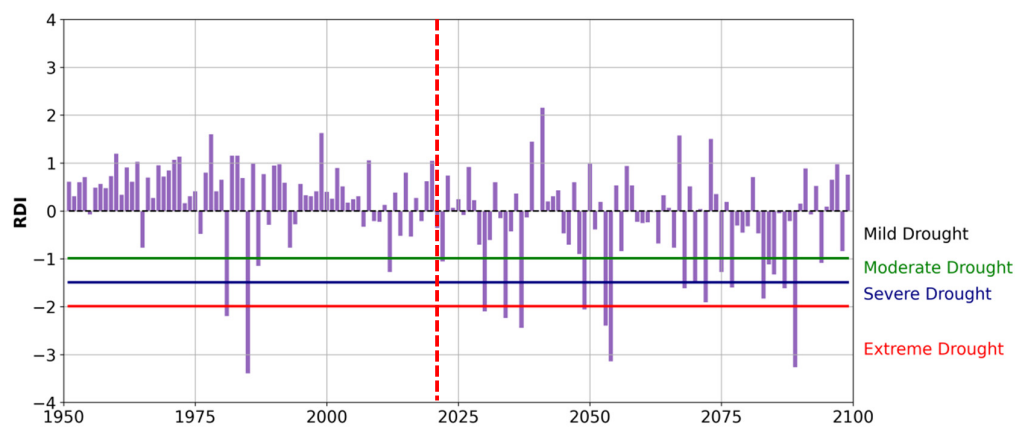
Annexure 4 - 2: RDI values of 1-month timescale for historical period and RCP 4.5 (Feb)



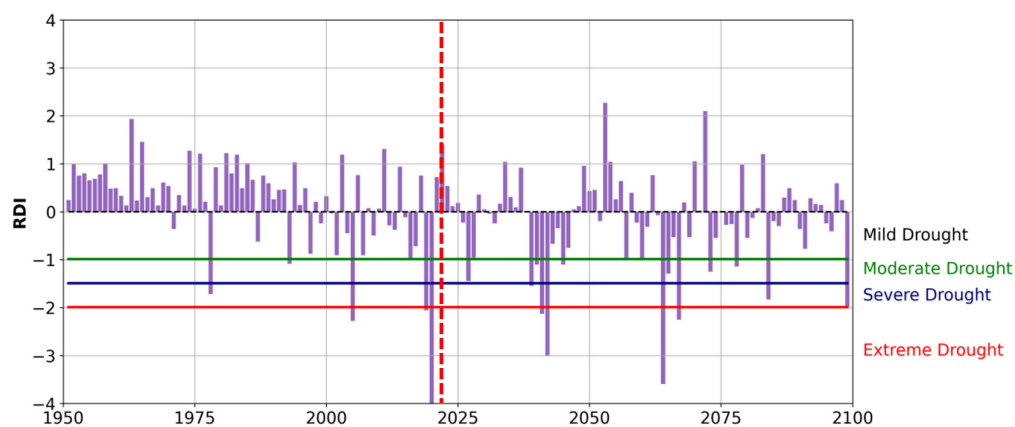
Annexure 4 - 3: RDI values of 1-month timescale for historical period and RCP 4.5 (Mar)



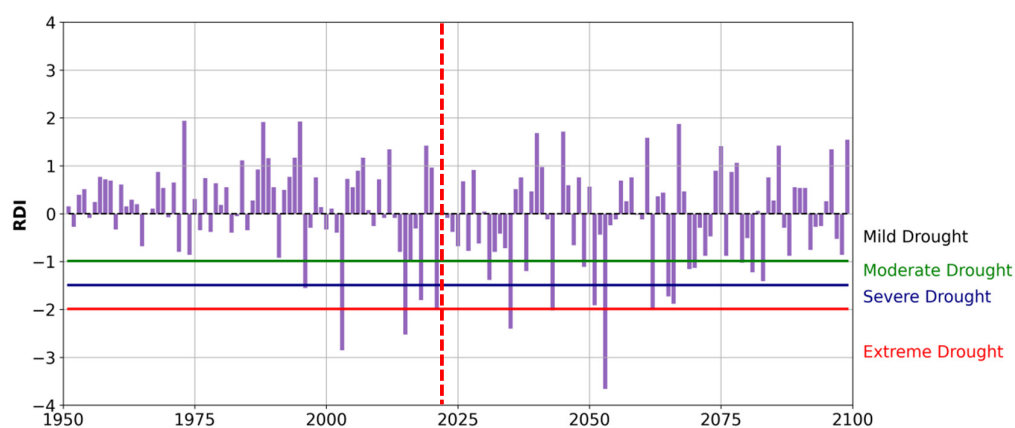
Annexure 4 - 4: RDI values of 1-month timescale for historical period and RCP 4.5 (Apr)



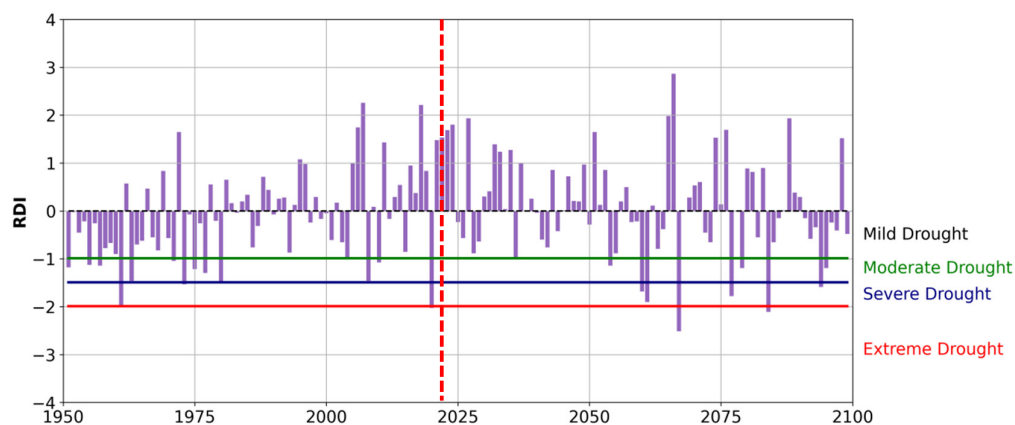
Annexure 4 - 5: RDI values of 1-month timescale for historical period and RCP 4.5 (May)



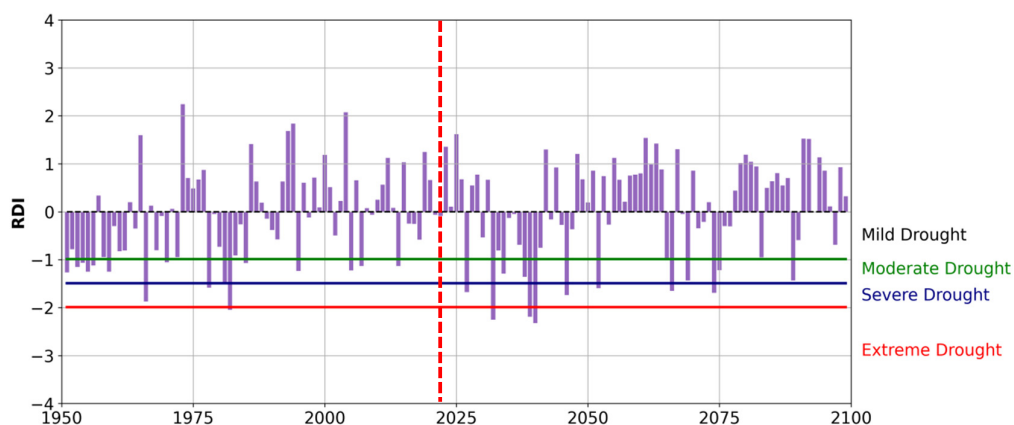
Annexure 4 - 6: RDI values of 1-month timescale for historical period and RCP 4.5 (Jun)



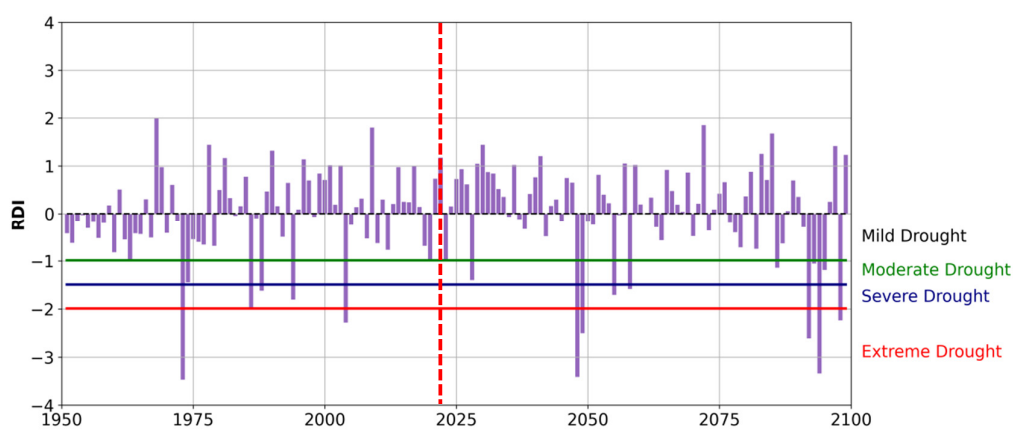
Annexure 4 - 7: RDI values of 1-month timescale for historical period and RCP 4.5 (Jul)



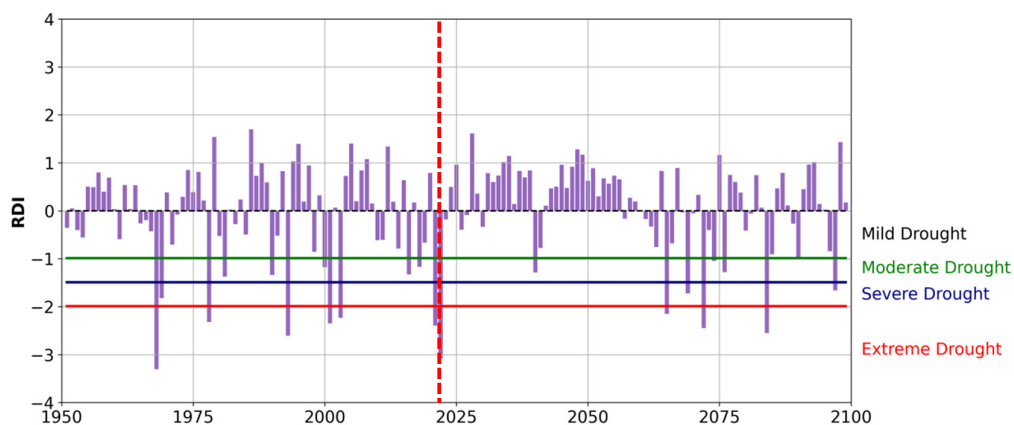
Annexure 4 - 8: RDI values of 1-month timescale for historical period and RCP 4.5 (Aug)



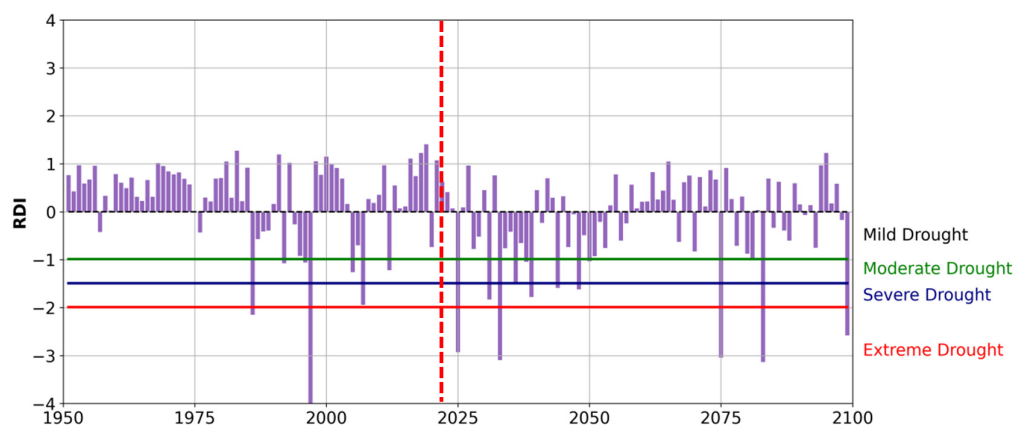
Annexure 4 - 9: RDI values of 1-month timescale for historical period and RCP 4.5 (Sep)



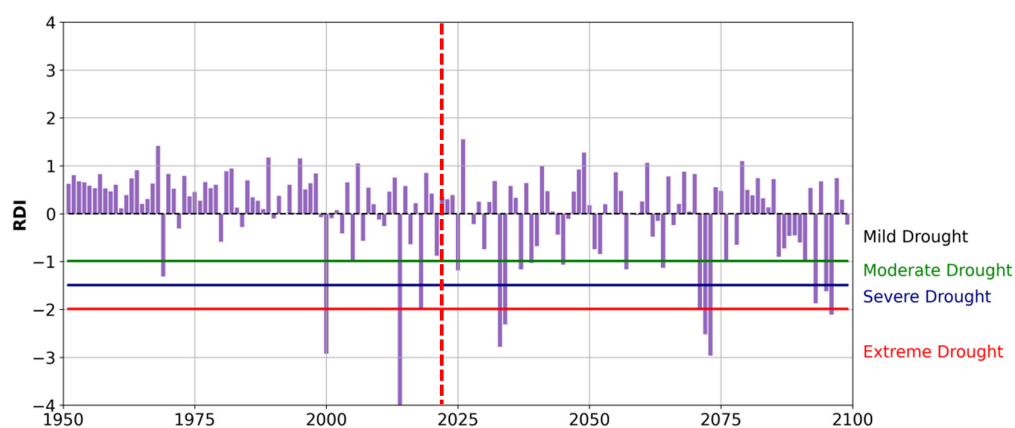
Annexure 4 - 10: RDI values of 1-month timescale for historical period and RCP 4.5 (Oct)



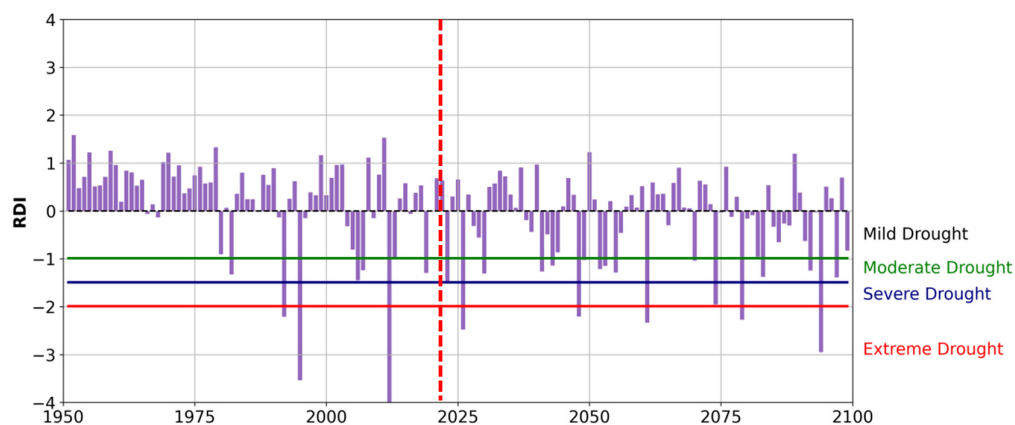
Annexure 4 - 11: RDI values of 1-month timescale for historical period and RCP 4.5 (Nov)



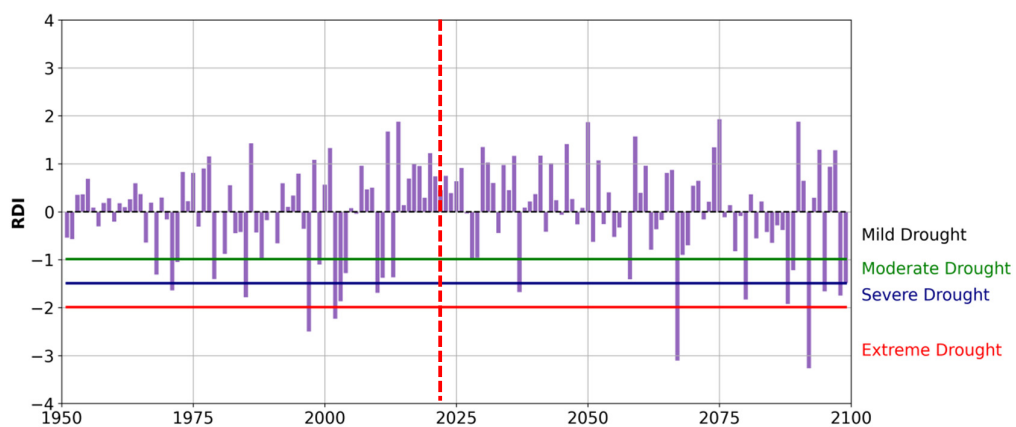
Annexure 4 - 12: RDI values of 1-month timescale for historical period and RCP 4.5 (Dec)



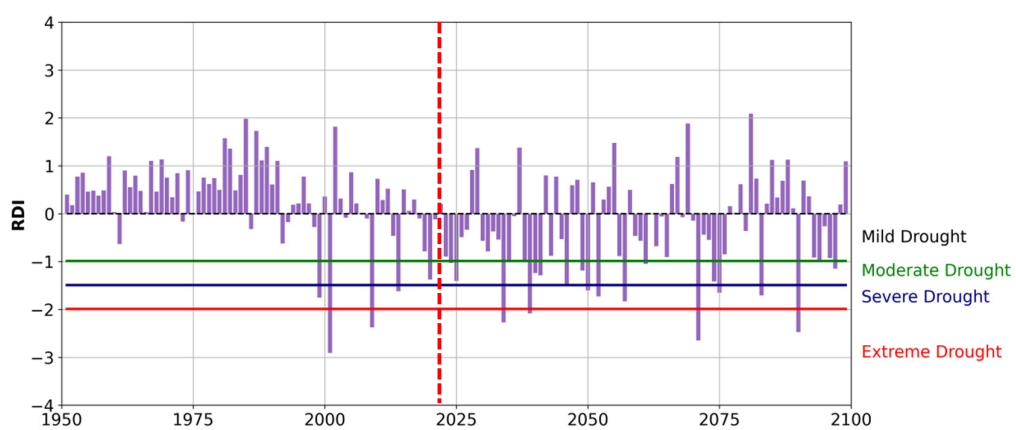
Annexure 4 - 13: RDI values of 1-month timescale for historical period and RCP 8.5 (Jan)



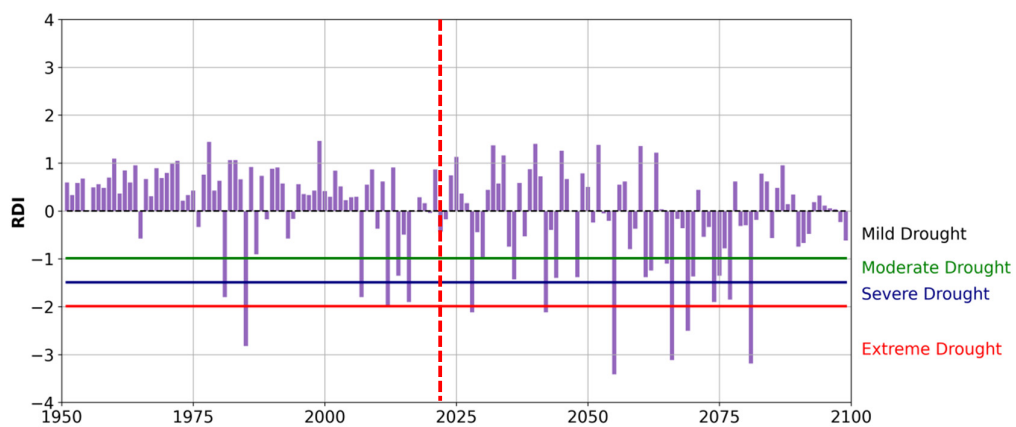
Annexure 4 - 14: RDI values of 1-month timescale for historical period and RCP 8.5 (Feb)



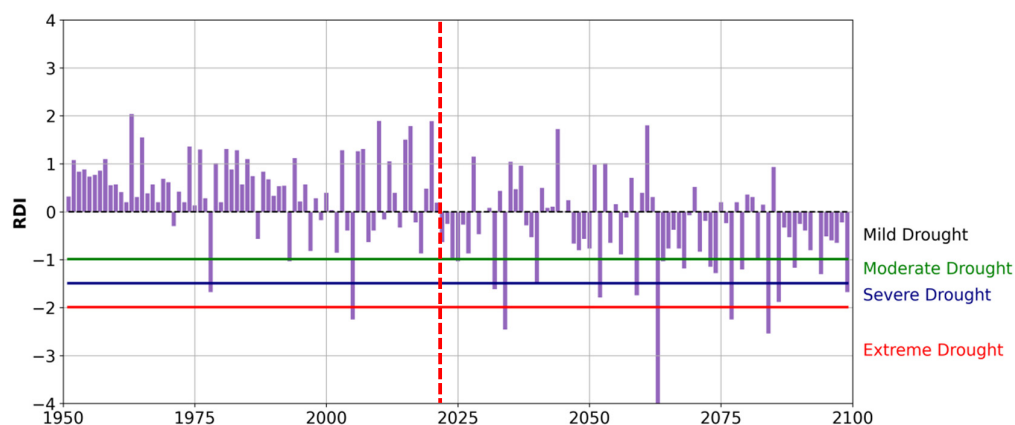
Annexure 4 - 15: RDI values of 1-month timescale for historical period and RCP 8.5 (Mar)



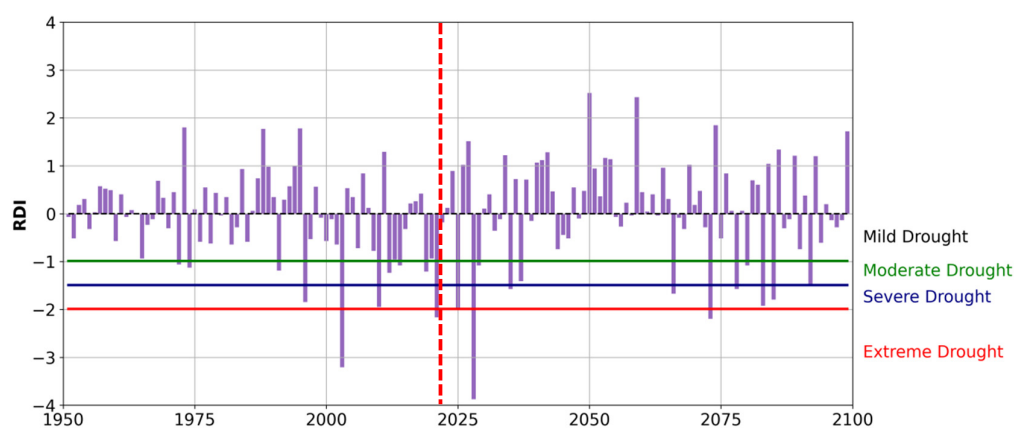
Annexure 4 - 16: RDI values of 1-month timescale for historical period and RCP 8.5 (Apr)



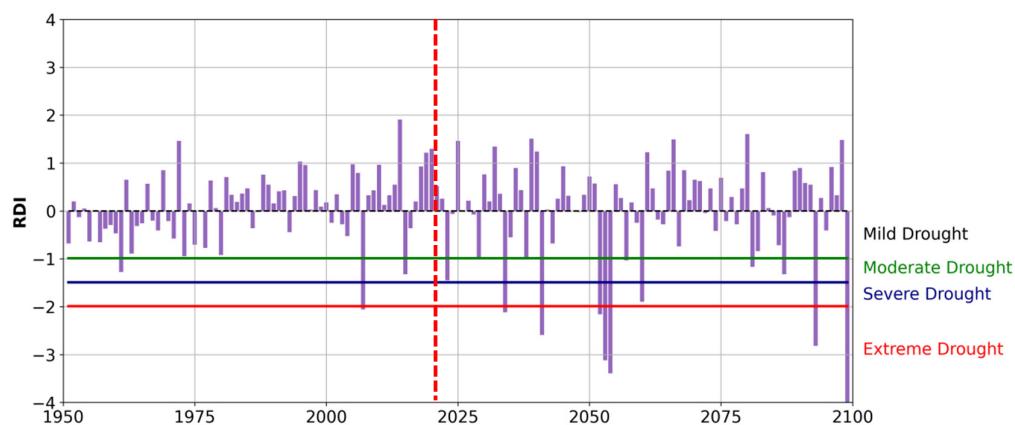
Annexure 4 - 17: RDI values of 1-month timescale for historical period and RCP 8.5 (May)



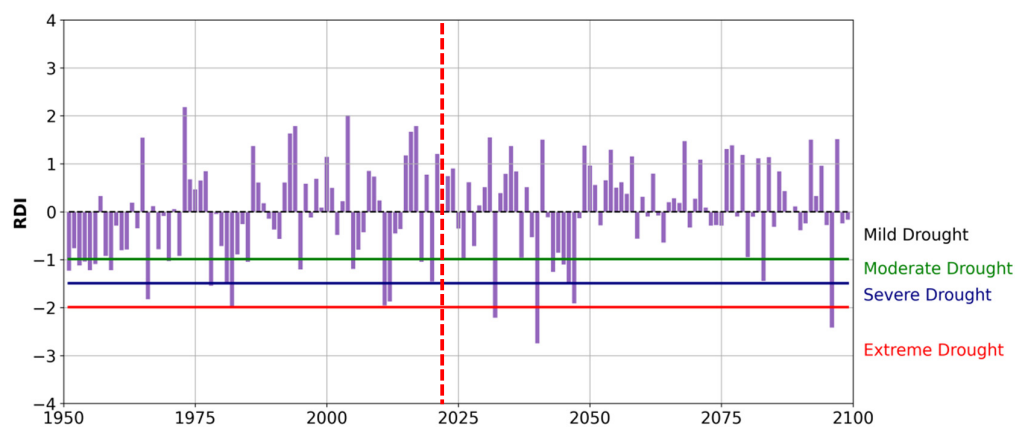
Annexure 4 - 18: RDI values of 1-month timescale for historical period and RCP 8.5 (Jun)



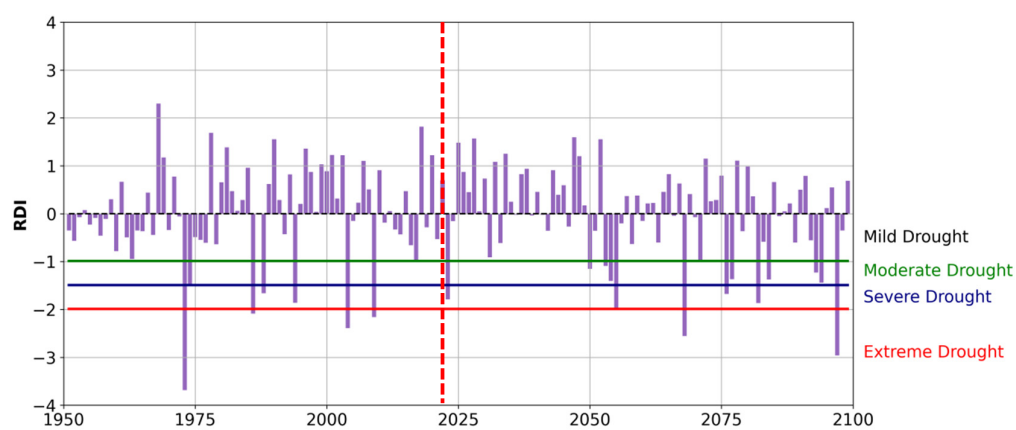
Annexure 4 - 19: RDI values of 1-month timescale for historical period and RCP 8.5 (Jul)



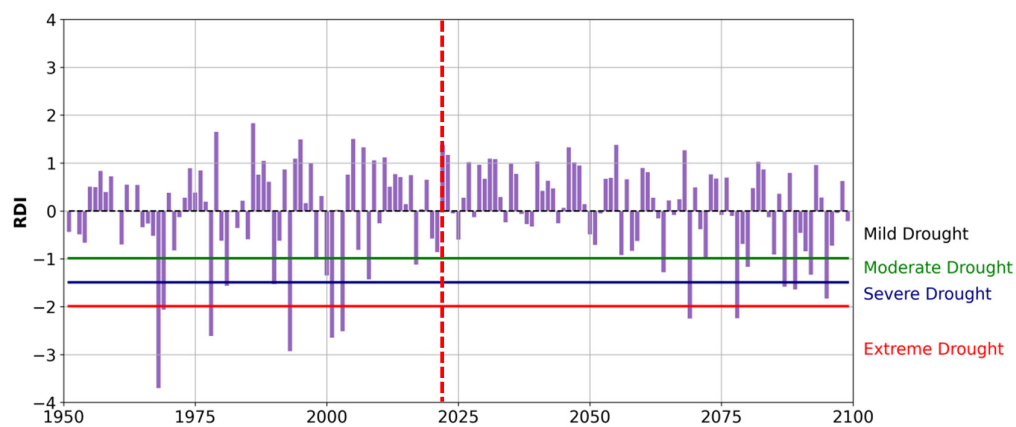
Annexure 4 - 20: RDI values of 1-month timescale for historical period and RCP 8.5 (Aug)



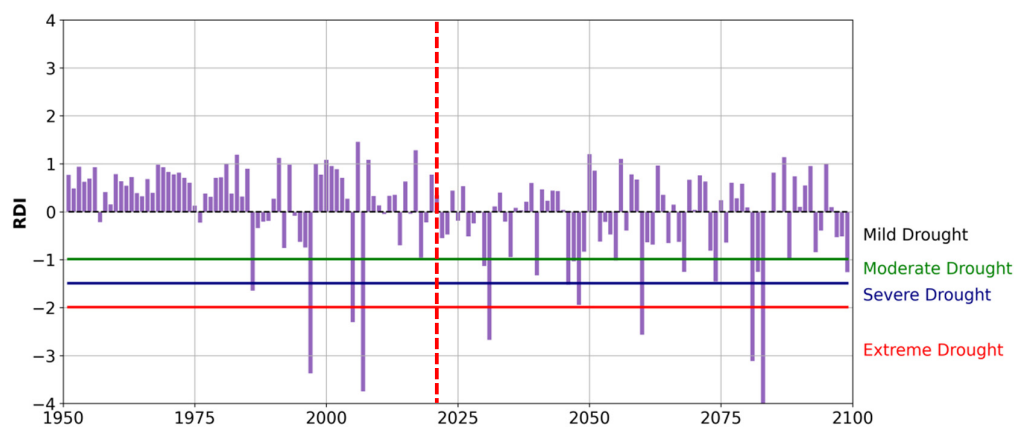
Annexure 4 - 21: RDI values of 1-month timescale for historical period and RCP 8.5 (Sep)



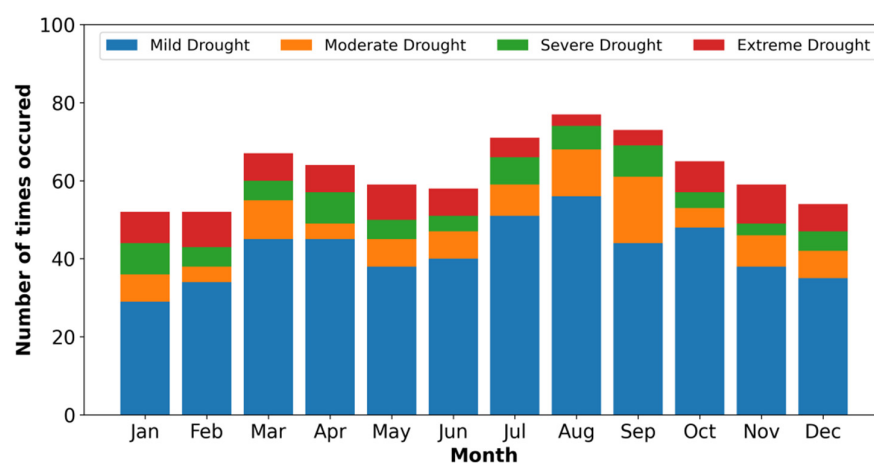
Annexure 4 - 22: RDI values of 1-month timescale for historical period and RCP 8.5 (Oct)



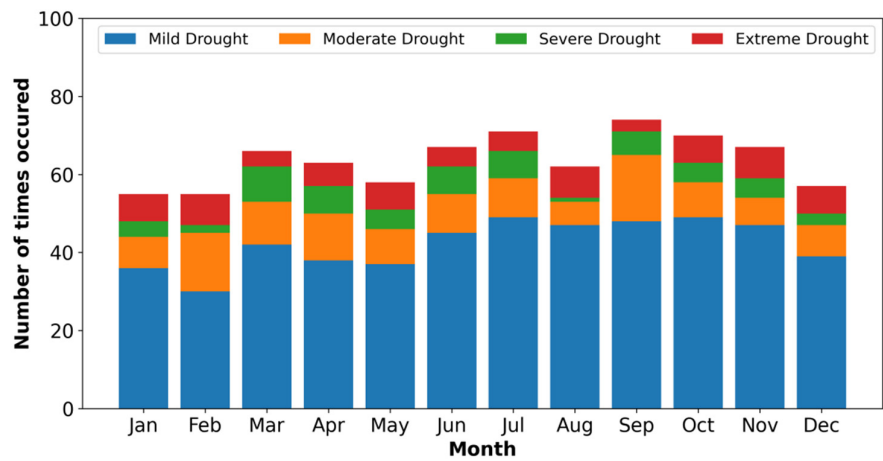
Annexure 4 - 23: RDI values of 1-month timescale for historical period and RCP 8.5 (Nov)



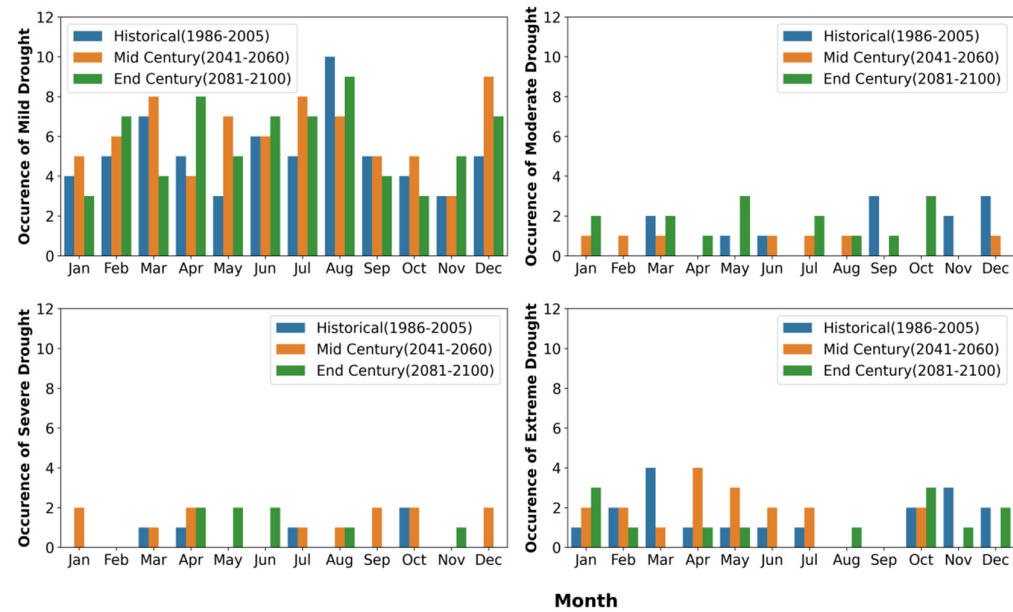
Annexure 4 - 24: RDI values of 1-month timescale for historical period and RCP 8.5 (Dec)



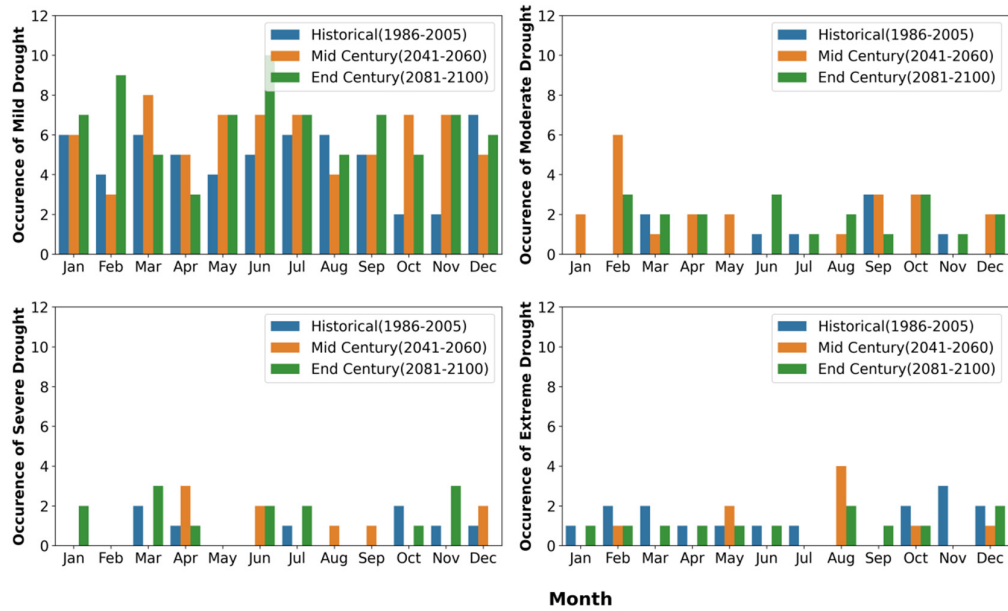
Annexure 4 - 25: Projected frequency and severity of drought events (RCP 4.5)



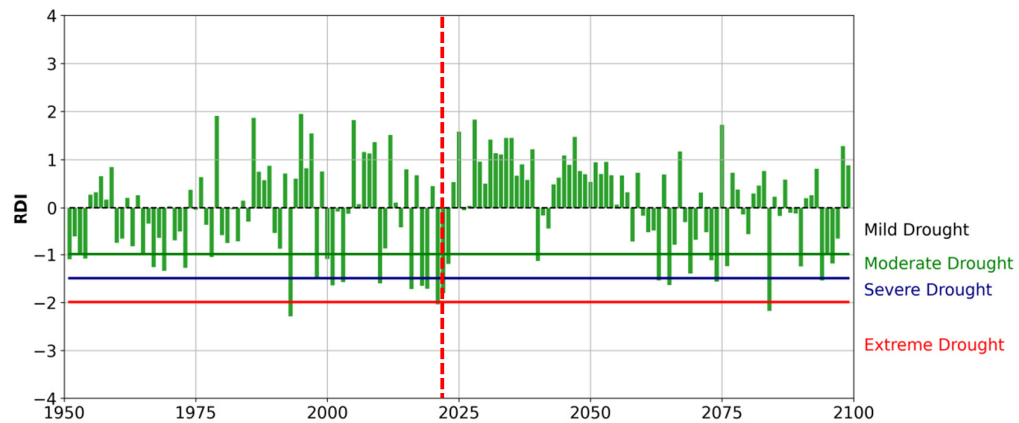
Annexure 4 - 26: Projected frequency and severity of drought events (RCP 8.5)



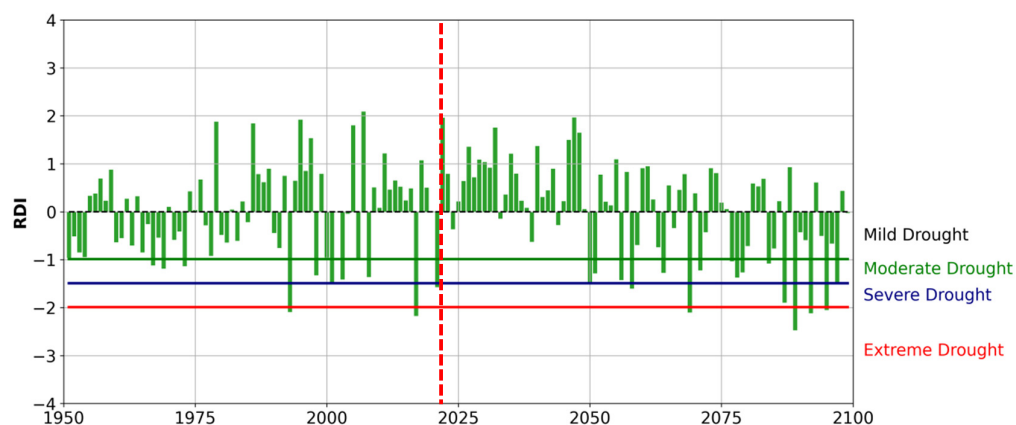
Annexure 4 - 27: Comparison of historical, mid-century and end-century RCP 4.5 drought events



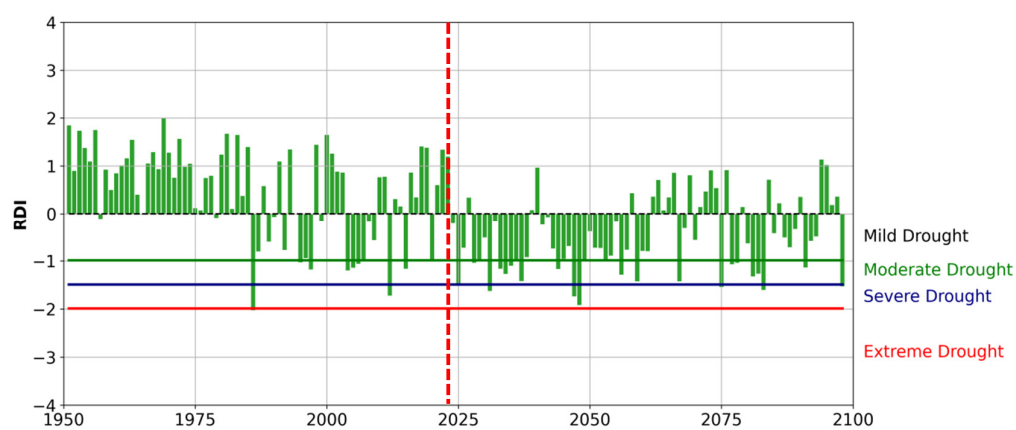
Annexure 4 - 28: Comparison of historical, mid-century and end-century RCP 8.5 drought events



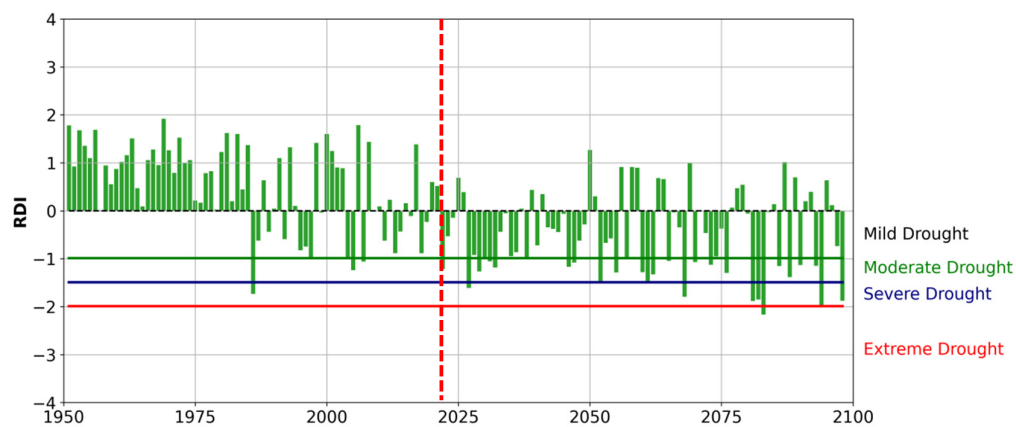
Annexure 4 - 29: RDI for historical period and RCP 4.5 (Second inter-monsoon (Oct-Nov))



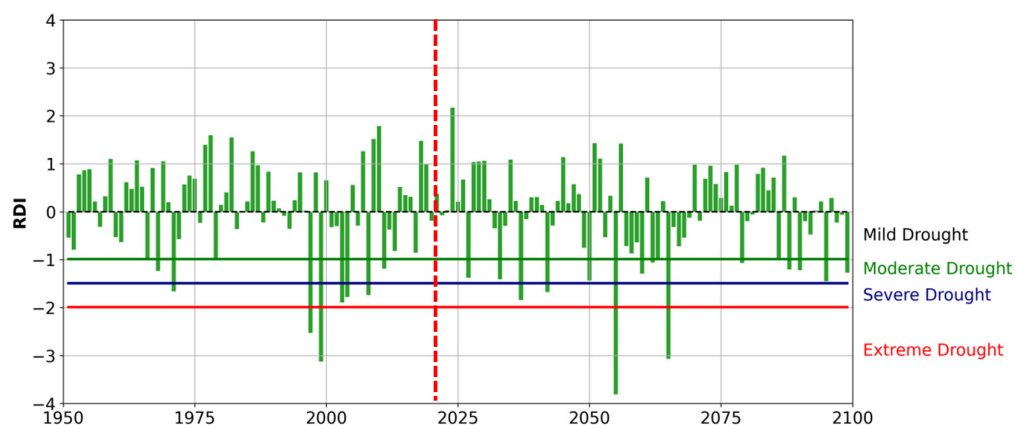
Annexure 4 - 30: RDI for historical period and RCP 8.5 (Second inter-monsoon (Oct-Nov))



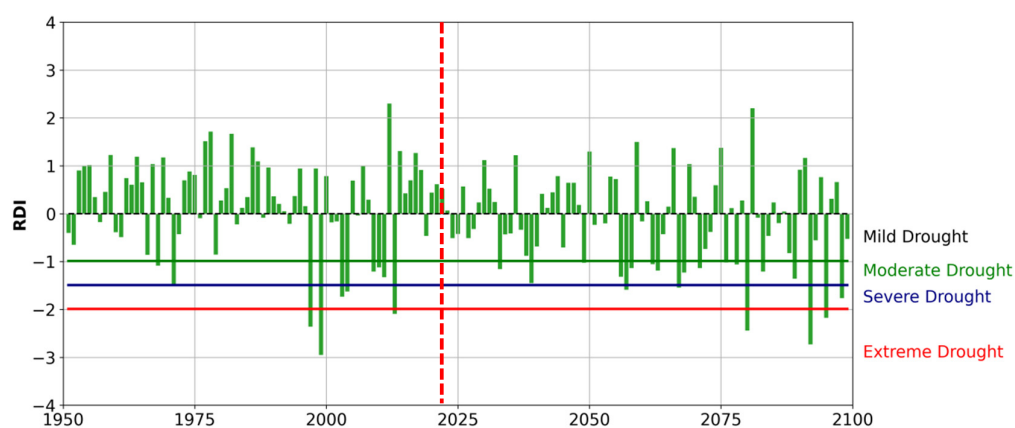
Annexure 4 - 31: RDI for historical period and RCP 4.5 (N-E Monsoon (Dec-Mar))



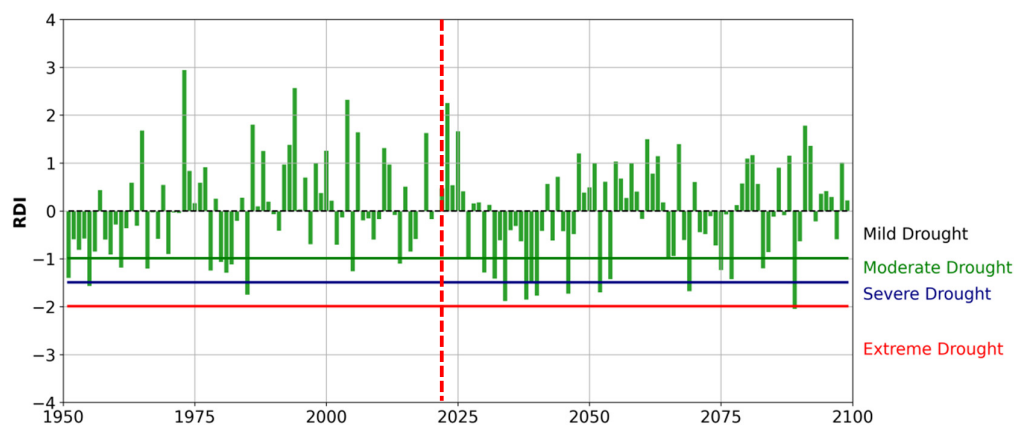
Annexure 4 - 32: RDI for historical period and RCP 8.5 (N-E Monsoon (Dec-Mar))



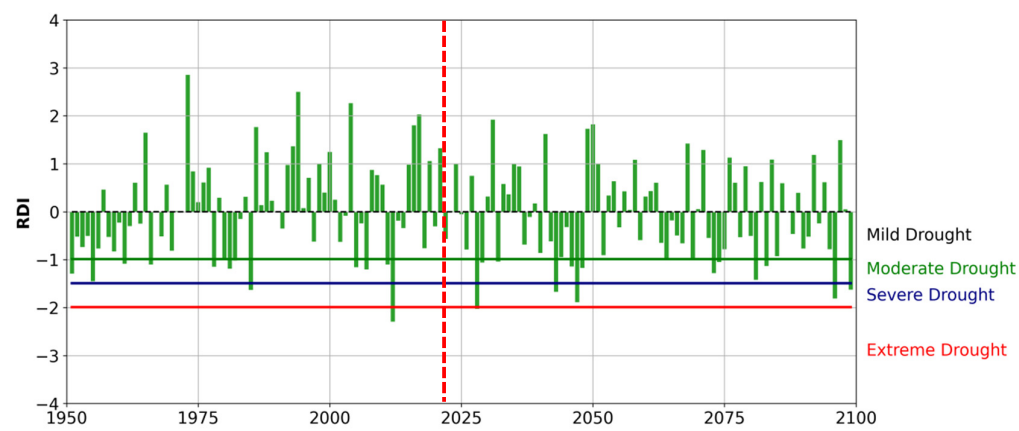
Annexure 4 - 33: RDI for historical period and RCP 4.5 (First inter-monsoon (Mar-Apr))



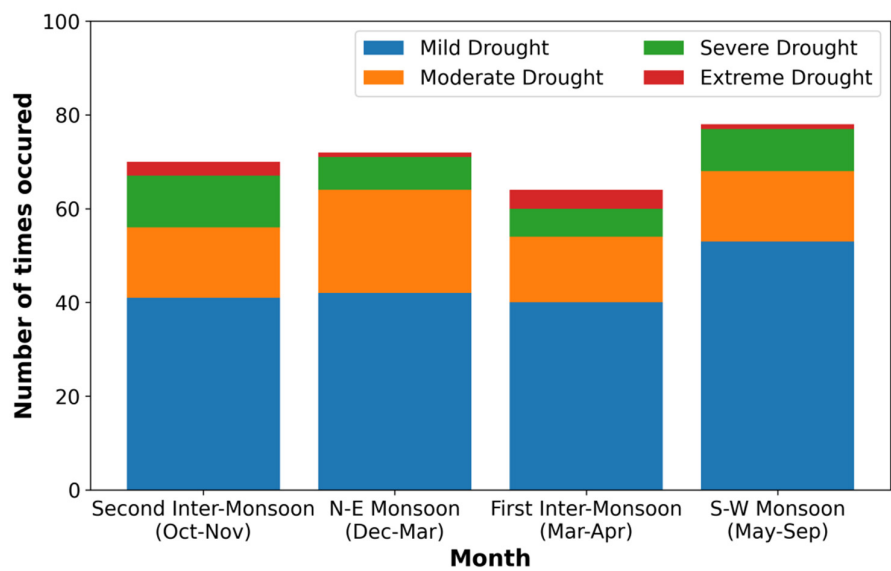
Annexure 4 - 34: RDI for historical period and RCP 8.5 (First inter-monsoon (Mar-Apr))



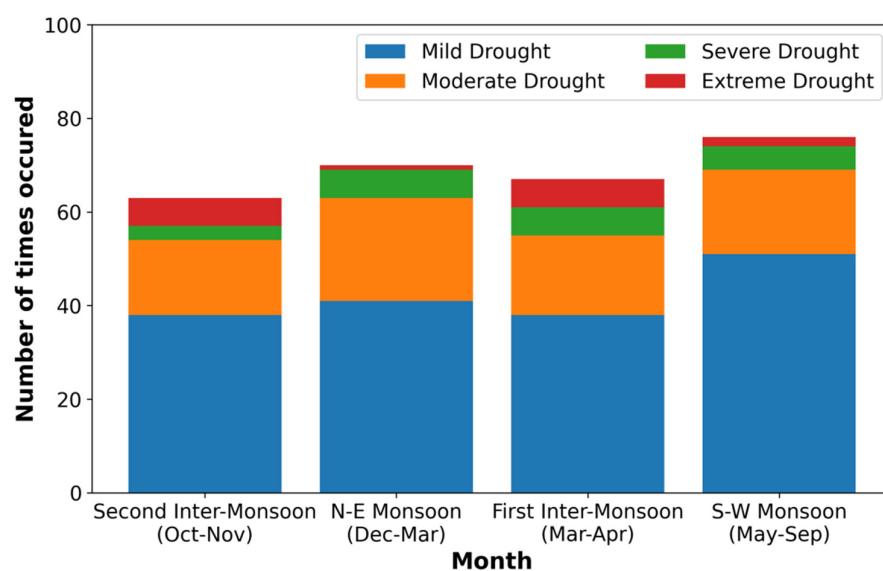
Annexure 4 - 35: RDI for historical period and RCP 8.5 (S-W Monsoon (May-Sep))



Annexure 4 - 36: RDI for historical period and RCP 8.5 (S-W Monsoon (May-Sep))



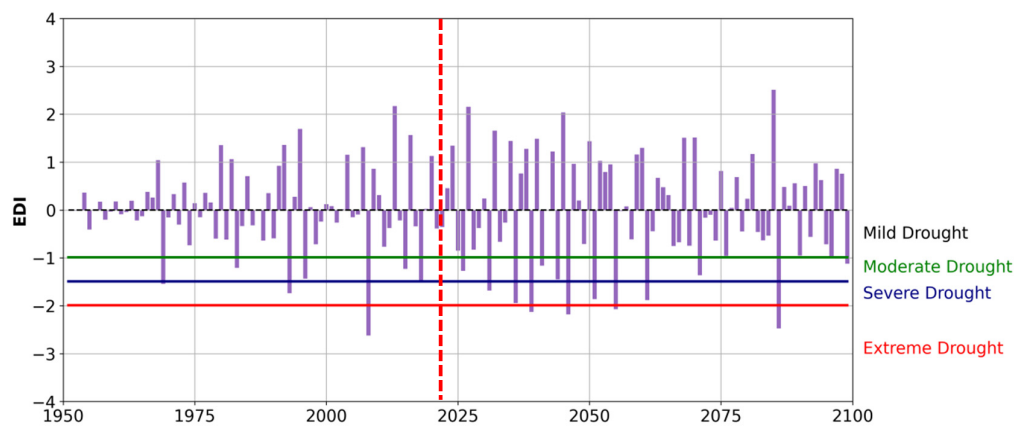
Annexure 4 - 37: Projected frequency and severity of seasonal drought events (RCP 4.5)



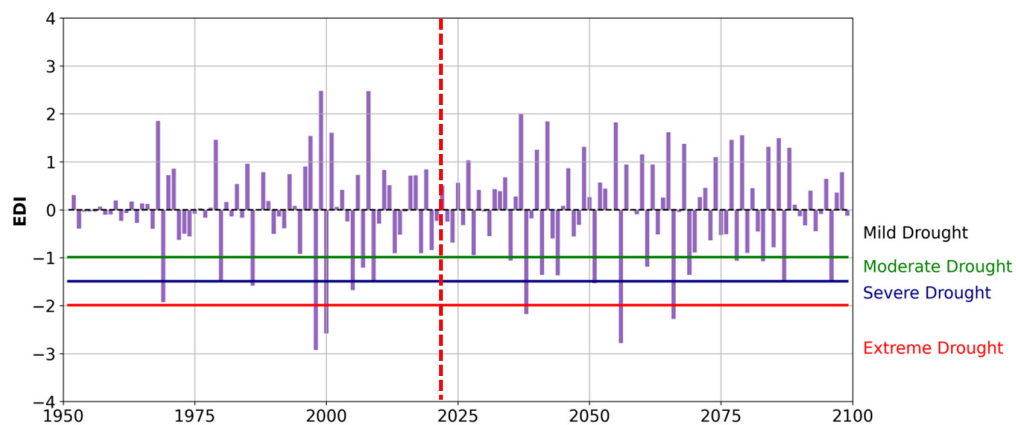
Annexure 4 - 38: Projected frequency and severity of seasonal drought events (RCP 8.5)

ANNEXURE 5

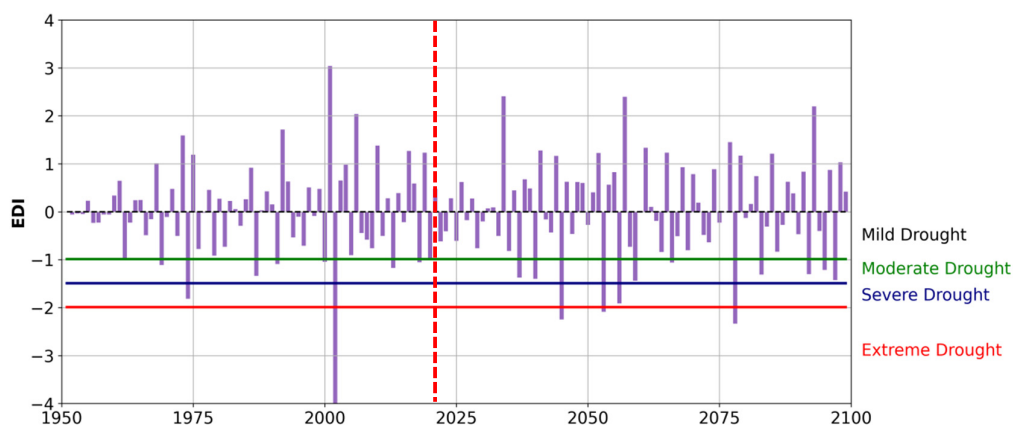
EDI



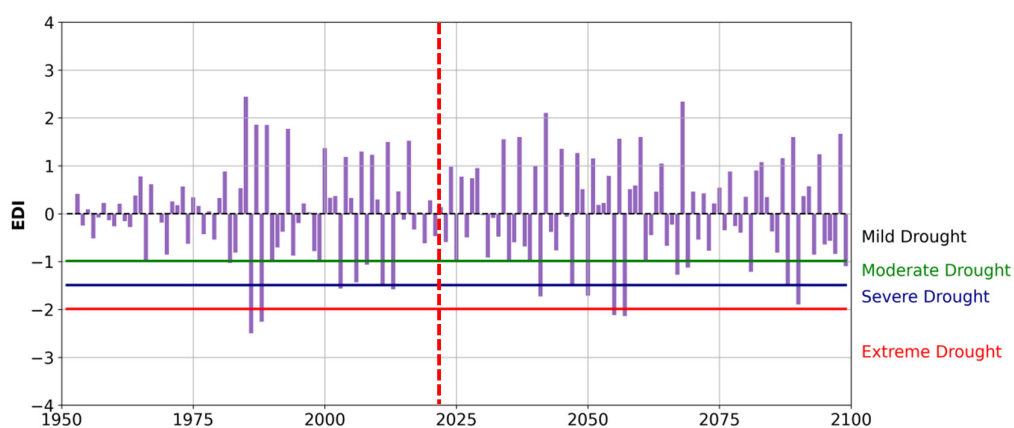
Annexure 5 - 1: EDI values of 1-month timescale for historical period and RCP 4.5 (Jan)



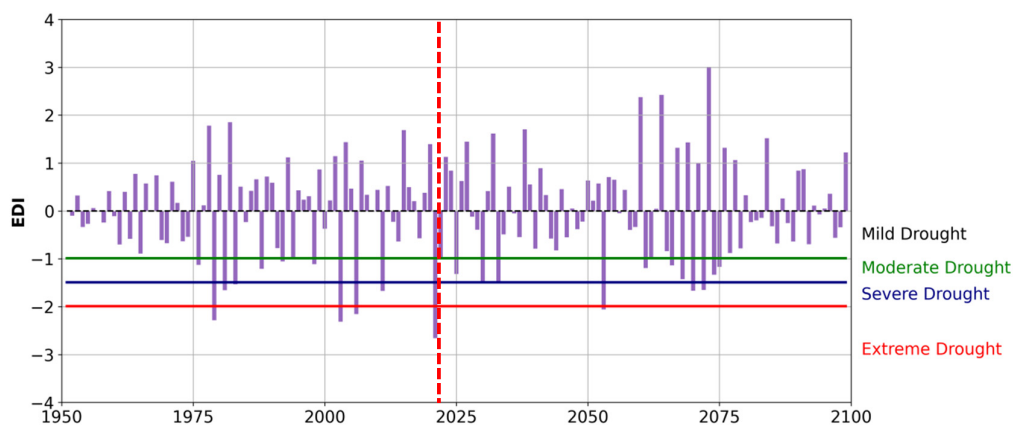
Annexure 5 - 2: EDI values of 1-month timescale for historical period and RCP 4.5 (Feb)



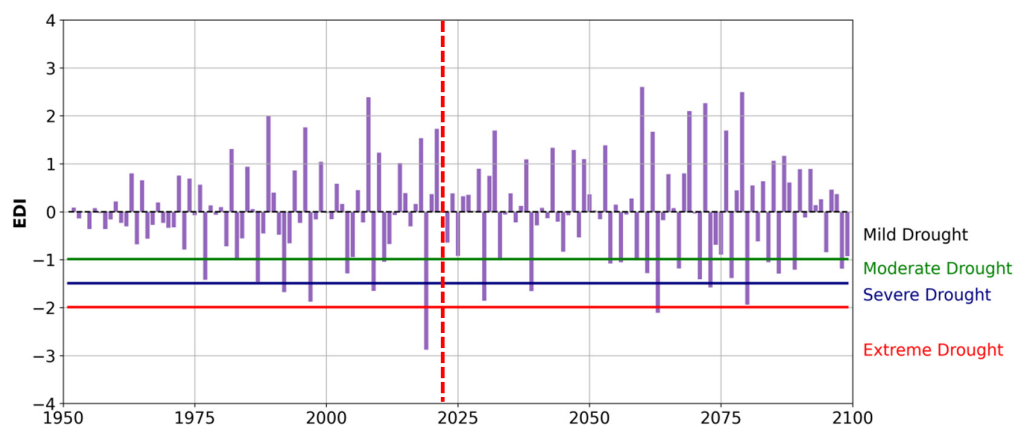
Annexure 5 - 3: EDI values of 1-month timescale for historical period and RCP 4.5 (Mar)



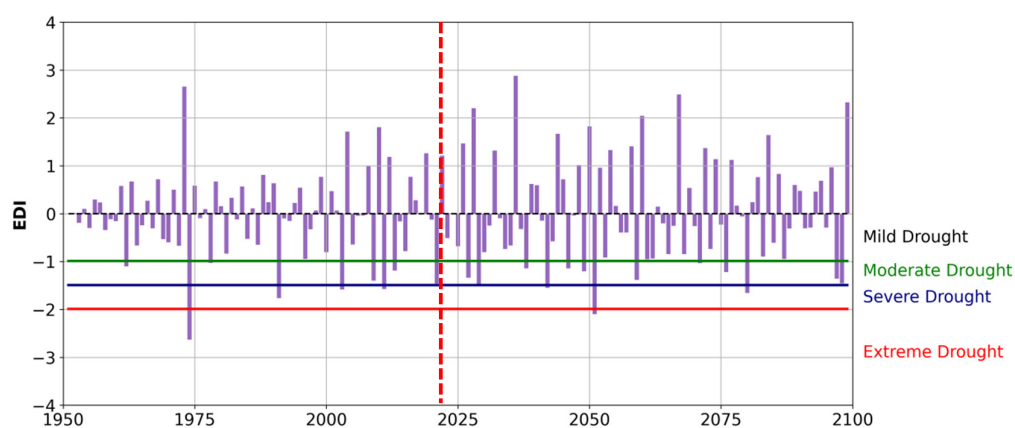
Annexure 5 - 4: EDI values of 1-month timescale for historical period and RCP 4.5 (Apr)



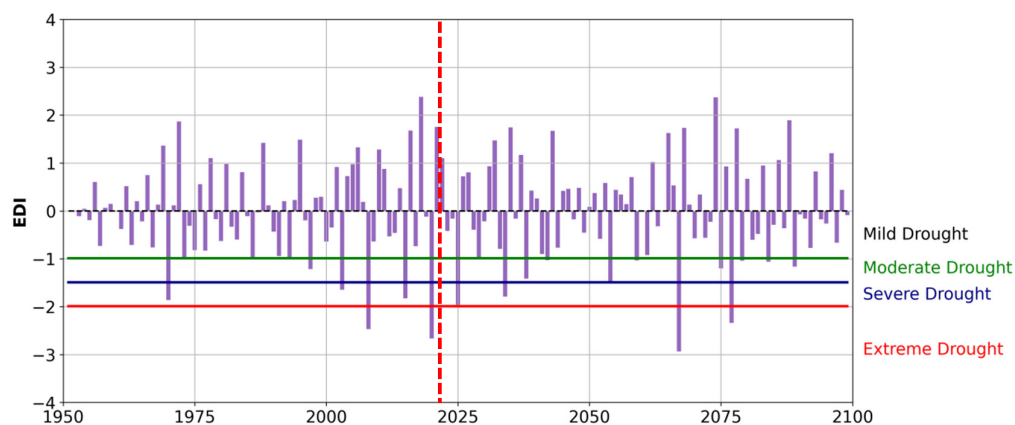
Annexure 5 - 5: EDI values of 1-month timescale for historical period and RCP 4.5 (May)



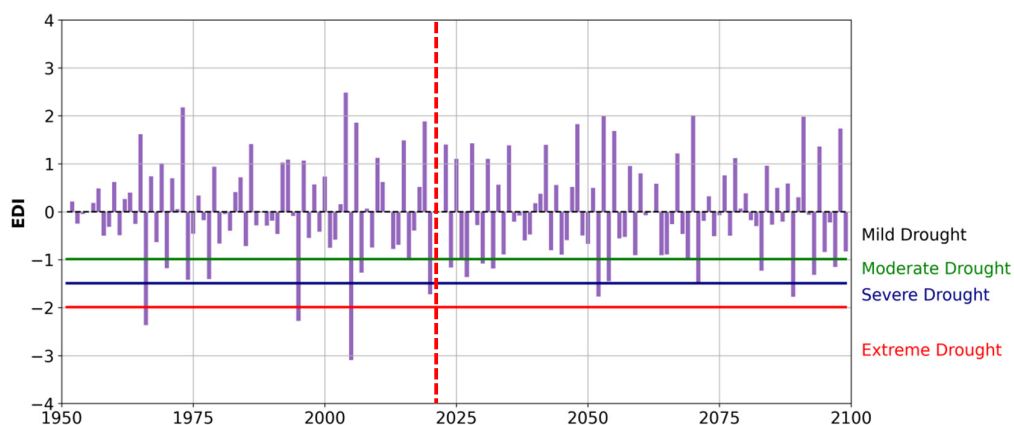
Annexure 5 - 6: EDI values of 1-month timescale for historical period and RCP 4.5 (Jun)



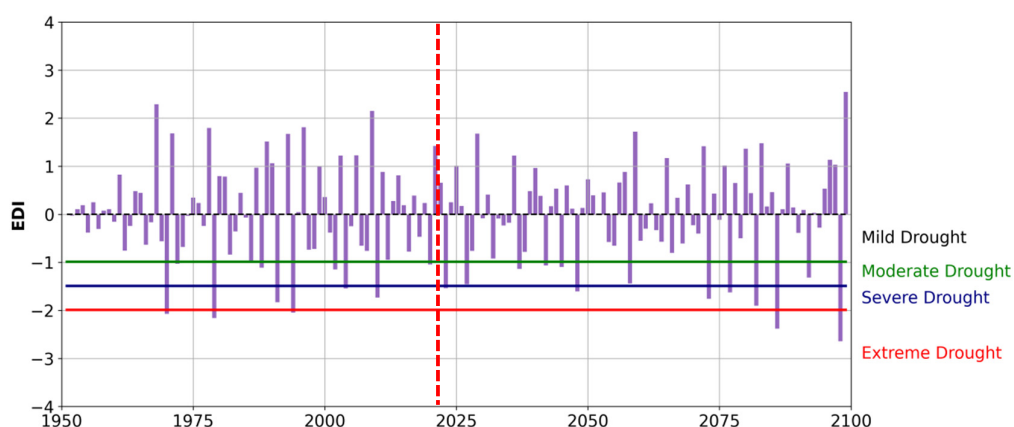
Annexure 5 - 7: EDI values of 1-month timescale for historical period and RCP 4.5 (Jul)



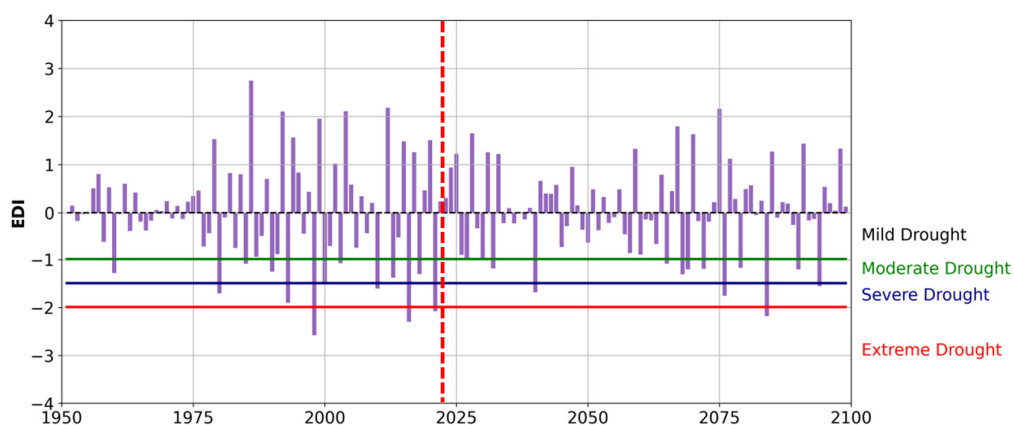
Annexure 5 - 8: EDI values of 1-month timescale for historical period and RCP 4.5 (Aug)



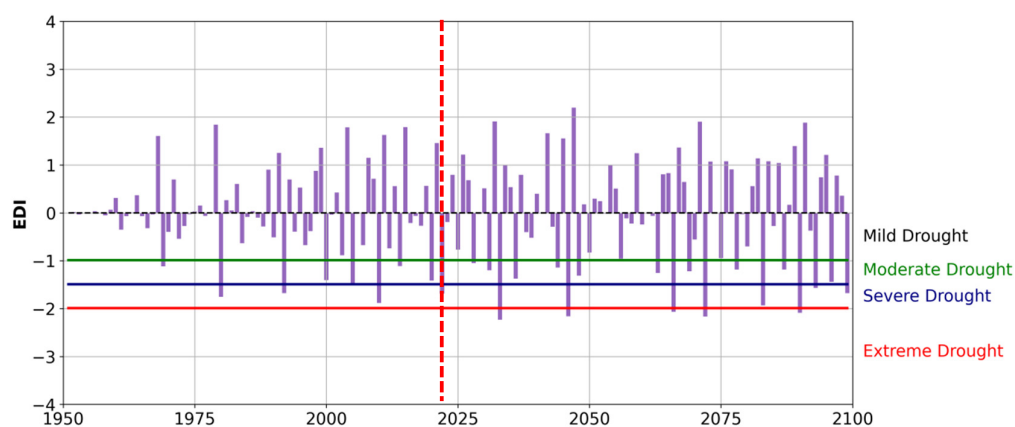
Annexure 5 - 9: EDI values of 1-month timescale for historical period and RCP 4.5 (Sep)



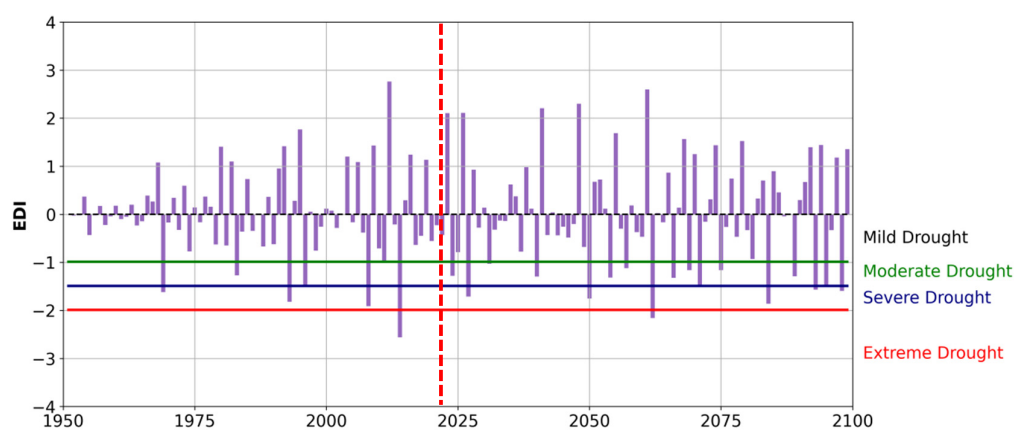
Annexure 5 - 10: EDI values of 1-month timescale for historical period and RCP 4.5 (Oct)



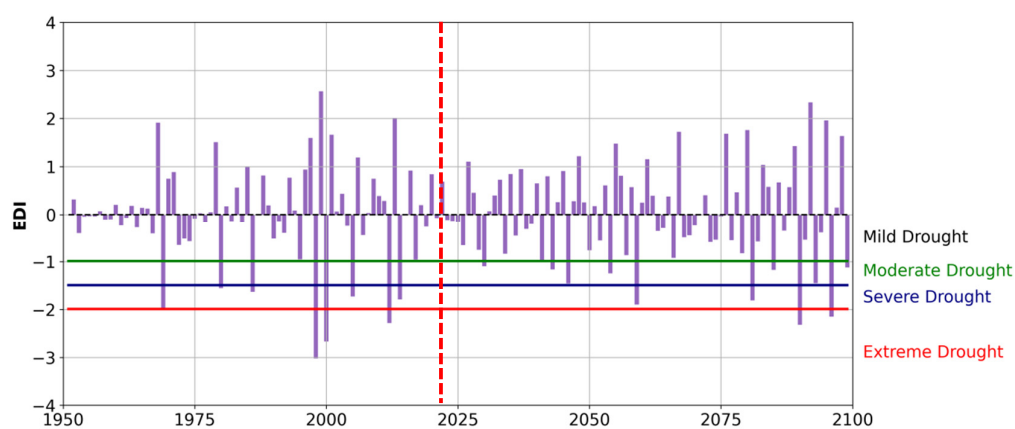
Annexure 5 - 11: EDI values of 1-month timescale for historical period and RCP 4.5 (Nov)



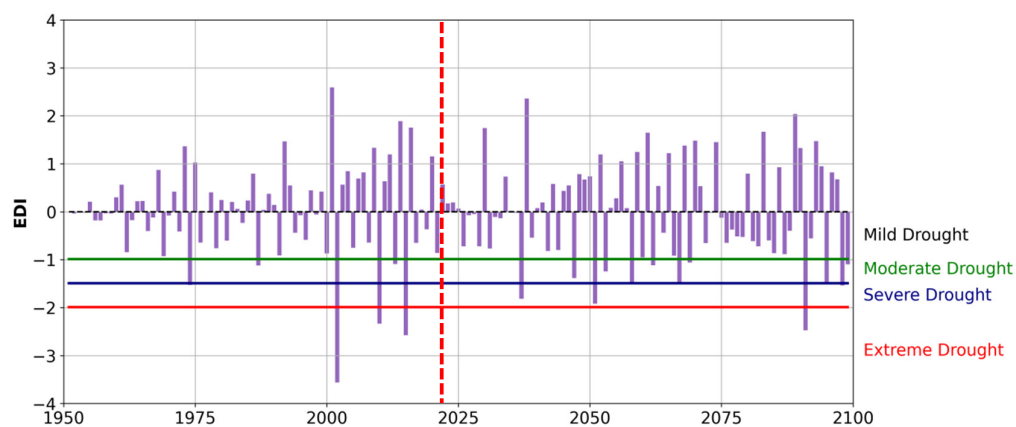
Annexure 5 - 12: EDI values of 1-month timescale for historical period and RCP 4.5 (Dec)



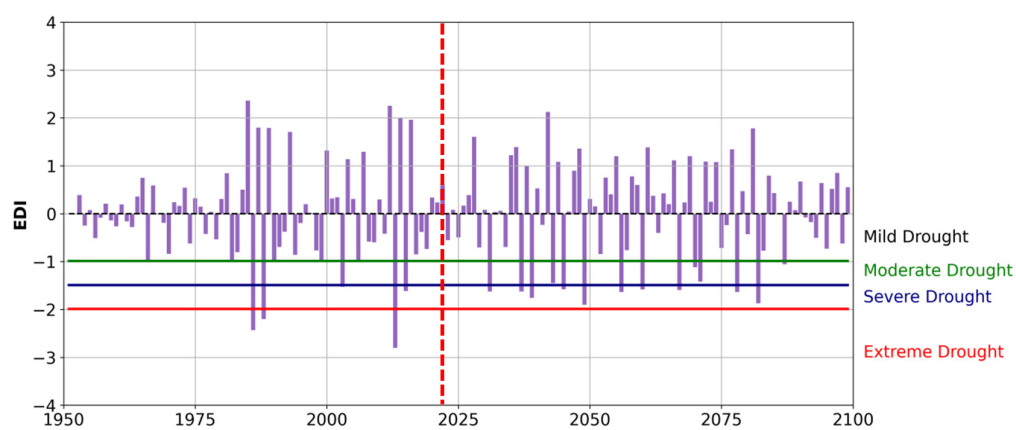
Annexure 5 - 13: EDI values of 1-month timescale for historical period and RCP 8.5 (Jan)



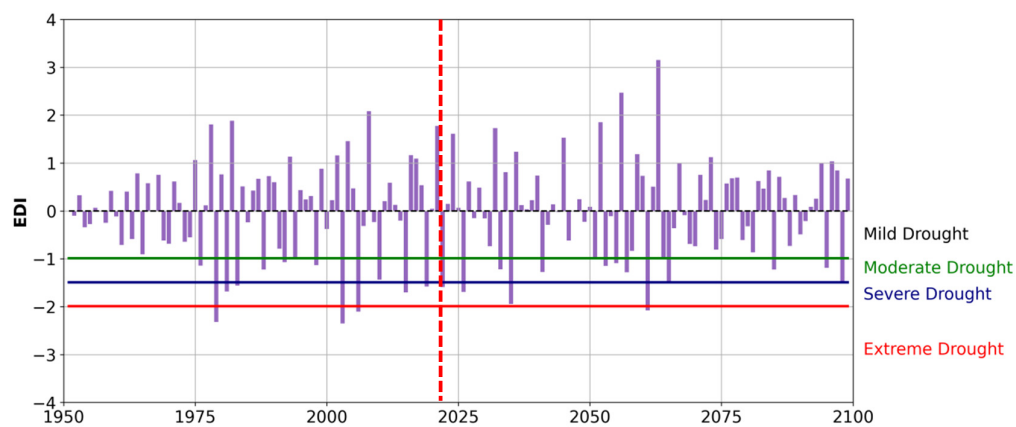
Annexure 5 - 14: EDI values of 1-month timescale for historical period and RCP 8.5 (Feb)



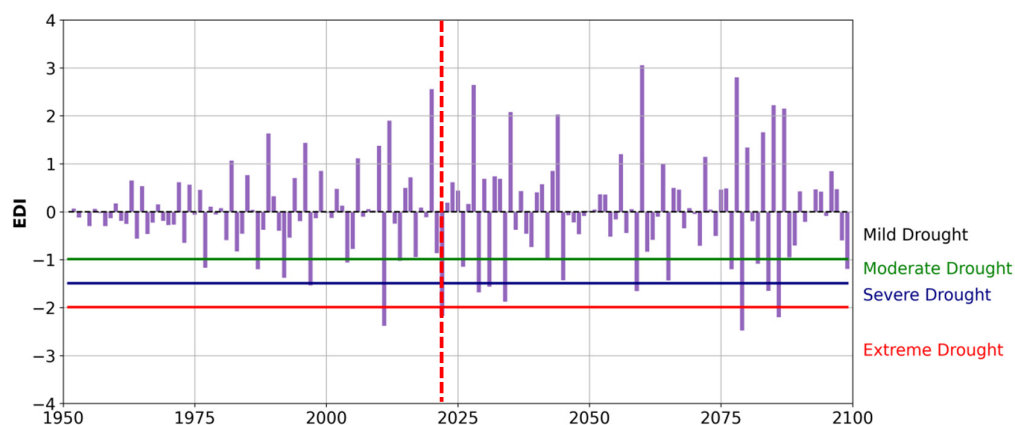
Annexure 5 - 15: EDI values of 1-month timescale for historical period and RCP 8.5 (Mar)



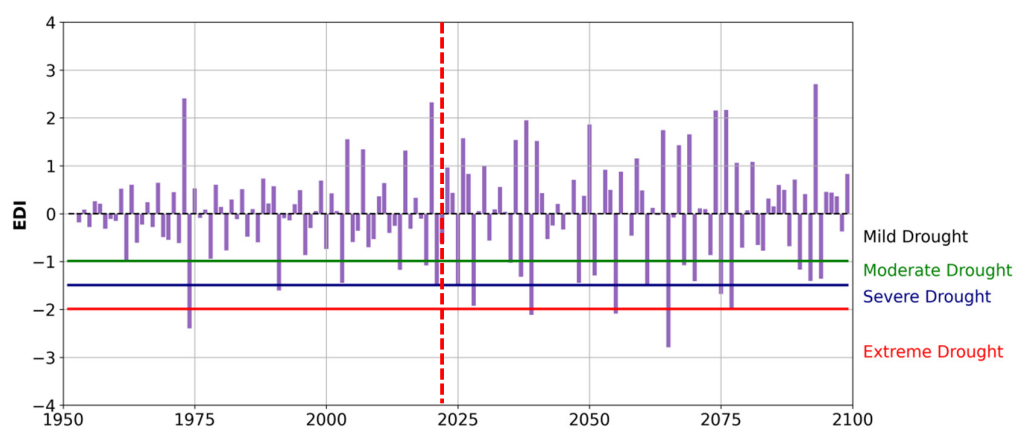
Annexure 5 - 16: EDI values of 1-month timescale for historical period and RCP 8.5 (Apr)



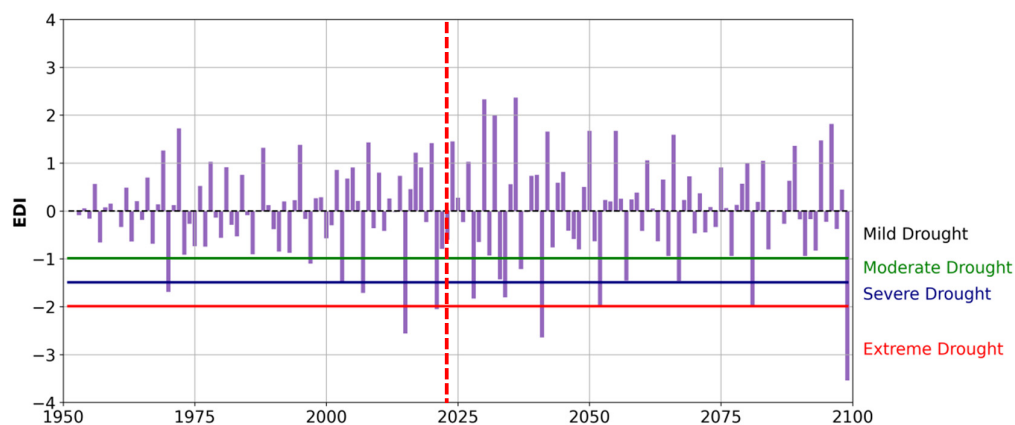
Annexure 5 - 17: EDI values of 1-month timescale for historical period and RCP 8.5 (May)



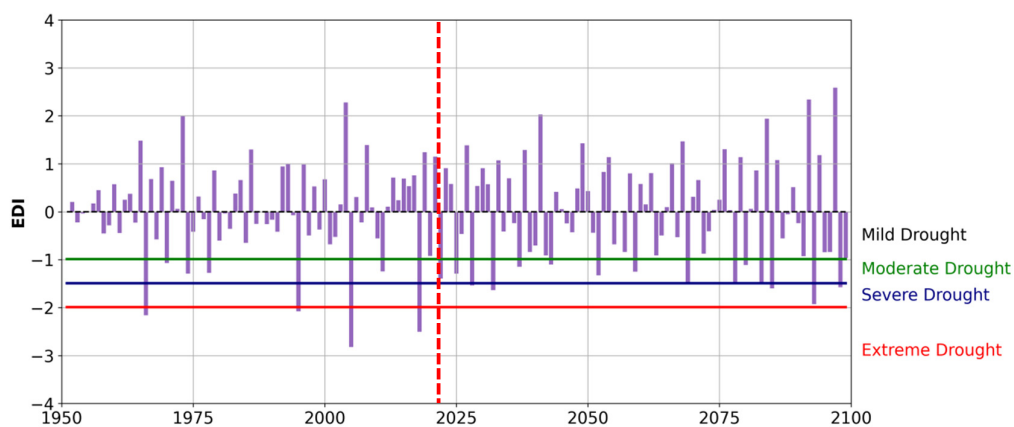
Annexure 5 - 18: EDI values of 1-month timescale for historical period and RCP 8.5 (Jun)



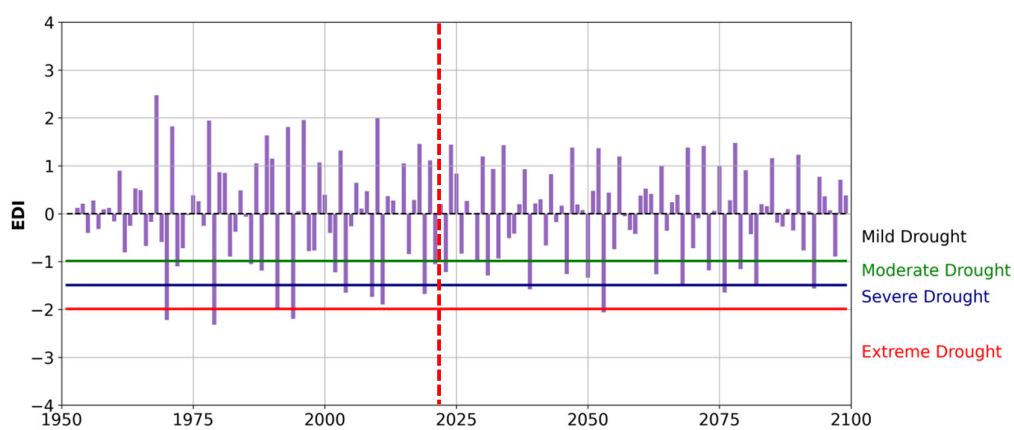
Annexure 5 - 19: EDI values of 1-month timescale for historical period and RCP 8.5 (Jul)



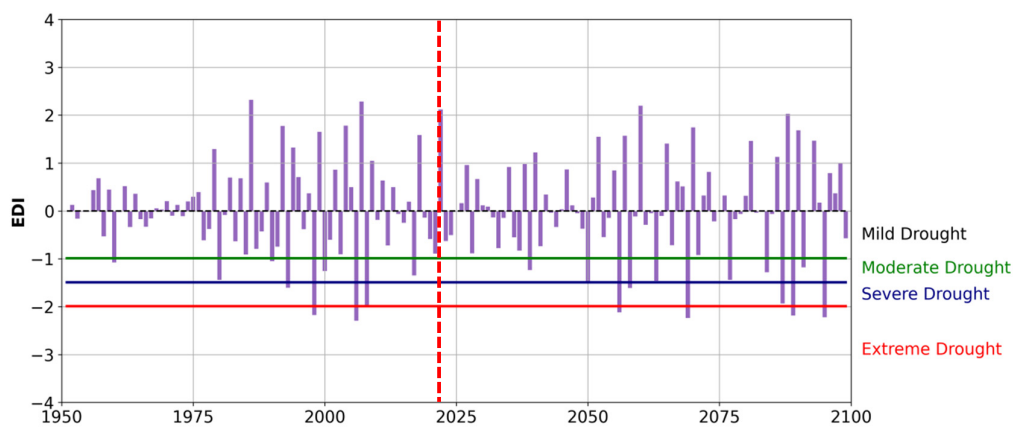
Annexure 5 - 20: EDI values of 1-month timescale for historical period and RCP 8.5 (Aug)



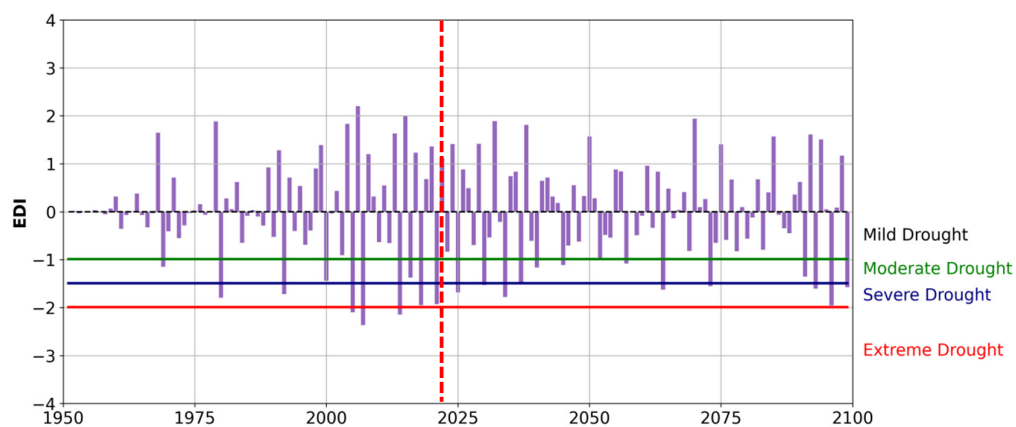
Annexure 5 - 21: EDI values of 1-month timescale for historical period and RCP 8.5 (Sep)



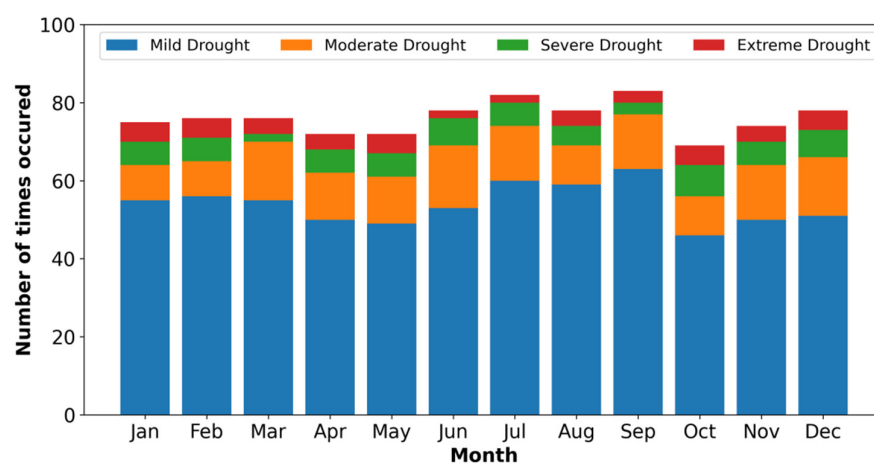
Annexure 5 - 22: EDI values of 1-month timescale for historical period and RCP 8.5 (Oct)



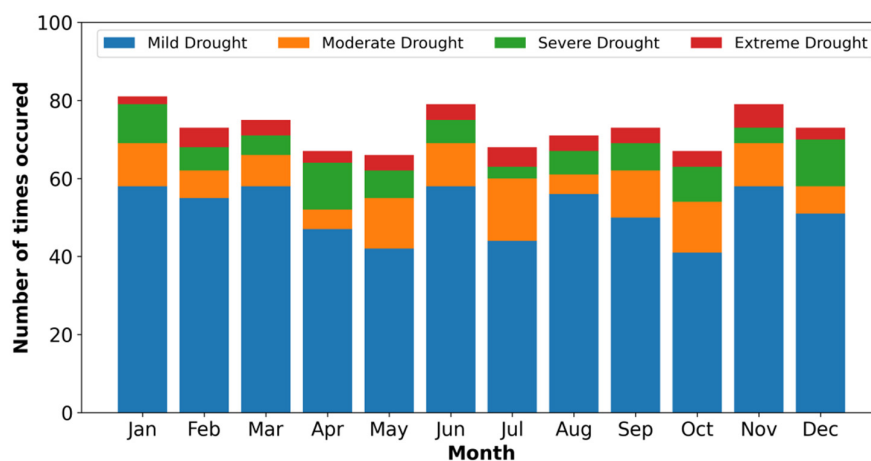
Annexure 5 - 23: EDI values of 1-month timescale for historical period and RCP 8.5 (Nov)



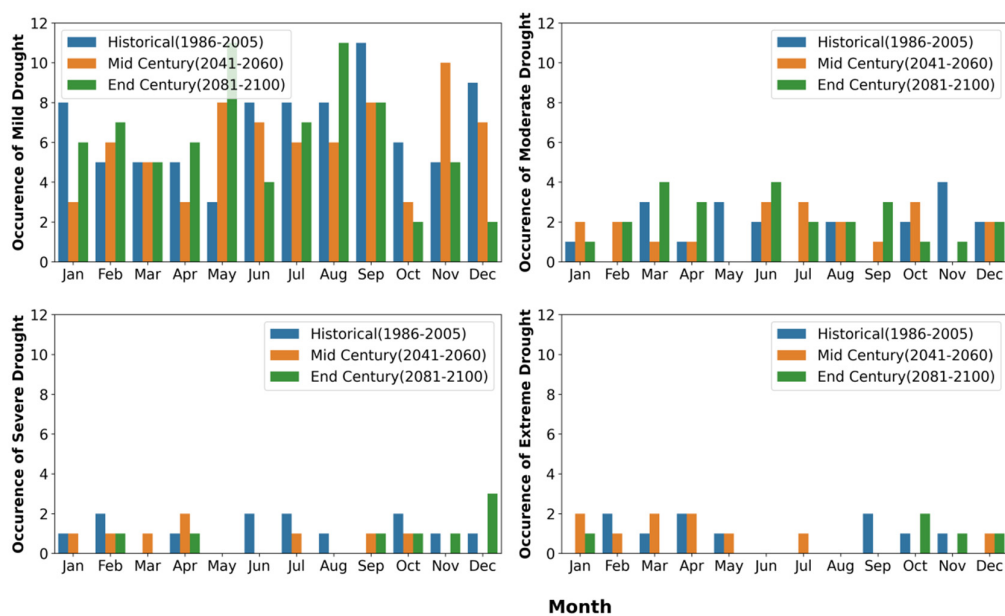
Annexure 5 - 24: EDI values of 1-month timescale for historical period and RCP 8.5 (Dec)



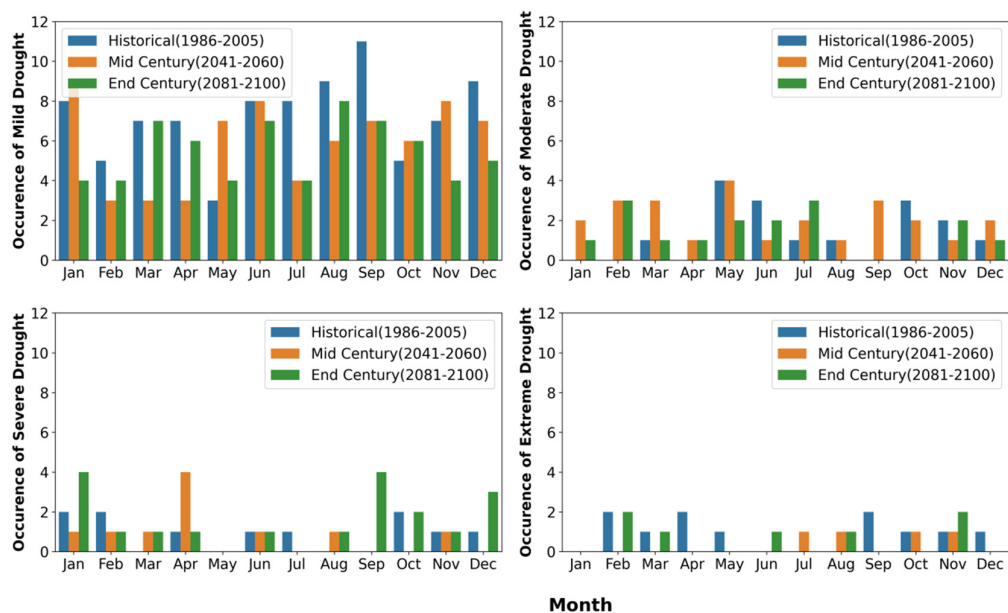
Annexure 5 - 25: Projected frequency and severity of drought events (RCP 4.5)



Annexure 5 - 26: Projected frequency and severity of drought events (RCP 8.5)



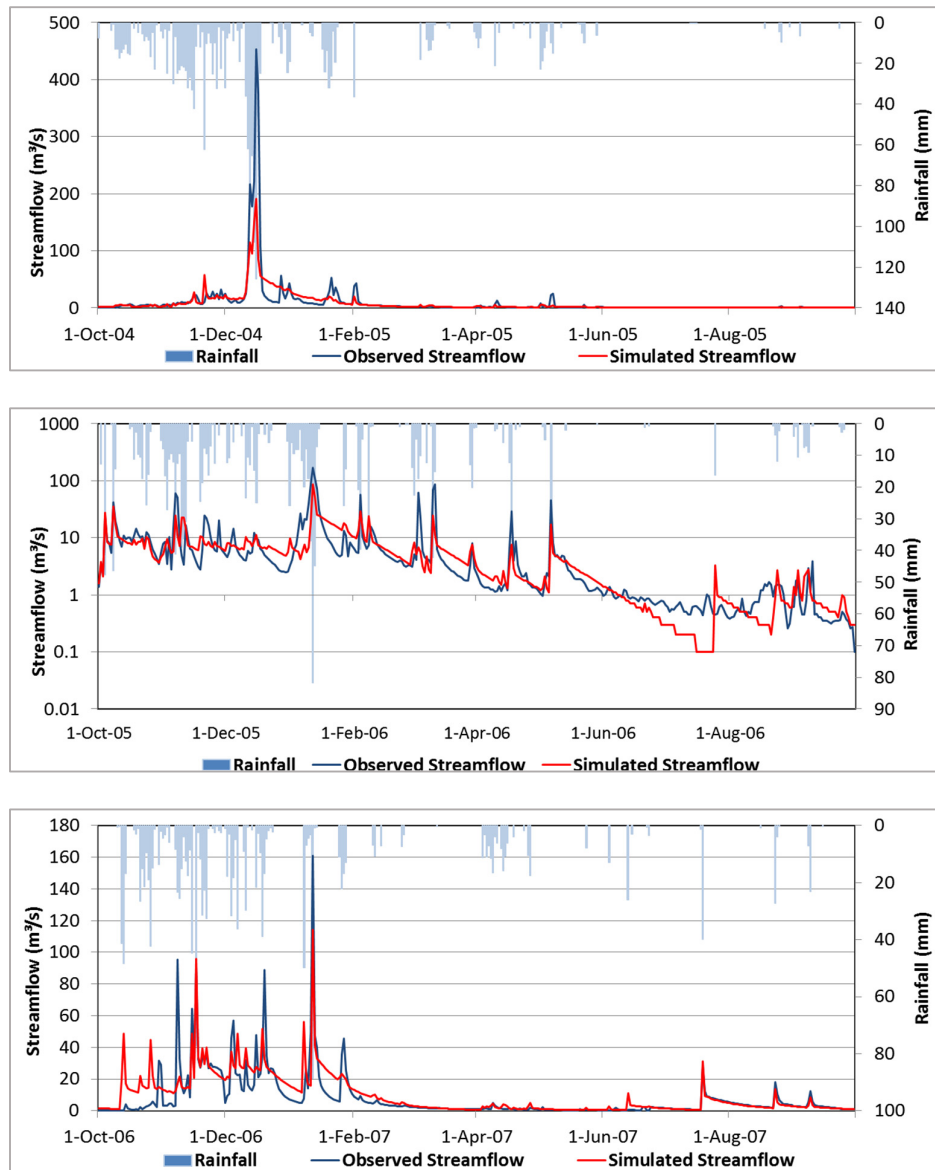
Annexure 5 - 27: Comparison of historical, mid-century and end-century RCP 4.5 drought events



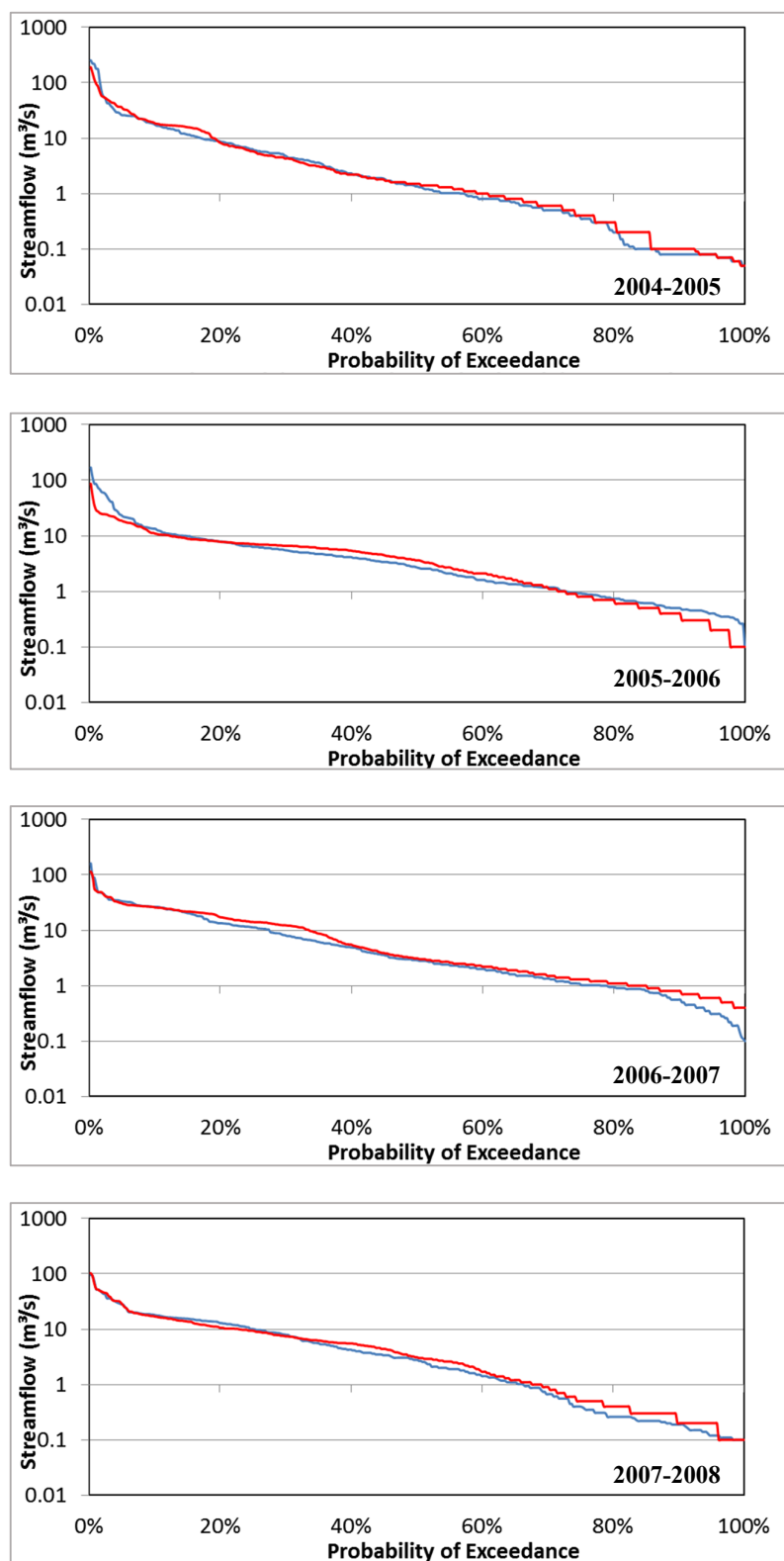
Annexure 5 - 28: Comparison of historical, mid-century and end-century RCP 4.5 drought events

ANNEXURE 6

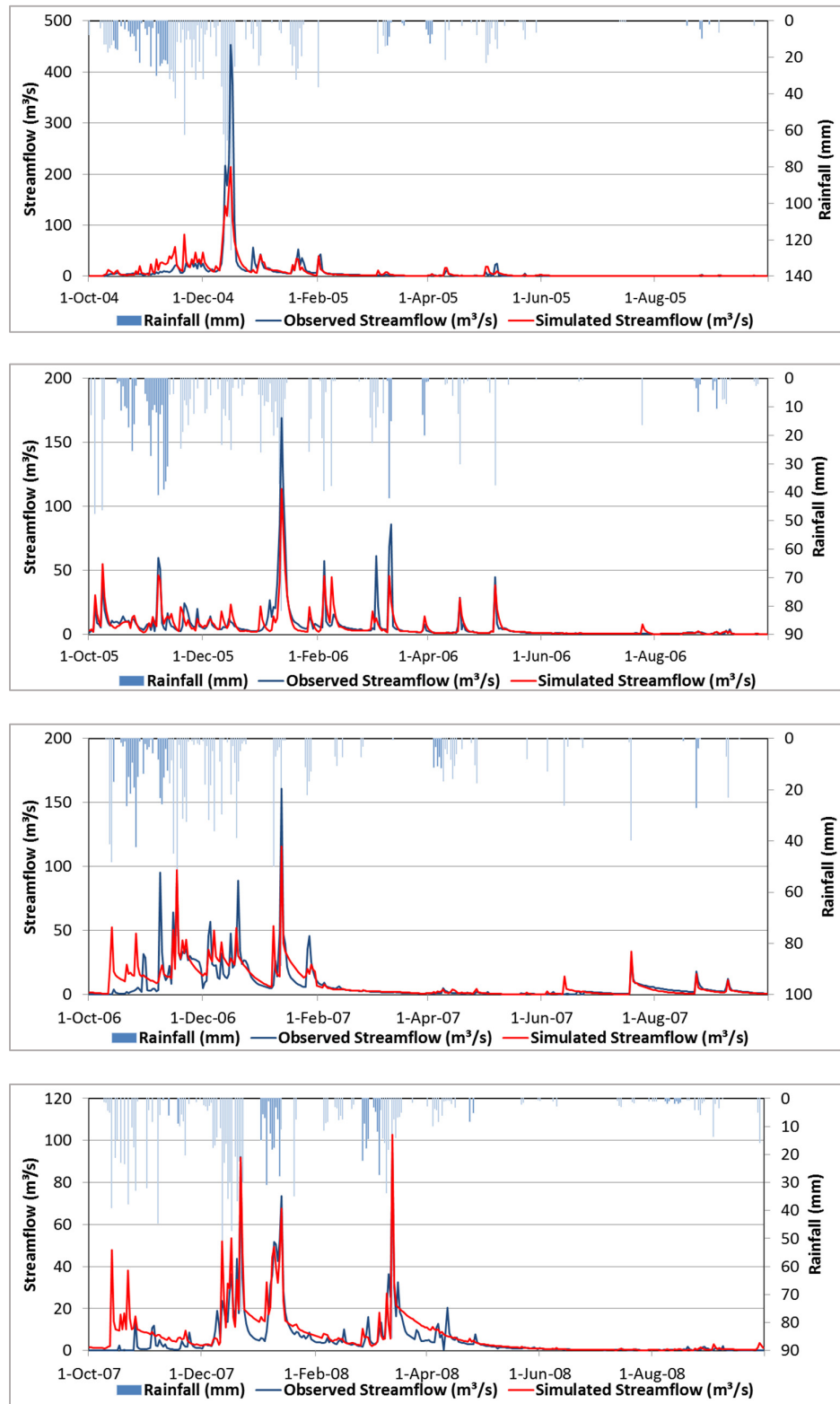
HEC-HMS MODEL OUTPUTS



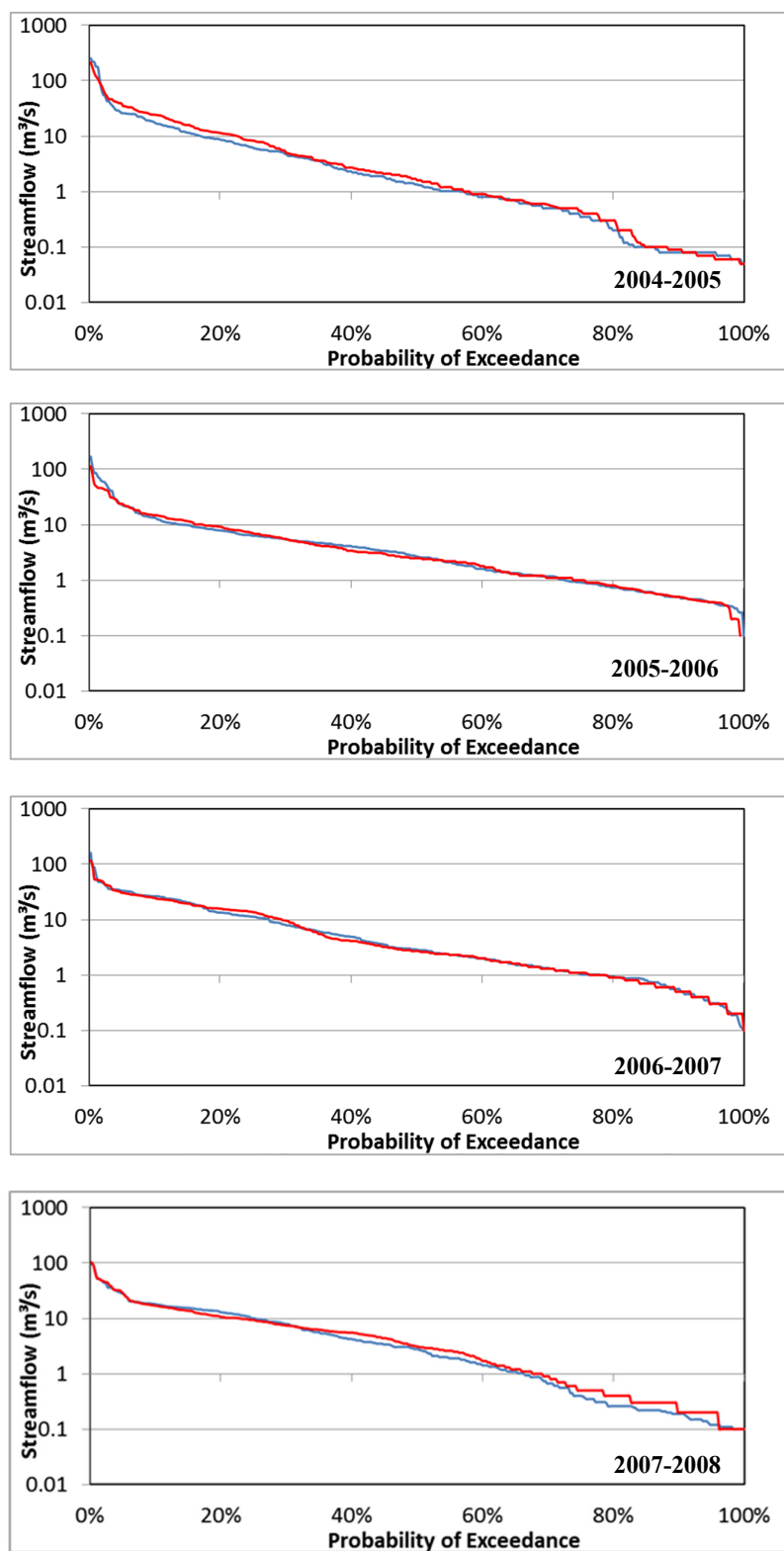
Annexure 6 - 1: Hydrographs for simulation run in Calibration period



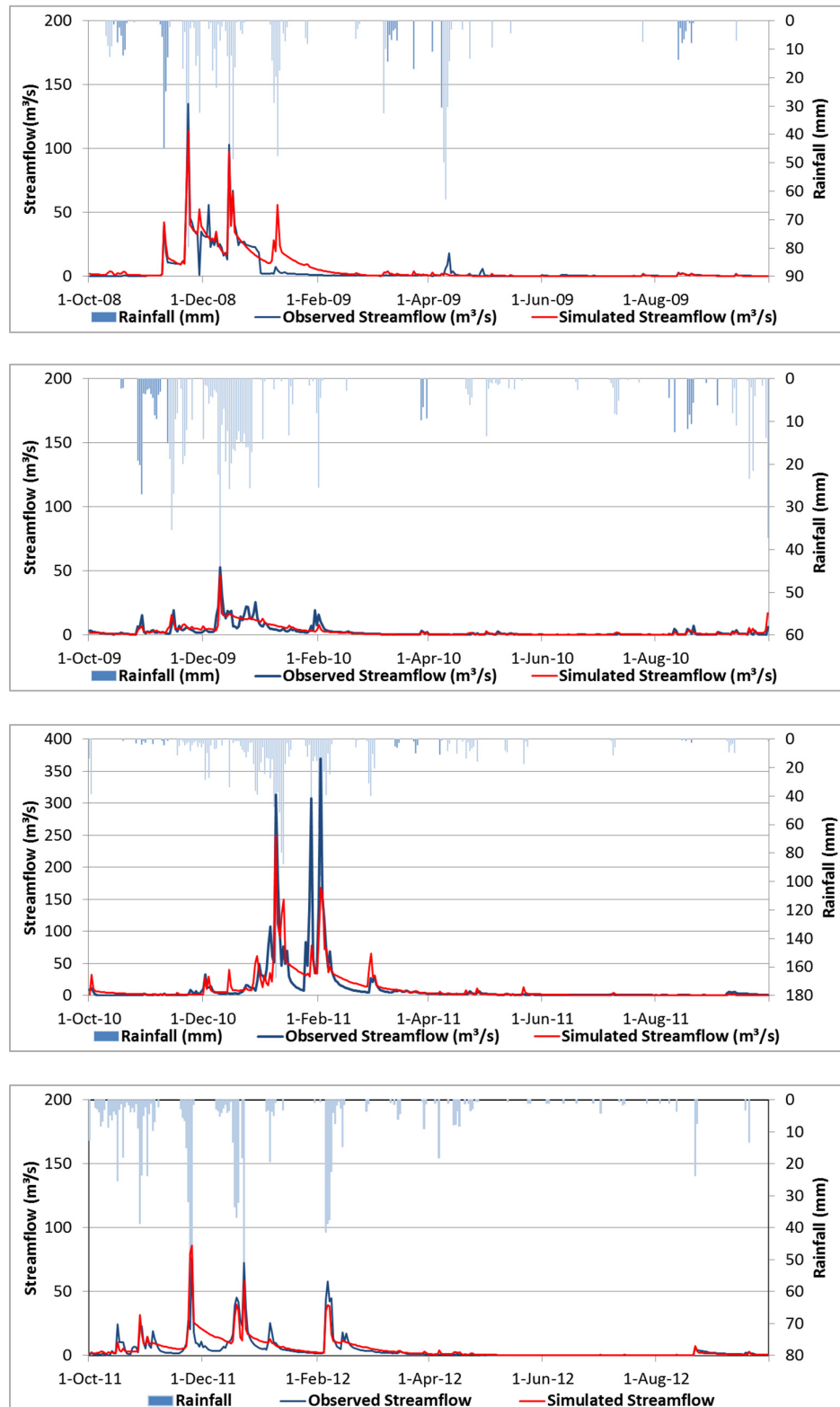
Annexure 6 - 2: FDC for simulation run in Calibration period



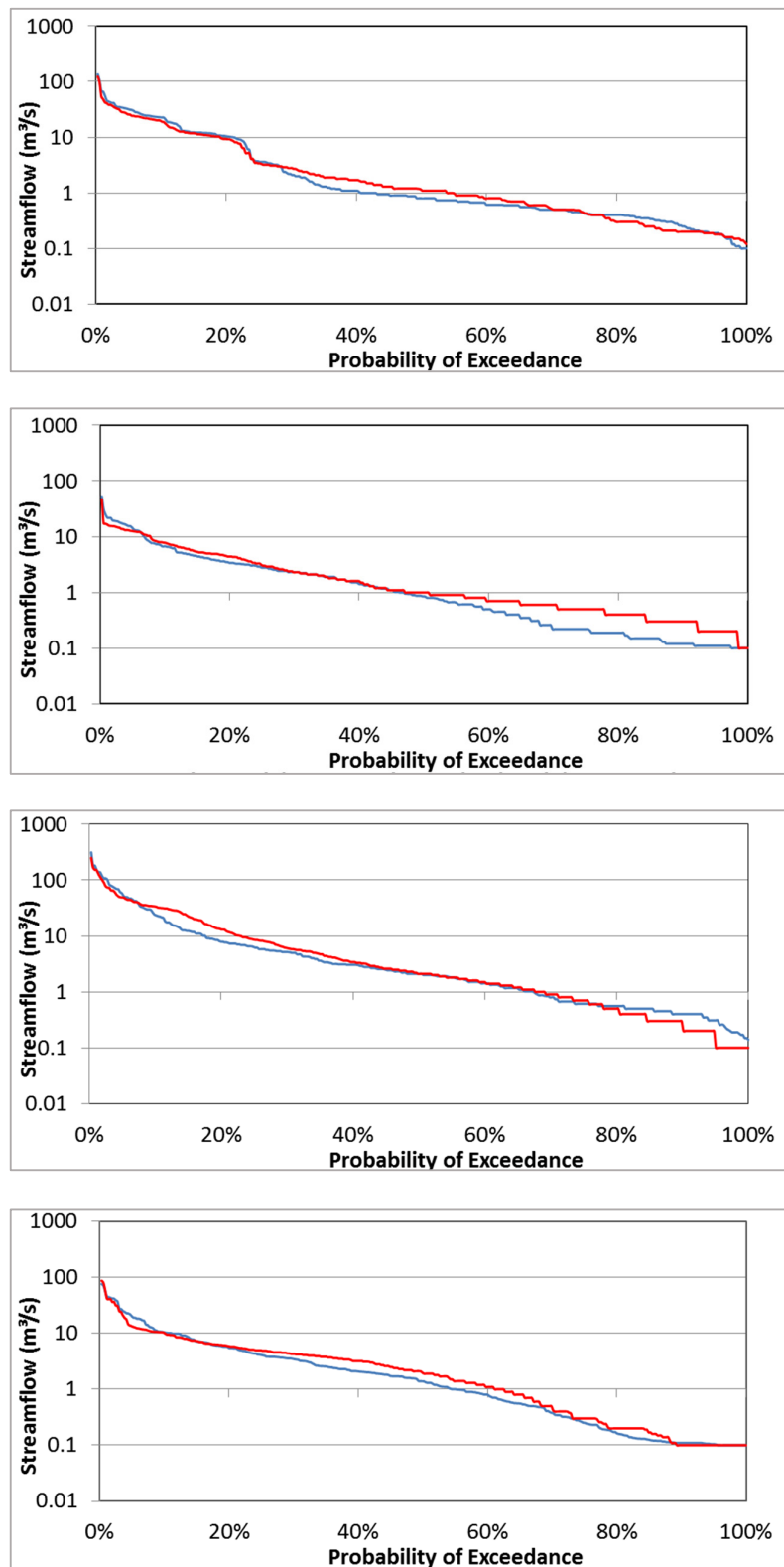
Annexure 6 - 3: Hydrographs for optimization run in Calibration period



Annexure 6 - 4: FDC for optimization run in Calibration period



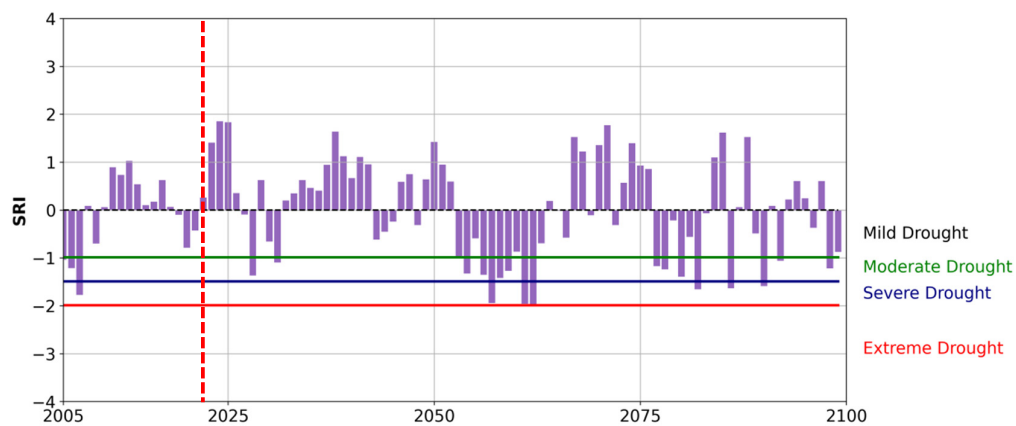
Annexure 6 - 5: Hydrographs for Padiyathalawa watershed in Validation period



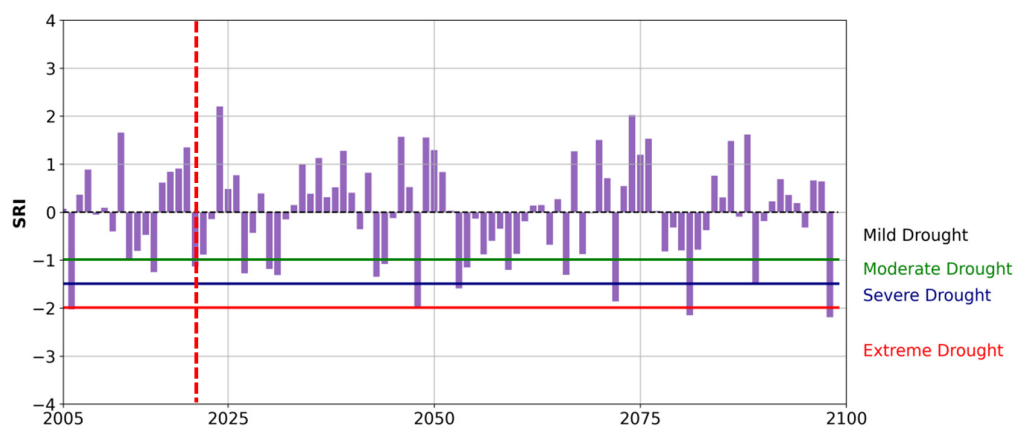
Annexure 6 - 6: FDC for Padiyathalawa watershed in Validation period

ANNEXURE 7

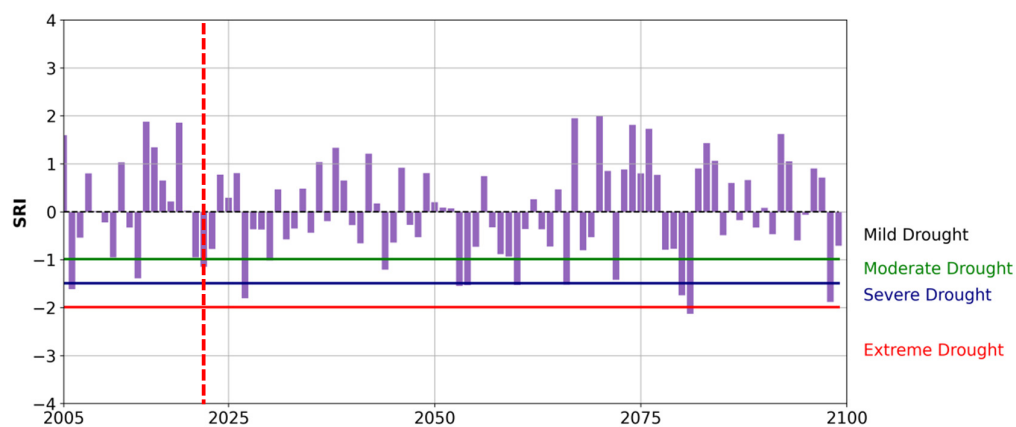
SRI



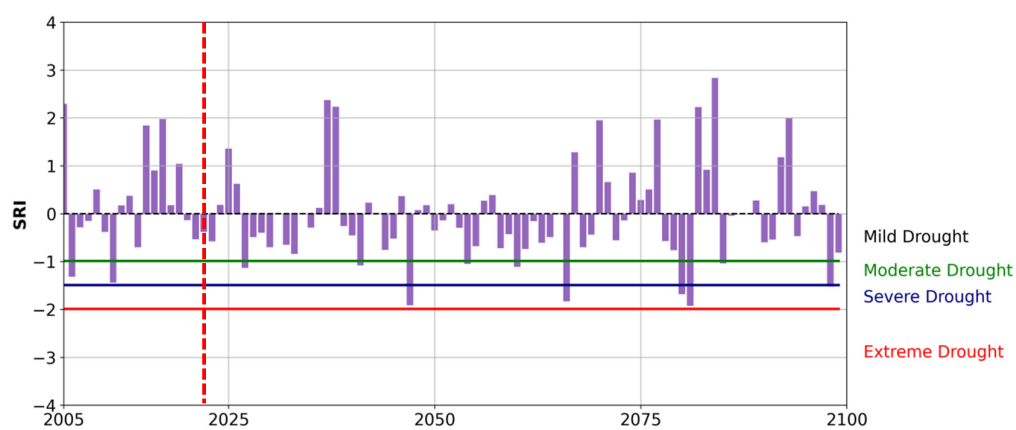
Annexure 7 - 1: SRI values of 1-month timescale for historical period and RCP 4.5 (Jan)



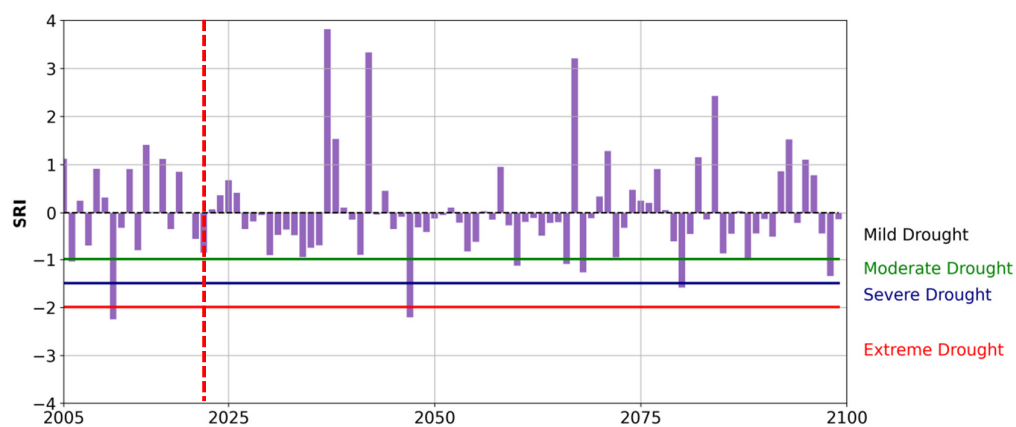
Annexure 7 - 2: SRI values of 1-month timescale for historical period and RCP 4.5 (Feb)



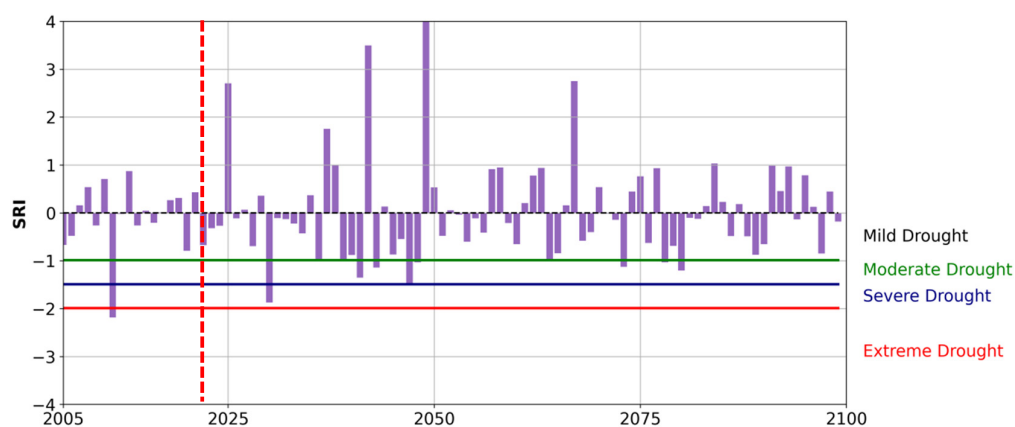
Annexure 7 - 3: SRI values of 1-month timescale for historical period and RCP 4.5 (Mar)



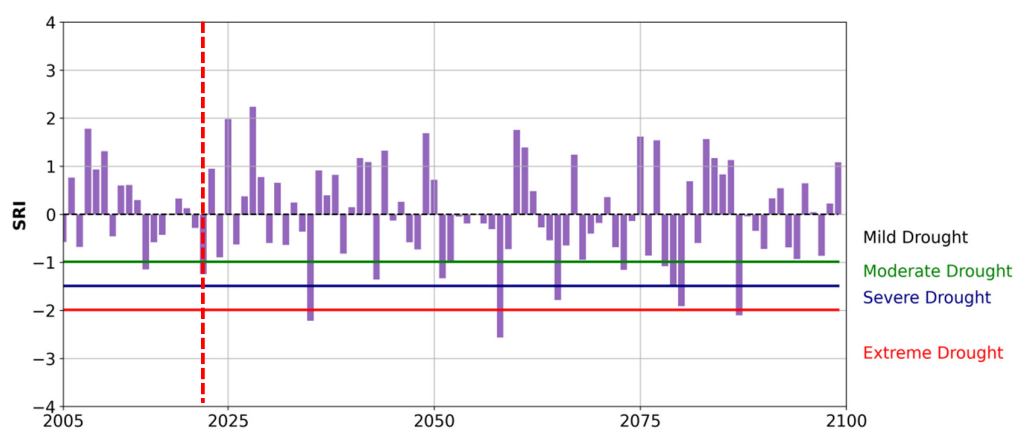
Annexure 7 - 4: SRI values of 1-month timescale for historical period and RCP 4.5 (Apr)



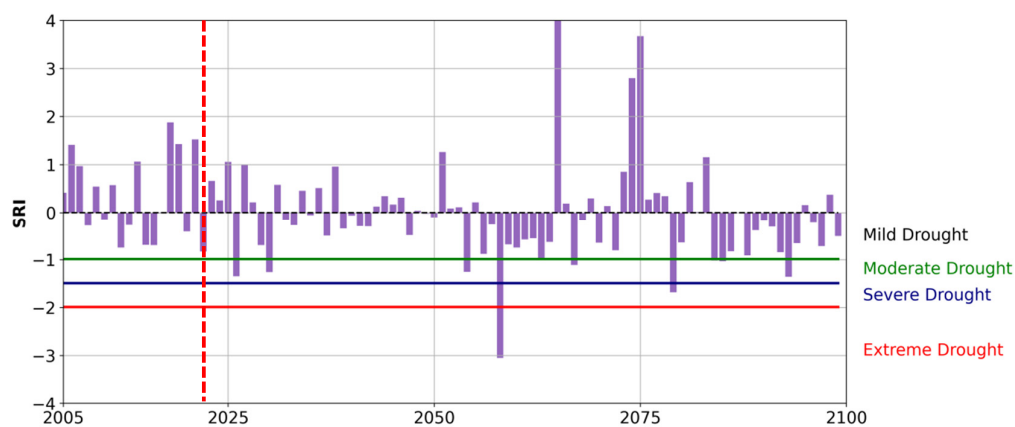
Annexure 7 - 5: SRI values of 1-month timescale for historical period and RCP 4.5 (May)



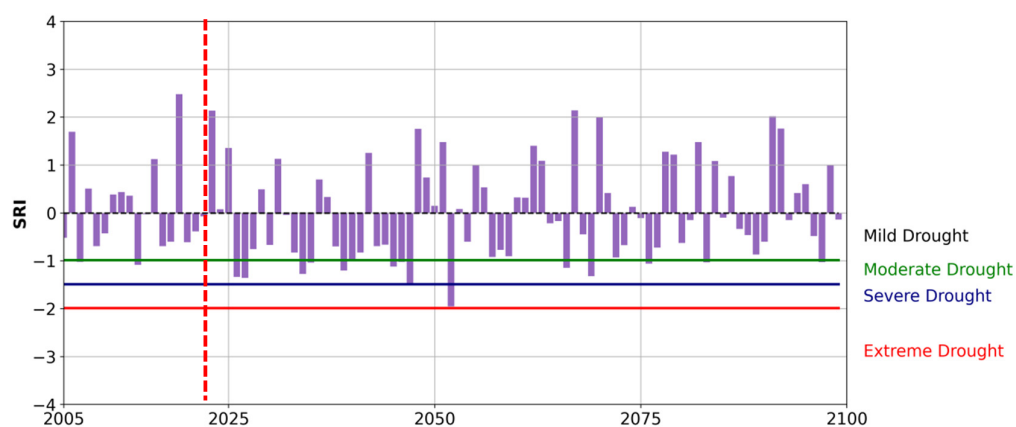
Annexure 7 - 6: SRI values of 1-month timescale for historical period and RCP 4.5 (Jun)



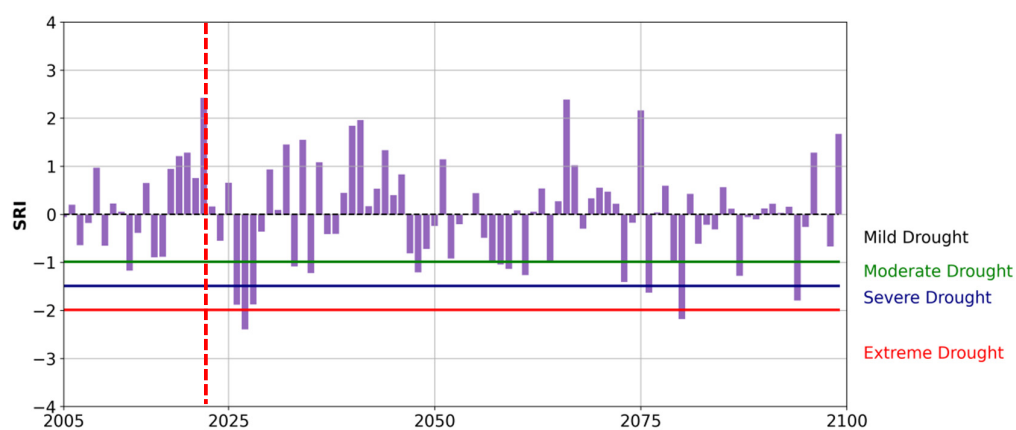
Annexure 7 - 7: SRI values of 1-month timescale for historical period and RCP 4.5 (Jul)



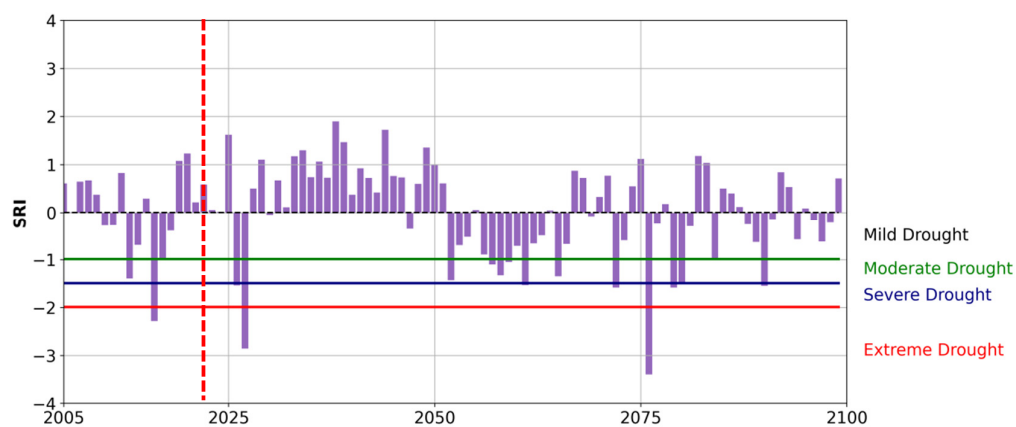
Annexure 7 - 8: SRI values of 1-month timescale for historical period and RCP 4.5 (Aug)



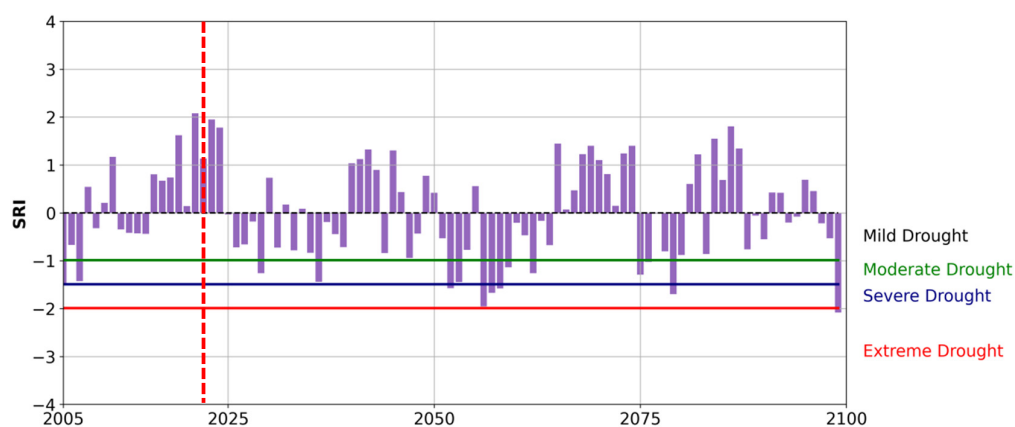
Annexure 7 - 9: SRI values of 1-month timescale for historical period and RCP 4.5 (Sep)



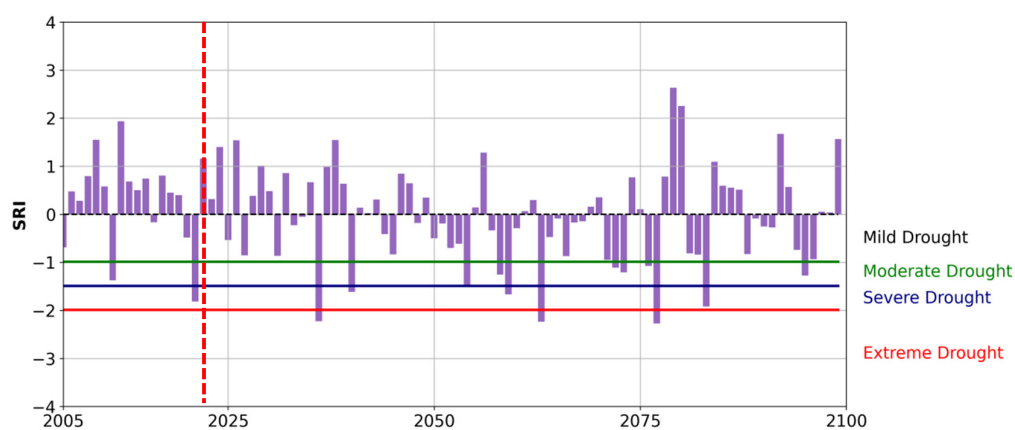
Annexure 7 - 10: SRI values of 1-month timescale for historical period and RCP 4.5 (Oct)



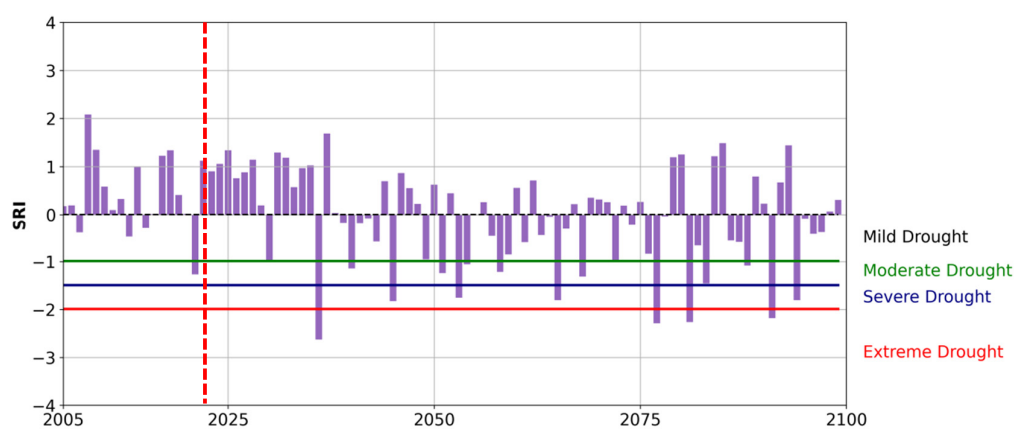
Annexure 7 - 11: SRI values of 1-month timescale for historical period and RCP 4.5 (Nov)



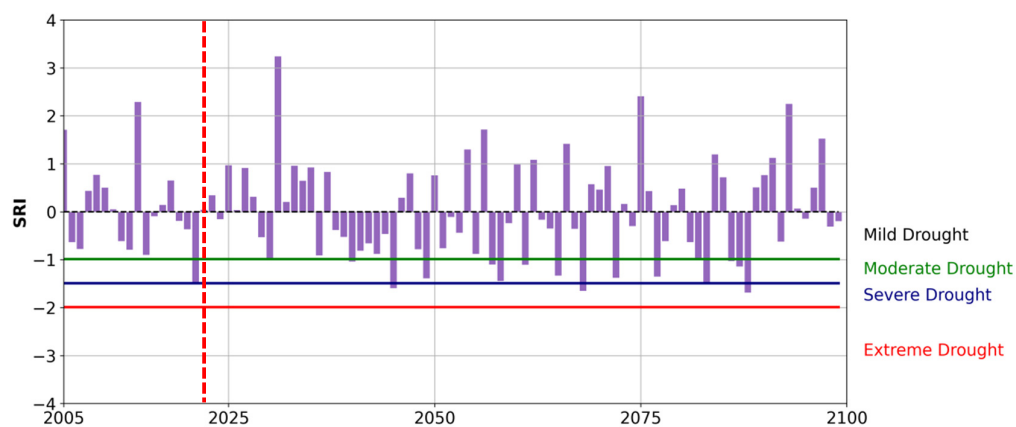
Annexure 7 - 12: SRI values of 1-month timescale for historical period and RCP 4.5 (Dec)



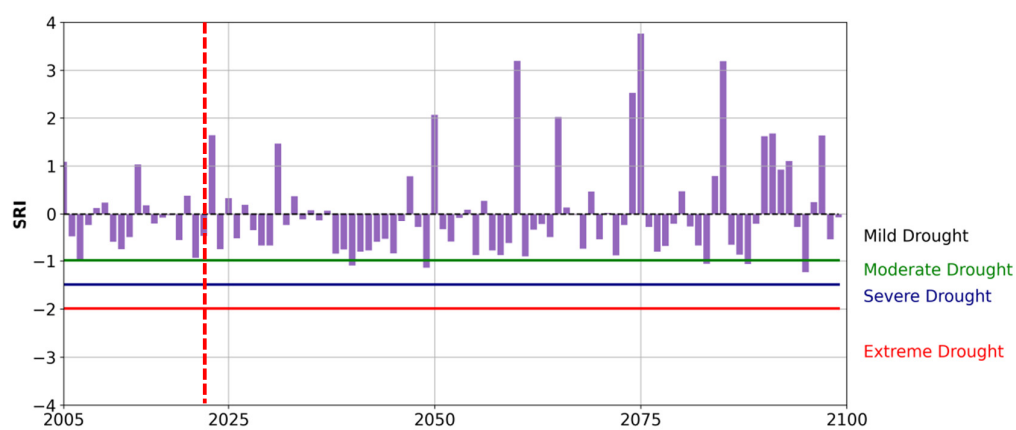
Annexure 7 - 13: SRI values of 1-month timescale for historical period and RCP 8.5 (Jan)



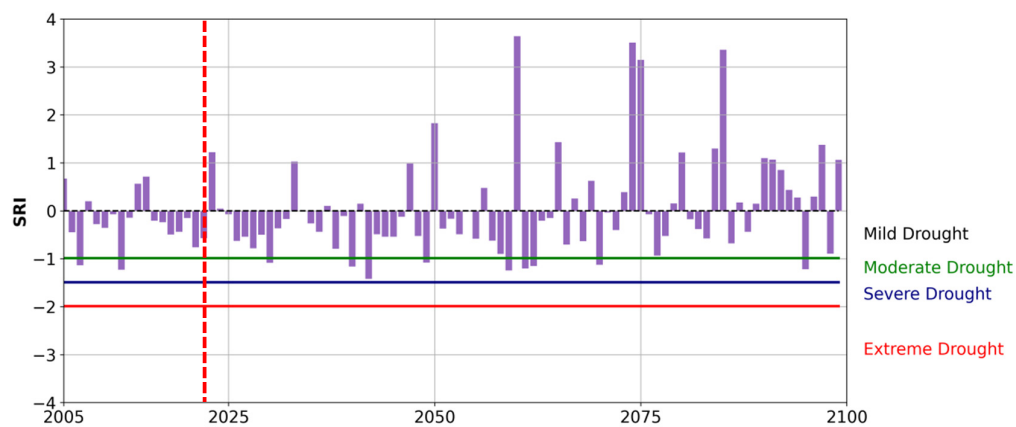
Annexure 7 - 14: SRI values of 1-month timescale for historical period and RCP 8.5 (Feb)



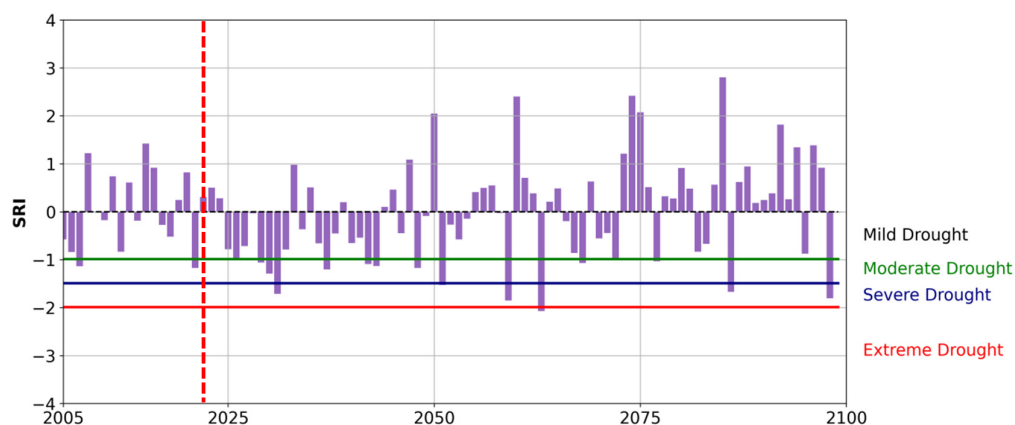
Annexure 7 - 15: SRI values of 1-month timescale for historical period and RCP 8.5 (Mar)



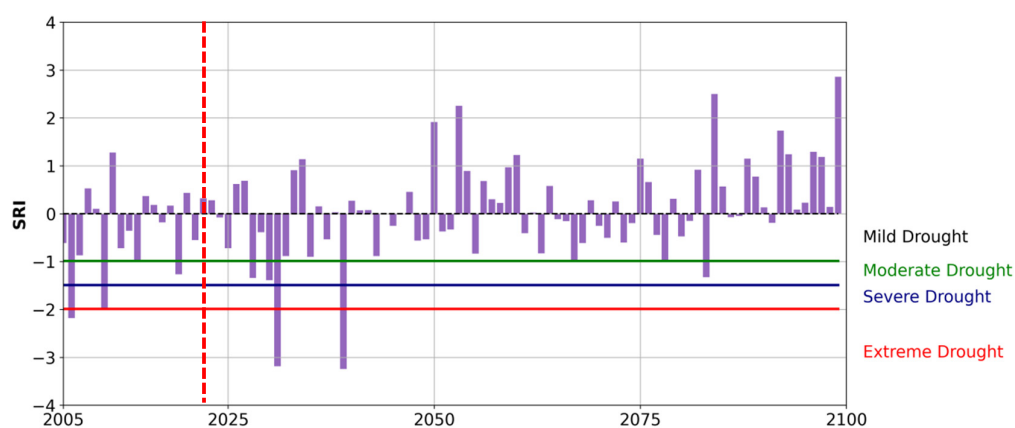
Annexure 7 - 16: SRI values of 1-month timescale for historical period and RCP 8.5 (Apr)



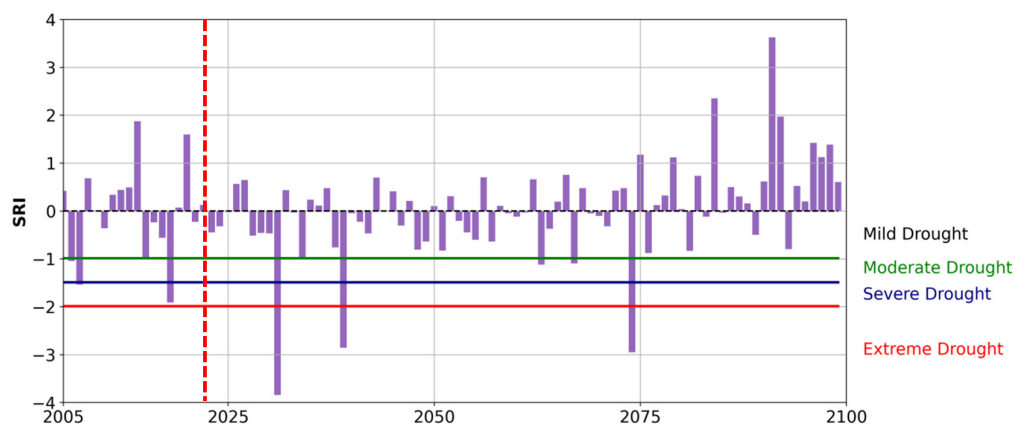
Annexure 7 - 17: SRI values of 1-month timescale for historical period and RCP 8.5 (May)



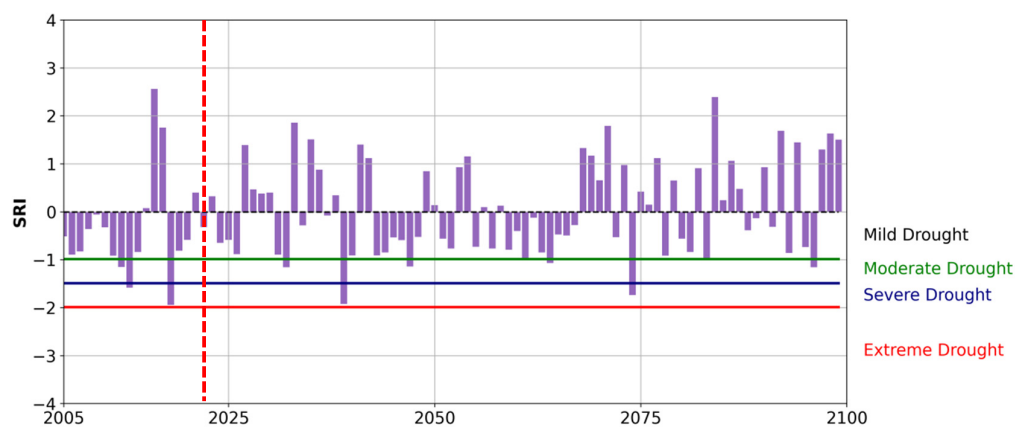
Annexure 7 - 18: SRI values of 1-month timescale for historical period and RCP 8.5 (Jun)



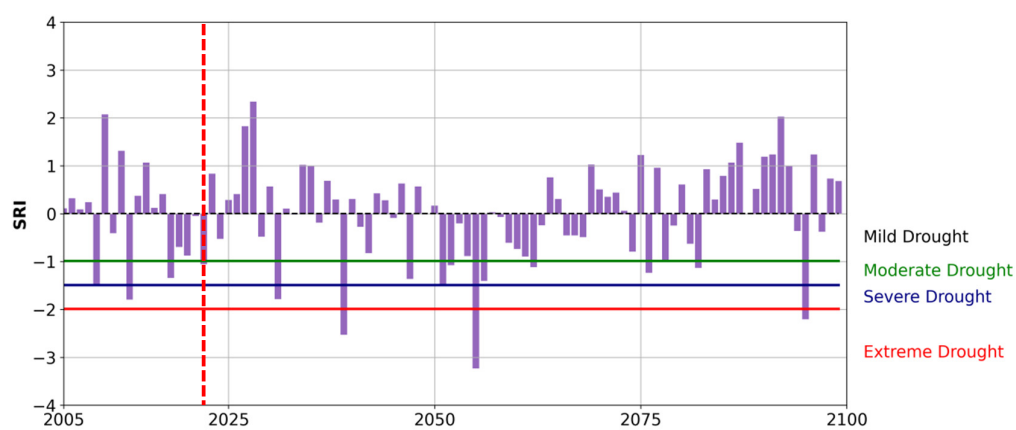
Annexure 7 - 19: SRI values of 1-month timescale for historical period and RCP 8.5 (Jul)



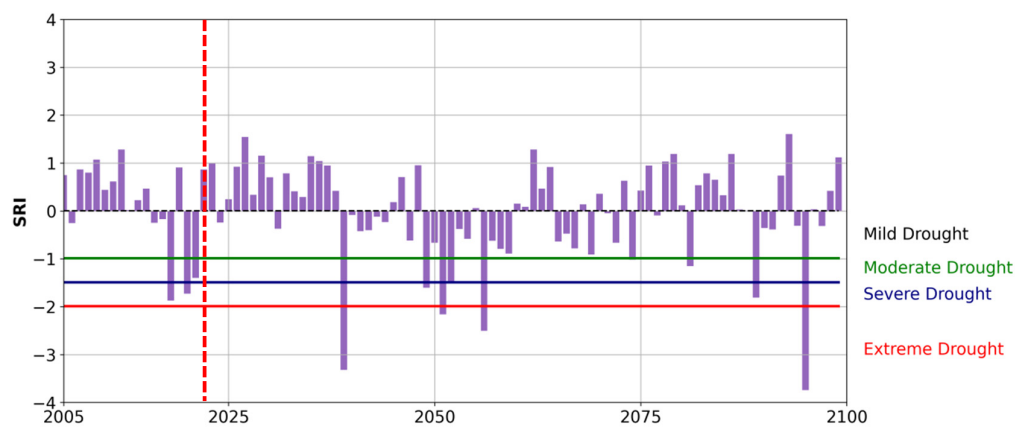
Annexure 7 - 20: SRI values of 1-month timescale for historical period and RCP 8.5 (Aug)



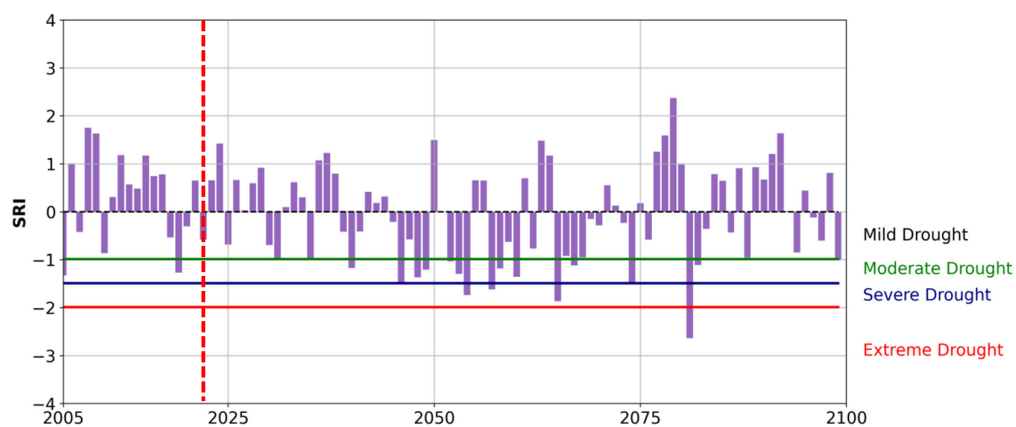
Annexure 7 - 21: SRI values of 1-month timescale for historical period and RCP 8.5 (Sep)



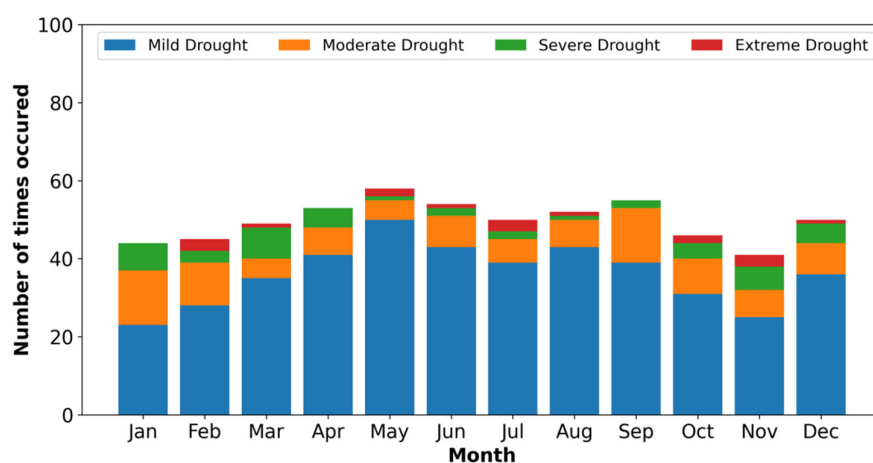
Annexure 7 - 22: SRI values of 1-month timescale for historical period and RCP 8.5 (Oct)



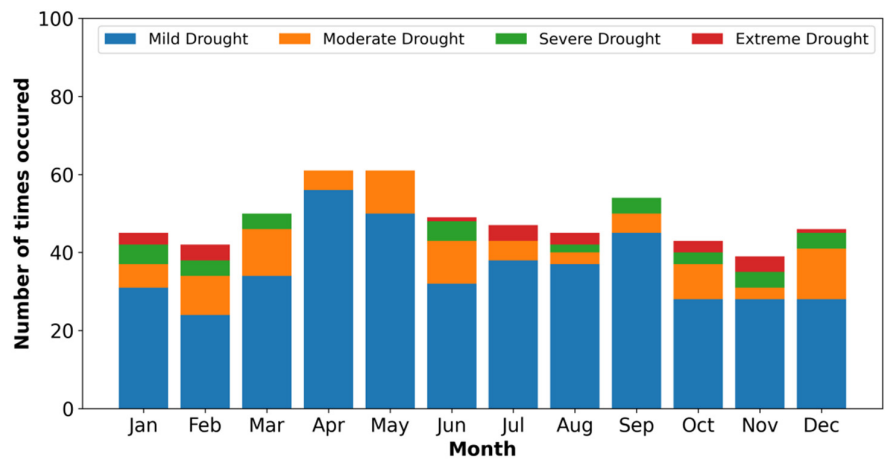
Annexure 7 - 23: SRI values of 1-month timescale for historical period and RCP 8.5 (Nov)



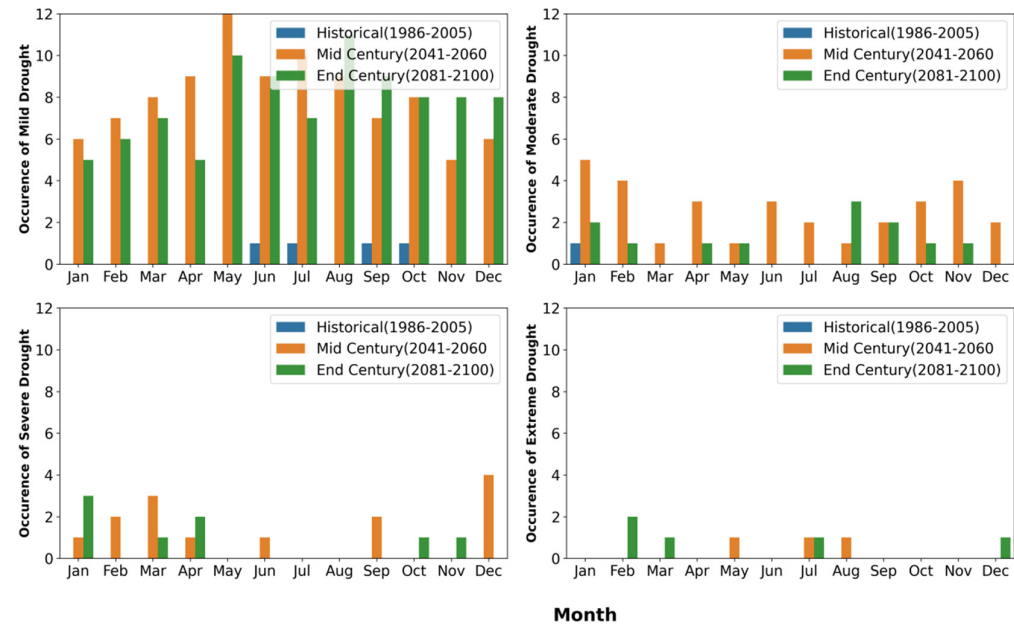
Annexure 7 - 24: SRI values of 1-month timescale for historical period and RCP 8.5 (Dec)



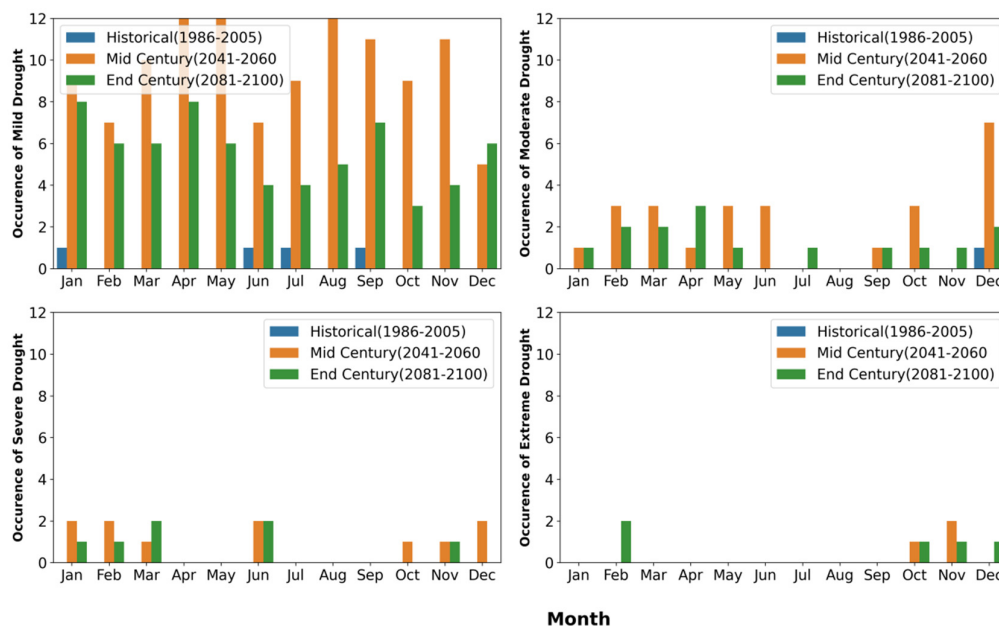
Annexure 7 - 25: Projected frequency and severity of drought events (RCP 4.5)



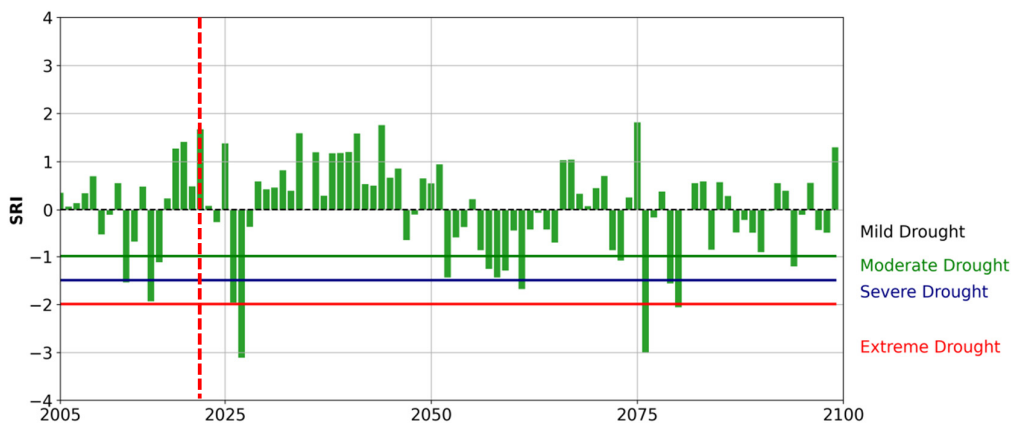
Annexure 7 - 26: Projected frequency and severity of drought events (RCP 8.5)



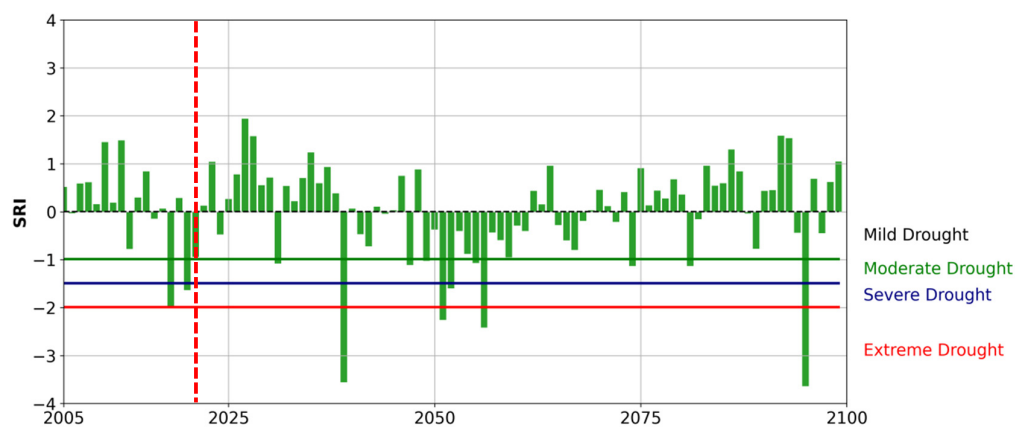
Annexure 7 - 27: Comparison of historical, mid-century and end-century RCP 4.5 drought events



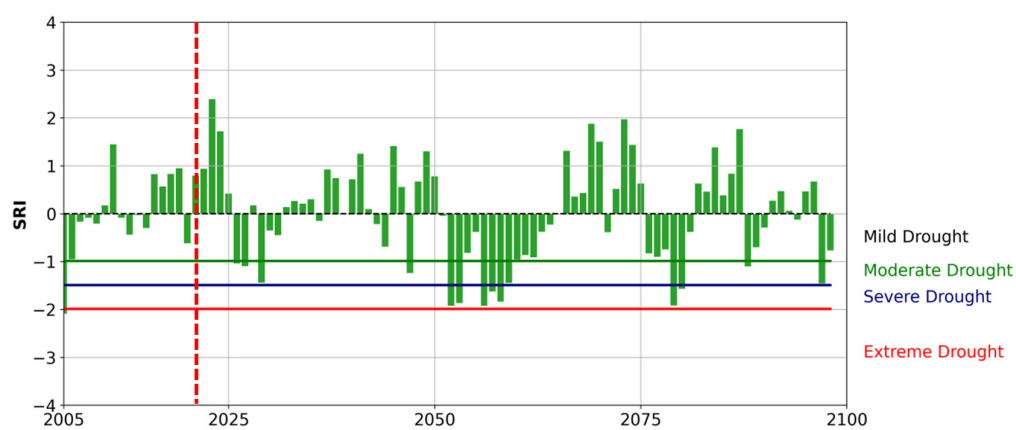
Annexure 7 - 28: Comparison of historical, mid-century and end-century RCP 8.5 drought events



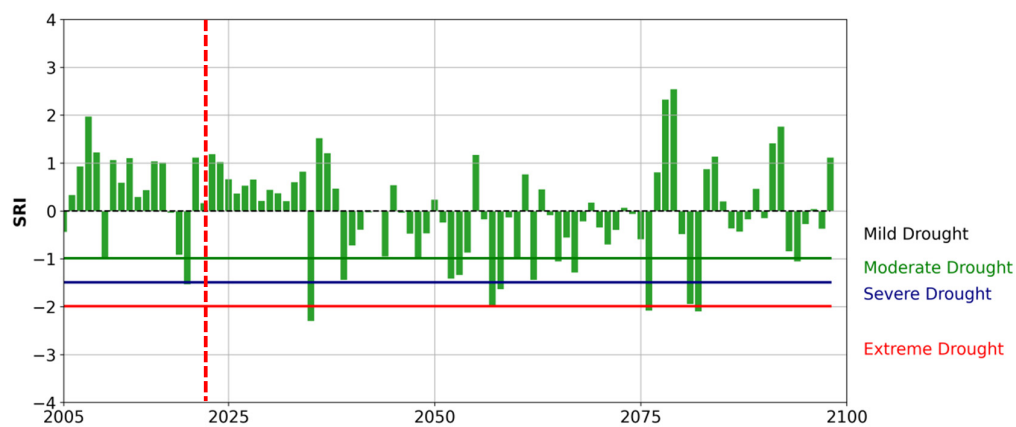
Annexure 7 - 29: SRI for historical period and RCP 4.5 (Second inter-monsoon (Oct-Nov))



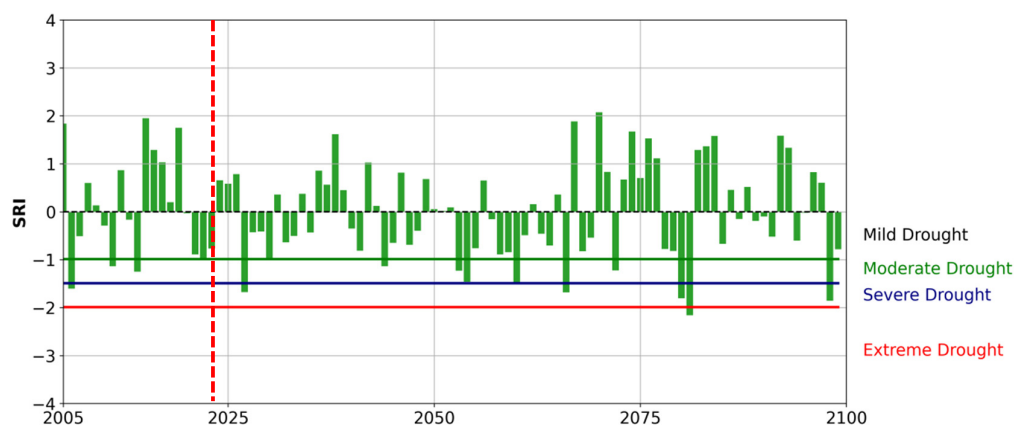
Annexure 7 - 30: SRI for historical period and RCP 8.5 (Second inter-monsoon (Oct-Nov))



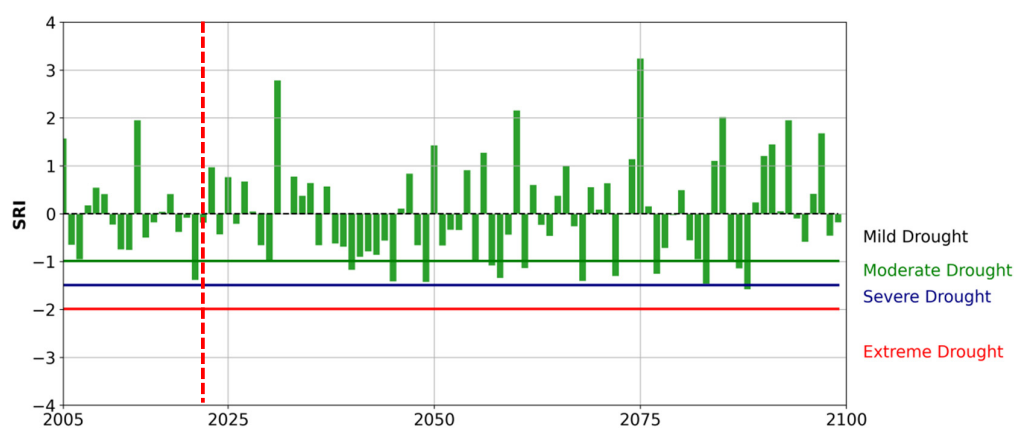
Annexure 7 - 31: SRI for historical period and RCP 4.5 (N-E Monsoon (Dec-Mar))



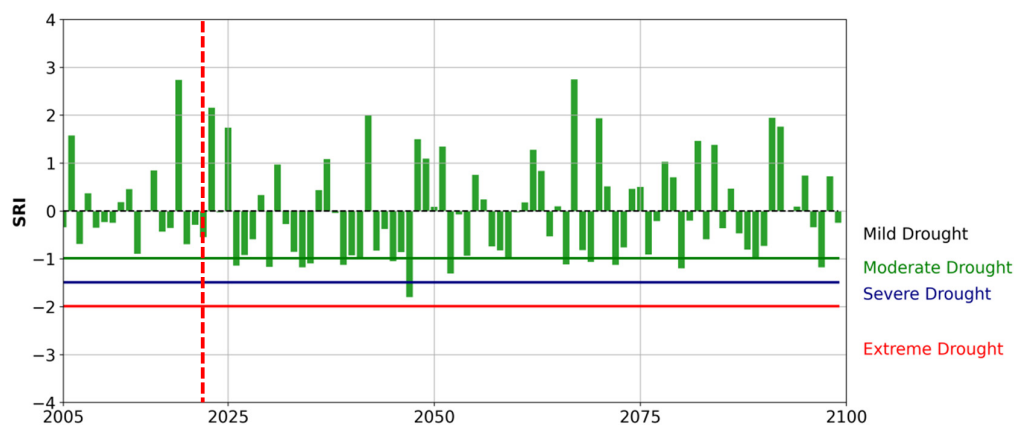
Annexure 7 - 32: SRI for historical period and RCP 8.5 (N-E Monsoon (Dec-Mar))



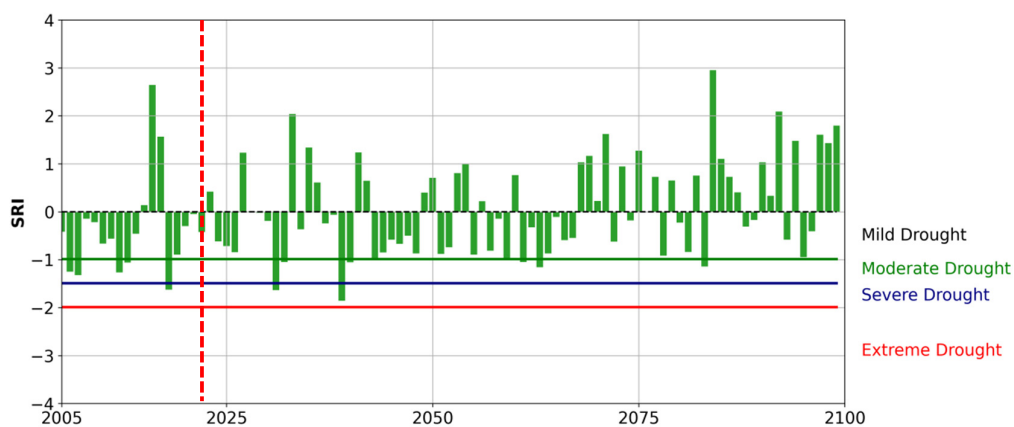
Annexure 7 - 33: SRI for historical period and RCP 4.5 (First inter-monsoon (Mar-Apr))



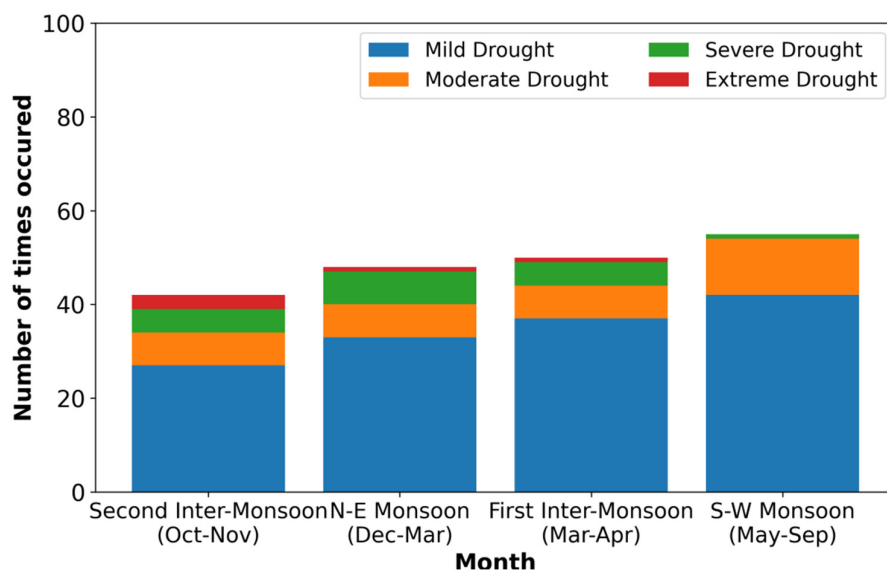
Annexure 7 - 34: SRI for historical period and RCP 8.5 (First inter-monsoon (Mar-Apr))



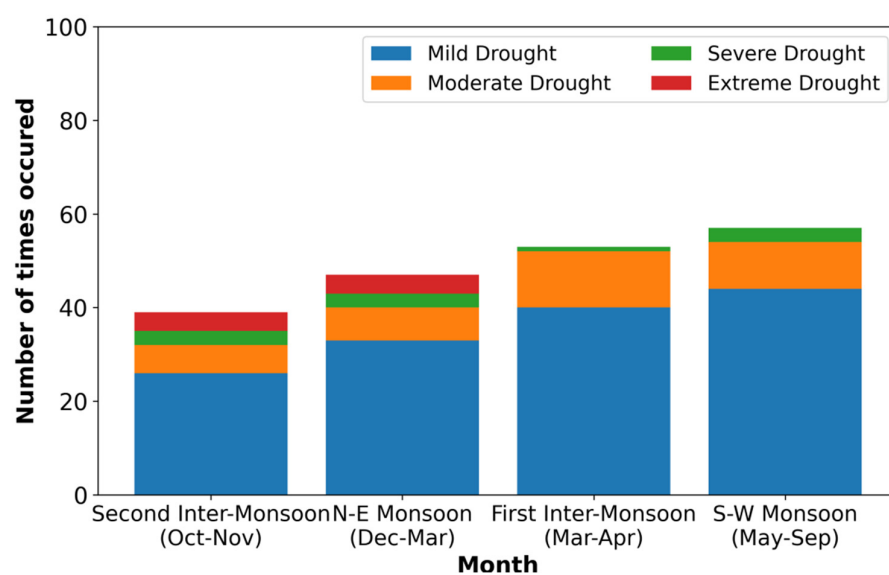
Annexure 7 - 35: SRI for historical period and RCP 4.5 (S-W Monsoon (May-Sep))



Annexure 7 - 36: SRI for historical period and RCP 8.5 (S-W Monsoon (May-Sep))



Annexure 7 - 37: Projected frequency and severity of seasonal drought events (RCP 4.5)



Annexure 7 - 38: Projected frequency and severity of seasonal drought events (RCP 8.5)

ANNEXURE 8

TREND ANALYSIS

Annexure 8 - 1: Monthly SPI trend for RCP 4.5

Month	Trend	h	p	z	T	s	slope	intercept
January	Decreasing	True	0.000	-3.494	-0.193	-2130	-0.005	0.768
February	No trend	False	0.527	-0.632	-0.035	-386	-0.001	0.314
March	Increasing	True	0.009	2.615	0.145	1594	0.005	-0.339
April	Decreasing	True	0.011	-2.546	-0.141	-1552	-0.004	0.413
May	Decreasing	True	0.006	-2.766	-0.153	-1686	-0.005	0.539
June	Decreasing	True	0.007	-2.700	-0.149	-1646	-0.004	0.436
July	No trend	False	0.580	0.553	0.031	338	0.001	-0.097
August	Increasing	True	0.004	2.890	0.160	1762	0.005	-0.468
September	Increasing	True	0.000	4.108	0.227	2504	0.008	-0.584
October	Increasing	True	0.023	2.280	0.126	1390	0.005	-0.273
November	No trend	False	0.174	1.361	0.075	830	0.002	0.032
December	No trend	False	0.068	-1.823	-0.101	-1112	-0.003	0.481

Annexure 8 - 2: Monthly SPI trend for RCP 8.5

Month	Trend	h	p	z	T	s	slope	intercept
January	No trend	False	0.055	-1.919	-0.106	-1170	-0.003	0.535
February	Decreasing	True	0.008	-2.657	-0.147	-1620	-0.004	0.553
March	Increasing	True	0.024	2.260	0.125	1378	0.005	-0.342
April	Decreasing	True	0.048	-1.974	-0.109	-1204	-0.004	0.441
May	No trend	False	0.057	-1.906	-0.105	-1162	-0.003	0.470
June	Decreasing	True	0.000	-4.184	-0.231	-2550	-0.007	0.668
July	Increasing	True	0.001	3.202	0.177	1952	0.005	-0.412
August	Increasing	True	0.012	2.526	0.140	1540	0.004	-0.242
September	Increasing	True	0.000	3.803	0.210	2318	0.008	-0.526
October	Increasing	True	0.023	2.273	0.126	1386	0.004	-0.322
November	No trend	False	0.148	1.446	0.080	882	0.003	-0.152
December	Decreasing	True	0.006	-2.746	-0.152	-1674	-0.005	0.595

Annexure 8 - 3: Seasonal SPI trend for RCP 4.5

Season	Trend	h	p	z	T	s	slope	intercept
Second inter-monsoon (Oct-Nov)	Increasing	True	0.003	2.933	0.162	1788	0.006	-0.458
N-E monsoon (Dec-Mar)	Decreasing	True	0.000	-3.662	-0.203	-2210	-0.008	0.496
First inter-monsoon (Mar-Apr)	No trend	False	0.534	0.622	0.034	380	0.001	0.011
S-W monsoon (May-Sep)	Increasing	True	0.000	4.075	0.225	2484	0.008	-0.706

Annexure 8 - 4: Seasonal SPI trend for RCP 8.5

Season	Trend	h	p	z	T	s	slope	intercept
Second inter-monsoon (Oct-Nov)	Increasing	True	0.001	3.455	0.191	2106	0.008	-0.540
N-E monsoon (Dec-Mar)	Decreasing	True	0.000	-4.249	-0.236	-2564	-0.009	0.696
First inter-monsoon (Mar-Apr)	No trend	False	0.265	1.114	0.062	680	0.002	-0.131
S-W monsoon (May-Sep)	Increasing	True	0.000	3.570	0.197	2176	0.007	-0.581

Annexure 8 - 5: Monthly SPEI trend for RCP 4.5

Month	Trend	h	p	z	T	s	slope	intercept
January	Decreasing	True	0.001	-3.340	-0.185	-2036	-0.004	0.630
February	No trend	False	0.104	-1.627	-0.090	-992	-0.003	0.424
March	No trend	False	0.447	-0.760	-0.042	-464	-0.001	0.170
April	Increasing	True	0.000	4.568	0.252	2784	0.009	-0.522
May	Increasing	True	0.000	5.983	0.331	3646	0.012	-0.907
June	Increasing	True	0.000	5.063	0.280	3086	0.010	-0.665
July	Increasing	True	0.000	4.610	0.255	2810	0.009	-0.659
August	No trend	False	0.369	0.898	0.050	548	0.002	0.009
September	Decreasing	True	0.002	-3.140	-0.174	-1914	-0.005	0.580
October	No trend	False	0.067	1.833	0.101	1118	0.004	-0.159
November	No trend	False	0.350	0.934	0.052	570	0.001	0.093
December	Decreasing	True	0.033	-2.135	-0.118	-1302	-0.003	0.470

Annexure 8 - 6: Monthly SPEI trend for RCP 8.5

Month	Trend	h	p	z	T	s	slope	intercept
January	Decreasing	True	0.006	-2.726	-0.151	-1662	-0.004	0.555
February	Decreasing	True	0.002	-3.045	-0.168	-1856	-0.005	0.437
March	No trend	False	0.330	0.973	0.054	594	0.002	0.005
April	Increasing	True	0.000	4.660	0.258	2840	0.009	-0.586
May	Increasing	True	0.000	6.337	0.350	3862	0.012	-0.918
June	Increasing	True	0.000	7.555	0.418	4604	0.014	-1.045
July	Increasing	True	0.000	3.744	0.207	2282	0.007	-0.479
August	No trend	False	0.158	1.413	0.078	862	0.003	-0.221
September	Decreasing	True	0.016	-2.405	-0.133	-1466	-0.003	0.442
October	No trend	False	0.457	0.744	0.041	454	0.001	-0.021
November	No trend	False	0.477	0.711	0.039	434	0.001	0.020
December	Decreasing	True	0.001	-3.248	-0.180	-1980	-0.005	0.656

Annexure 8 - 7: Seasonal SPEI trend for RCP 4.5

Season	Trend	h	p	z	T	s	slope	intercept
Second inter-monsoon (Oct-Nov)	Increasing	True	0.025	2.244	0.124	1368	0.005	-0.249
N-E monsoon (Dec-Mar)	Decreasing	True	0.000	-4.322	-0.240	-2608	-0.008	0.725
First inter-monsoon (Mar-Apr)	Increasing	True	0.003	2.949	0.163	1798	0.006	-0.329
S-W monsoon (May-Sep)	Increasing	True	0.000	3.570	0.197	2176	0.007	-0.512

Annexure 8 - 8: Seasonal SPEI trend for RCP 8.5

Season	Trend	h	p	z	T	s	slope	intercept
Second inter-monsoon (Oct-Nov)	No trend	False	0.104	1.627	0.090	992	0.003	-0.151
N-E monsoon (Dec-Mar)	Decreasing	True	0.000	-4.581	-0.254	-2764	-0.009	0.766
First inter-monsoon (Mar-Apr)	Increasing	True	0.000	5.106	0.282	3112	0.010	-0.782
S-W monsoon (May-Sep)	Increasing	True	0.000	5.523	0.305	3366	0.011	-0.793

Annexure 8 - 9: Monthly RDI trend for RCP 4.5

Month	Trend	h	p	z	T	s	slope	intercept
January	Decreasing	True	0.006	-2.726	-0.151	-1662	-0.004	0.555
February	Decreasing	True	0.002	-3.045	-0.168	-1856	-0.005	0.437
March	No trend	False	0.330	0.973	0.054	594	0.002	0.005
April	Increasing	True	0.000	4.660	0.258	2840	0.009	-0.586
May	Increasing	True	0.000	6.337	0.350	3862	0.012	-0.918
June	Increasing	True	0.000	7.555	0.418	4604	0.014	-1.045
July	Increasing	True	0.000	3.744	0.207	2282	0.007	-0.479
August	No trend	False	0.158	1.413	0.078	862	0.003	-0.221
September	Decreasing	True	0.016	-2.405	-0.133	-1466	-0.003	0.442
October	No trend	False	0.457	0.744	0.041	454	0.001	-0.021
November	No trend	False	0.477	0.711	0.039	434	0.001	0.020
December	Decreasing	True	0.001	-3.248	-0.180	-1980	-0.005	0.656

Annexure 8 - 10: Monthly RDI trend for RCP 8.5

Month	Trend	h	p	z	T	s	slope	intercept
January	Decreasing	True	0.006	-2.726	-0.151	-1662	-0.004	0.555
February	Decreasing	True	0.002	-3.045	-0.168	-1856	-0.005	0.437
March	No trend	False	0.330	0.973	0.054	594	0.002	0.005
April	Increasing	True	0.000	4.660	0.258	2840	0.009	-0.586
May	Increasing	True	0.000	6.337	0.350	3862	0.012	-0.918
June	Increasing	True	0.000	7.555	0.418	4604	0.014	-1.045
July	Increasing	True	0.000	3.744	0.207	2282	0.007	-0.479
August	No trend	False	0.158	1.413	0.078	862	0.003	-0.221
September	Decreasing	True	0.016	-2.405	-0.133	-1466	-0.003	0.442
October	No trend	False	0.457	0.744	0.041	454	0.001	-0.021
November	No trend	False	0.477	0.711	0.039	434	0.001	0.020
December	Decreasing	True	0.001	-3.248	-0.180	-1980	-0.005	0.656

Annexure 8 - 11: Seasonal RDI trend for RCP 4.5

Season	Trend	h	p	z	T	s	slope	intercept
Second inter-monsoon (Oct-Nov)	No trend	False	0.468	0.725	0.040	443	0.002	-0.008
N-E monsoon (Dec-Mar)	Decreasing	True	0.000	-5.201	-0.288	-3138	-0.011	0.804
First inter-monsoon (Mar-Apr)	No trend	False	0.134	-1.499	-0.083	-914	-0.003	0.408
S-W monsoon (May-Sep)	No trend	False	0.312	1.011	0.056	617	0.002	-0.199

Annexure 8 - 12: Seasonal RDI trend for RCP 8.5

Season	Trend	h	p	z	T	s	slope	intercept
Second inter-monsoon (Oct-Nov)	No trend	False	0.653	-0.450	-0.025	-275	-0.001	0.249
N-E monsoon (Dec-Mar)	Decreasing	True	0.000	-6.618	-0.367	-3993	-0.013	0.991
First inter-monsoon (Mar-Apr)	Decreasing	True	0.004	-2.918	-0.161	-1779	-0.006	0.563
S-W monsoon (May-Sep)	No trend	False	0.991	-0.011	-0.001	-8	0.000	-0.051

Annexure 8 - 13: Monthly EDI trend for RCP 4.5

Month	Trend	h	p	z	T	s	slope	intercept
January	No trend	False	0.769	-0.293	-0.016	-178	-0.000	0.042
February	No trend	False	0.851	0.187	0.010	114	0.000	-0.062
March	No trend	False	0.675	0.419	0.023	254	0.000	-0.089
April	No trend	False	0.991	0.012	0.001	8	0.001	-0.006
May	No trend	False	0.870	0.164	0.009	100	0.001	0.000
June	No trend	False	0.622	0.492	0.027	298	0.000	-0.099
July	No trend	False	0.927	0.091	0.005	56	0.001	-0.108
August	No trend	False	0.831	0.214	0.012	130	0.001	-0.084
September	No trend	False	0.677	-0.416	-0.023	-252	-0.001	-0.022
October	No trend	False	0.670	0.426	0.024	258	0.000	0.016
November	No trend	False	0.972	0.035	0.002	22	0.000	-0.017
December	No trend	False	0.973	0.034	0.002	22	0.000	-0.009

Annexure 8 - 14: Monthly EDI trend for RCP 8.5

Month	Trend	h	p	z	T	s	slope	intercept
January	No trend	False	0.844	-0.197	-0.011	-120	0.000	-0.024
February	No trend	False	0.925	-0.095	-0.005	-58	0.000	0.005
March	No trend	False	0.943	-0.071	-0.004	-44	0.000	-0.011
April	No trend	False	0.558	0.585	0.033	354	0.001	-0.005
May	No trend	False	0.634	0.476	0.026	288	0.001	0.013
June	No trend	False	0.767	0.297	0.017	180	0.000	-0.086
July	No trend	False	0.471	0.721	0.040	436	0.001	-0.051
August	No trend	False	0.795	0.260	0.015	158	0.001	-0.004
September	No trend	False	0.670	-0.426	-0.024	-258	-0.001	0.089
October	No trend	False	0.962	0.048	0.003	30	0.000	0.080
November	No trend	False	0.867	0.167	0.009	102	0.000	-0.050
December	No trend	False	0.910	-0.113	-0.006	-70	0.000	0.016

Annexure 8 - 15: Monthly SRI trend for RCP 4.5

Month	Trend	h	p	z	T	s	slope	intercept
January	No trend	False	0.365	-0.907	-0.063	-283	-0.004	0.253
February	No trend	False	0.913	0.109	0.008	35	0.001	0.000
March	No trend	False	0.882	0.148	0.011	47	0.000	-0.196
April	No trend	False	0.822	-0.225	-0.016	-71	-0.001	-0.118
May	No trend	False	0.728	-0.347	-0.024	-109	-0.001	-0.097
June	No trend	False	0.571	0.566	0.040	177	0.001	-0.182
July	No trend	False	0.274	-1.093	-0.076	-341	-0.004	0.147
August	Decreasing	True	0.011	-2.546	-0.178	-793	-0.008	0.259
September	No trend	False	0.475	0.714	0.050	223	0.002	-0.270
October	No trend	False	0.594	-0.534	-0.037	-167	-0.002	0.134
November	No trend	False	0.100	-1.646	-0.115	-513	-0.006	0.388
December	No trend	False	0.857	-0.180	-0.013	-57	-0.001	-0.049

Annexure 8 - 16: Monthly SRI trend for RCP 8.5

Month	Trend	h	p	z	T	s	slope	intercept
January	Decreasing	True	0.046	-2.000	-0.140	-623	-0.008	0.417
February	Decreasing	True	0.007	-2.720	-0.190	-847	-0.011	0.695
March	No trend	False	0.767	-0.296	-0.021	-93	-0.001	-0.080
April	No trend	False	0.667	0.431	0.030	135	0.001	-0.306
May	No trend	False	0.071	1.807	0.126	563	0.005	-0.457
June	No trend	False	0.068	1.826	0.127	569	0.007	-0.339
July	Increasing	True	0.002	3.099	0.216	965	0.011	-0.481
August	Increasing	True	0.009	2.598	0.181	809	0.008	-0.366
September	Increasing	True	0.024	2.263	0.158	705	0.008	-0.691
October	No trend	False	0.234	1.190	0.083	371	0.005	-0.109
November	No trend	False	0.215	-1.241	-0.087	-387	-0.004	0.343
December	No trend	False	0.452	-0.752	-0.053	-235	-0.003	0.178

Annexure 8 - 17: Seasonal SRI trend for RCP 4.5

Season	Trend	h	p	z	T	s	slope	intercept
Second inter-monsoon (Oct-Nov)	No trend	False	0.144	-1.460	-0.102	-455	-0.005	0.450
N-E monsoon (Dec-Mar)	No trend	False	0.840	-0.203	-0.014	-63	-0.001	0.039
First inter-monsoon (Mar-Apr)	No trend	False	0.995	-0.006	-0.001	-3	0.000	-0.096
S-W monsoon (May-Sep)	No trend	False	0.753	0.315	0.022	99	0.001	-0.295

Annexure 8 - 18: Seasonal SRI trend for RCP 8.5

Season	Trend	h	p	z	T	s	slope	intercept
Second inter-monsoon (Oct-Nov)	No trend	False	0.908	0.116	0.008	37	0.000	0.136
N-E monsoon (Dec-Mar)	Decreasing	True	0.017	-2.391	-0.168	-733	-0.010	0.449
First inter-monsoon (Mar-Apr)	No trend	False	0.827	0.219	0.015	69	0.001	-0.227
S-W monsoon (May-Sep)	Increasing	True	0.002	3.093	0.216	963	0.012	-0.772

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