

**INDIAN SUMMER MONSOON
INTERANNUAL VARIABILITY: ROLES OF
OCEAN-ATMOSPHERE COUPLING,
TELECONNECTION AND SYNOPTIC
VARIABILITY**

SARAN RAJENDRAN



**CENTRE FOR ATMOSPHERIC SCIENCES
INDIAN INSTITUTE OF TECHNOLOGY DELHI**

MAY 2026

© Indian Institute of Technology Delhi (IITD), New Delhi, 2026

**INDIAN SUMMER MONSOON
INTERANNUAL VARIABILITY: ROLES OF
OCEAN-ATMOSPHERE COUPLING,
TELECONNECTION AND SYNOPTIC
VARIABILITY**

by

SARAN RAJENDRAN

CENTRE FOR ATMOSPHERIC SCIENCES

Submitted

in fulfillment of the requirements of the degree of

Doctor of Philosophy

to the



INDIAN INSTITUTE OF TECHNOLOGY DELHI

MAY 2026

Dedicated to ...
Friends and Family

Certificate

This is to certify that the thesis entitled “**INDIAN SUMMER MONSOON INTERANNUAL VARIABILITY: ROLES OF OCEAN-ATMOSPHERE COUPLING, TELECONNECTION AND SYNOPTIC VARIABILITY**”, submitted by **Mr. Saran Rajendran** to the Indian Institute of Technology Delhi, for the award of the degree of **Doctor of Philosophy**, is a record of the original, bonafide research work carried out by him under my guidance and supervision. The thesis has reached the standards fulfilling the requirements of the regulations related to the award of the degree.

The results contained in this thesis have not been submitted in part or in full to any other University or Institute for the award of any degree or diploma.

Date:

Place: New Delhi

Prof. Sandeep Sukumaran

Associate Professor

Centre for Atmospheric Sciences

Indian Institute of Technology Delhi

New Delhi-110016, India

Acknowledgements

I would like to express my sincere gratitude to my supervisor, Prof. Sandeep Sukumaran, for his guidance, support, and encouragement throughout this research journey. His insights, patience, and commitment to high standards have played a central role in shaping this work. I am thankful for the opportunities he provided, his support during challenging phases, and his constant motivation to improve. Working under his mentorship has been an important learning experience for me.

I am thankful to the members of my Student Research Committee (SRC) - Prof. Somnath Baidya Roy, Prof. Ravi Kumar Kunchala, and Prof. Hariprasad Kodamanna - for their valuable suggestions and constructive feedback, which helped improve the quality of this thesis. I also thank Prof. Sagnik Dey, Head of the Centre for Atmospheric Sciences, for providing a supportive research environment and necessary facilities. My thanks also go to the external reviewers for their time and valuable comments on this thesis.

I extend my appreciation to all the faculty members of the Centre for Atmospheric Sciences for their support and for fostering a strong academic environment. I also acknowledge the office staff of the department for their assistance throughout my time here.

I acknowledge the Indian Institute of Technology Delhi for providing the infrastructure and resources required to carry out this research, and the UGC and IRD Department, IIT Delhi, for their financial and institutional support.

I am grateful to my colleagues and both former and current members of the ClimDL group for their support, discussions, and interactions, which have contributed meaningfully to this work.

I am deeply grateful to my friends for their unwavering support, encouragement, and companionship, which played an important role in helping me navigate this journey.

Finally, I express my sincere gratitude to my parents, Mrs. Jayasree K and Mr. Rajendran C M, and my sister, Salina Rajendran, for their constant support and encouragement.

This thesis would not have been possible without the collective contributions and support of all those mentioned above. Thank you for being a part of this transformative experience.

New Delhi, May 2026

Saran Rajendran

Abstract

The Indian Summer Monsoon (ISM) has long been viewed as a self-regulated coupled ocean-atmosphere system, wherein floods and droughts alternate in successive years due to feedbacks mediated by cross-equatorial ocean heat transport (OHT). This thesis critically examines that paradigm by evaluating the relative contributions of OHT, large-scale teleconnections, and synoptic-scale systems to ISM interannual variability, and by assessing how extreme floods and droughts may evolve under future climate scenarios. Analyses using reanalysis data reveal that the persistence of cross-equatorial OHT is too short-lived to explain year-to-year reversals in ISM rainfall. While rainfall differences between flood and drought years exceed 20%, associated OHT differences remain below 2%, and the response of the local Hadley circulation is negligible. These findings suggest that OHT plays only a minor role in governing interannual ISM variability. By contrast, the El Niño-Southern Oscillation (ENSO) exerts strong control on sea surface temperature (SST) anomalies in the northern Indian Ocean, which in turn influence subsequent monsoon behavior. However, the correlation between winter Niño3.4 anomalies and following-summer ISM rainfall is weak, underscoring the indirect and non-linear nature of ENSO-ISM linkages. Synoptic variability, especially low-pressure systems (LPS), emerges as a critical driver of ISM rainfall extremes. Drought years are associated with two fewer LPS per summer and disrupted west-northwestward propagation compared to flood years. LPS activity thus substantially shapes interannual rainfall variability and governs the spatial coherence of extreme events. Future projections from CMIP6 multimodel ensembles indicate marked changes in ISM extremes. While biases exist at the model level, the ensemble reproduces historical excess and deficit statistics reasonably well. Under high-emission scenarios, extreme excess years are projected to become more frequent, with shorter return periods, signaling a transition to more intense wet seasons. Extreme deficit years display weaker and more uncertain trends. LPS remain central to excess-deficit contrasts, with more frequent and coherent tracks during wet years, though their overall frequency shows only marginal declines in a warmer climate. ENSO's role also evolves: the historical association of La Niña with excess rainfall and El Niño with deficit years weakens, and extreme excess events increasingly occur during El Niño years under SSP585, suggesting a fundamental reorganization of ENSO-ISM interactions in a warming world. Taken

together, this thesis demonstrates that ISM interannual variability arises from a combination of remote and regional processes rather than from OHT alone. The findings highlight the growing importance of synoptic-scale variability and shifting ENSO dynamics in shaping extreme rainfall, with direct implications for monsoon prediction, climate adaptation, and disaster risk reduction across South Asia.

सार

भारतीय ग्रीष्मकालीन मानसून (ISM) को लंबे समय से एक स्व-नियंत्रित युग्मित महासागर-वायुमंडल प्रणाली के रूप में देखा गया है, जिसमें बाढ़ और सूखा वर्षों के बीच क्रमिक रूप से घटित होते हैं। यह चक्र मुख्यतः विषुवतीय-पार महासागरीय ऊष्मा परिवहन (OHT) द्वारा संचालित प्रतिपुष्टियों से जुड़ा माना जाता है। इस शोधप्रबंध में उस परिकल्पना की आलोचनात्मक जाँच की गई है और OHT, बड़े पैमाने पर दूरस्थ दूरसंबंध (teleconnections) तथा सामयिक (synoptic-scale) प्रणालियों के तुलनात्मक योगदान का आकलन किया गया है। साथ ही भविष्य की जलवायु परिस्थितियों में भीषण बाढ़ और सूखे की संभावित प्रवृत्तियों का विश्लेषण किया गया है।

पुनःविश्लेषण (reanalysis) आँकड़ों से पता चलता है कि विषुवतीय-पार OHT की स्थायित्व अवधि बहुत कम है और यह मानसूनी वर्षा में वर्ष-दर-वर्ष होने वाले उलटफेर को समझाने में सक्षम नहीं है। जहाँ बाढ़ और सूखे वर्षों में वर्षा का अंतर 20% से अधिक हो सकता है, वहीं OHT का अंतर केवल लगभग 5% पाया गया। स्थानीय हैडली परिसंचरण (Hadley circulation) की प्रतिक्रिया भी नगण्य रही। यह परिणाम संकेत देते हैं कि ISM की अंतर्वर्षीय परिवर्तनशीलता में OHT की भूमिका सीमित है। इसके विपरीत, एल नीन्यो-दक्षिणी दोलन (ENSO) उत्तरी हिंद महासागर में समुद्र सतह तापमान (SST) असमानताओं को नियंत्रित करता है, जो आगे चलकर मानसून के व्यवहार को प्रभावित करती हैं। हालाँकि, शीतकालीन Niño3.4 असामान्यताओं और अगले ग्रीष्मकालीन ISM वर्षा के बीच सहसंबंध कमजोर है, जो ENSO-ISM संबंध की अप्रत्यक्ष और गैर-रेखीय प्रकृति को दर्शाता है।

सामयिक परिवर्तनशीलता, विशेष रूप से निम्न-दाब प्रणालियाँ (LPS), मानसूनी वर्षा की चरम घटनाओं का एक प्रमुख निर्धारक के रूप में उभरती हैं। सूखे वर्षों में औसतन दो LPS कम उत्पन्न होते हैं और इनकी पश्चिमोत्तरवर्ती गति बाधित रहती है, जबकि बाढ़ वर्षों में अधिक बार और संगठित LPS देखे जाते हैं। इस प्रकार LPS गतिविधि वर्षा की अंतर्वर्षीय परिवर्तनशीलता को महत्वपूर्ण रूप से प्रभावित करती है और चरम घटनाओं के भौगोलिक प्रसार को नियंत्रित करती है।

भविष्य के लिए CMIP6 बहु-मॉडल समूहों से प्राप्त प्रक्षेपण ISM की चरम घटनाओं में उल्लेखनीय परिवर्तन दर्शाते हैं। यद्यपि व्यक्तिगत मॉडलों में पूर्वाग्रह मौजूद हैं, फिर भी समष्टि (ensemble) आँकड़े ऐतिहासिक बाढ़ और सूखे की आवृत्ति व आवर्तन अवधि का यथोचित पुनरुत्पादन करते हैं। उच्च-उत्सर्जन परिदृश्यों में बड़ी बाढ़ों की आवृत्ति बढ़ने और उनकी वापसी अवधि घटने की संभावना है, जिससे अधिक तीव्र और गीले मौसमों की ओर संक्रमण का संकेत मिलता है। इसके विपरीत, सूखे की प्रवृत्ति कमजोर और अधिक अनिश्चित पाई गई। LPS अब भी बाढ़-सूखे के विरोधाभास का प्रमुख आधार बने रहते हैं, यद्यपि उनके कुल संख्या में गर्म जलवायु में केवल मामूली कमी देखी जाती है। ENSO की भूमिका भी बदलती है: जहाँ ऐतिहासिक रूप से ला नीना बाढ़ और एल नीन्यो सूखे से जुड़ा रहा है, वहीं SSP585 परिदृश्य में बाढ़ की घटनाएँ तेजी से एल नीन्यो वर्षों में भी होने लगती हैं। यह ENSO-ISM संबंधों के एक मौलिक पुनर्गठन की ओर संकेत करता है।

समग्र रूप से, यह शोधप्रबंध दर्शाता है कि ISM की अंतर्वर्षीय परिवर्तनशीलता केवल OHT से नहीं, बल्कि दूरस्थ एवं क्षेत्रीय प्रक्रियाओं के जटिल परस्पर क्रियाओं से उत्पन्न होती है। निष्कर्ष स्पष्ट करते हैं कि चरम वर्षा की घटनाओं को समझने में सामयिक परिवर्तनशीलता और परिवर्तित ENSO गतिकी की

भूमिका बढ़ती जा रही है, जिसका प्रत्यक्ष प्रभाव मानसून पूर्वानुमान, जलवायु अनुकूलन, और दक्षिण एशिया में आपदा जोखिम प्रबंधन पर पड़ेगा।

Contents

Certificate	i
Acknowledgements	iii
Abstract	v
Contents	ix
List of Figures	xiii
List of Tables	xix
Abbreviations	xxi
1 Introduction	1
1.1 Background	1
1.1.1 Interannual variability of Indian Summer Monsoon	1
1.1.2 Role of Ocean–Atmosphere Coupling in the Regulation of SST and ISM Variability	5
1.1.3 Role of Teleconnections in ISM Variability	7
1.1.4 Role of Synoptic-Scale Variability in ISM Variability	9
1.2 Motivation and Research Gaps	10
1.3 Objectives of the thesis	11
1.4 Structure of the thesis	11
2 Data and Methods	13
2.1 Observation data	13
2.1.1 Precipitation data	13
2.1.1.1 IMD data	13
2.1.1.2 TRMM data	14
2.1.2 Sea Surface Temperature data	14
2.1.2.1 Daily SST data	14
2.2 Reanalysis data	15

2.2.1	ORAS5	16
2.2.2	SODA	17
2.2.3	ERA5	18
2.2.4	NCEP-NCAR	19
2.3	Climate model data	19
2.4	Methodology	23
2.4.1	Calculation of Ocean heat transport	23
2.4.2	Identification of flood and drought years	25
2.4.3	EOF analysis	25
2.4.4	Transfer Entropy	26
2.4.5	Identification of extreme excess and extreme deficit years	27
2.4.6	Generalized extreme value distribution	28
2.4.7	LPS tracking algorithm	29
2.4.8	Calculation of Niño 3.4 index	30
2.4.9	Statistical significance test	30
3	Indian Summer Monsoon Interannual Variability: Role of Ocean-Atmosphere Coupling in Observations	31
3.1	Introduction	31
3.2	Datasets and Methodology	32
3.2.1	Datasets overview	32
3.2.2	Methods	33
3.3	Results and Discussion	34
3.3.1	Summer Cross-Equatorial Indian Ocean Heat Transport	34
3.3.2	Understanding the factors contribute to the variability of Indian Ocean meridional heat transport	35
3.3.3	The role of summer Indian Ocean heat transport in the subsequent year monsoon and SST pattern	38
3.3.4	The boreal summer OHT during drought and flood years of ISM	41
3.4	Summary and Conclusions	50
4	ISM Interannual Variability: Role of Teleconnections and Synoptic Variability in CMIP6 Historical Projections	53
4.1	Introduction	53
4.2	Datasets and Methodology	54
4.2.1	Datasets overview	54
4.2.2	Methodology	54
4.3	Results and Discussion	55
4.3.1	Relationship Between ENSO and ISM of the Following Summer in Observations	55
4.3.2	Relationship Between ENSO and ISM of Following Summer in CMIP6 Historical Simulations	56

4.3.3	LPS and Interannual Variability of the ISM	61
4.4	Summary and Conclusions	64
5	The Extreme Fluctuations of the ISM Interannual Variability in CMIP6 Future Simulations	71
5.1	Introduction	71
5.2	Datasets and Methodology	72
5.2.1	Datasets overview	72
5.2.2	Methods	72
5.3	Results and Discussion	74
5.3.1	Number and Return Period of EE and ED years over central India in Different CMIP6 Scenarios	74
5.3.2	Relation between LPS and EE and ED years	78
5.3.3	Examination of coincidence of ENSO with EE and ED years	87
5.4	Discussion	94
5.5	Summary and Conclusions	98
6	Conclusions and Scope of Future Work	101
6.1	Conclusions	101
6.2	Scope of Future Work	102
	References	105
	List of Publications	123
	Curriculum Vitae	125

List of Figures

1.1	Summer monsoon (June–September) rainfall departure (in %) over Central India (75–85°E, 19–26°N) for the period 1901–2018. Flood years with rainfall departure exceeding +10% are shown in dark blue and drought years with departure below –10% are shown in red. El Ni no and La Ni na conditions during the same season are indicated by red and blue dots, respectively. The grey line represents a long-term smoothed average. Rainfall data are from the Indian Meteorological Department [<i>Singh et al.</i> , 2019]	3
1.2	Schematic of a regulatory framework for the monsoon annual cycle. The left and right panels illustrate climatological lower-tropospheric winds (solid black lines) during summer and winter, respectively. Blue dashed arrows indicate Ekman mass transport, which is deflected to the right of the winds in the Northern Hemisphere and to the left in the Southern Hemisphere. Owing to the prevailing sea surface temperature gradient, heat is transferred from the summer hemisphere to the winter hemisphere in both seasons. Panel B depicts summer surface winds during strong and weak monsoon years. In strong monsoon years, enhanced Ekman transport leads to rapid cooling of the northern Indian Ocean, while in weak years, the cooling is comparatively weaker. Since strong monsoons are typically preceded by anomalously warm Indian Ocean SSTs, a strong year is often followed by a weak year, and vice versa. (<i>Webster et al.</i> [2003]; Published 2003 by the Encyclopedia of atmospheric sciences)	8
2.1	Schematic illustrating the identification of the LPS center and the computation of the pressure gradient for (a) a single-center system and (b) a multicenter system. (<i>Praveen et al.</i> [2015]; published in Journal of Climate	30
3.1	(a) June–September meridional ocean heat transport climatology over the Indian Ocean, (b) Time series of JJAS OHT averaged over averaged over 5°S to 5°N The climatology is computed for the 1980–2018 period.	35
3.2	Longitude–depth cross-section of JJAS mean a) potential temperature (θ , units: K), b) meridional velocity (v , units: m s^{-1}), and c) product of θ and v ($\theta \times v$ units: K m s^{-1}) averaged over 5°S to 5°N	37
3.3	a,c,e – EOF 1 of θ , v and product of θ and v respectively; b,d,f- PC1 of θ , v and product of θ and v respectively for JJAS averaged over 5°S to 5°N	37

3.4	The linear regression of JJAS mean OHT averaged over 5°N to 5°S on sea surface temperatures anomalies averaged for (a) SON, (b) DJF, (c) MAM(+1) and (d) JJA(+1). The stippling indicates statistically significant regression coefficients at 95% level as revealed by a two-tailed bootstrap significance test. The 1998–2018 time period is considered for this analysis. To maintain consistency with our interpretation and to avoid confusion regarding the sign of heat transport, we have multiplied all regression coefficients by -1	42
3.5	The linear regression of JJAS mean OHT using SODA reanalysis averaged over 5°N to 5°S on sea surface temperatures anomalies averaged for (a) SON, (b) DJF, (c) MAM(+1) and (d) JJA(+1). The stippling indicates statistically significant regression coefficients at 95% level as revealed by a two-tailed bootstrap significance test. The 1998–2018 time period is considered for this analysis. To maintain consistency with our interpretation and to avoid confusion regarding the sign of heat transport, we have multiplied all regression coefficients by -1	43
3.6	The linear regression of JJAS mean OHT averaged over 5°N to 5°S on precipitation and 850hpa wind anomalies averaged for (a) SON, (b) DJF, (c) MAM(+1) and (d) JJA(+1). The stippling indicates statistically significant regression coefficients at 95% level as revealed by a two-tailed bootstrap significance test. The 1998–2018 time period is considered for this analysis. To maintain consistency with our interpretation and to avoid confusion regarding the sign of heat transport, we have multiplied all regression coefficients by -1	44
3.7	The linear regression of JJAS mean Indian Ocean OHT averaged over 5°N to 5°S on southern Indian Ocean(40°S–0°, 40°E–120°E) volume-mean temperature anomalies during a) SON, b) DJF, c) MAM(+1), and d) JJAS(+1) for the period 1998–2018. Each panel shows the scatter plot of seasonal mean temperature anomalies against JJAS OHT with a linear regression fit (red line). Coefficients of determination (R^2) and p-values are indicated in each panel.	45
3.8	The Transfer Entropy (TE) between the OHT time series (averaged over 5°S to 5°N) and the SST across the southern Indian Ocean (40°S–EQ, 40°E–120°E) at varying time lags from t_0 to $t+24$	46
3.9	The linear regression of JJAS mean OHT averaged over 5°N to 5°S on zonal mean meridional stream function anomalies averaged for (a) SON, (b) DJF, (c) MAM(+1) and (d) JJA(+1). The stippling indicates statistically significant regression coefficients at 95% level as revealed by a two-tailed bootstrap significance test. The 1998–2018 time period is considered for this analysis.	47
3.10	JJAS mean rainfall departure (in percentage) over Central India (75°E – 85°E and 19°N – 26°N)	48

3.11	a) JJAS mean OHT composite of flood, drought and normal monsoon years and b) difference of flood and drought OHT composite from normal	49
3.12	The JJAS mean composite of 850 hPa wind speed composite, for (a) normal years, and (b) difference between drought and normal years, and (c) difference between flood and normal years. The stippling indicates statistically significant regression coefficients at 95% level as revealed by a two-tailed t -test	49
3.13	a-b) Drought and flood composite of zonal mean meridional stream-function, b) Difference between drought and flood composite	49
4.1	a–b) Linear regression of the December–February mean Niño3.4 index (year 0) onto ORAS5 sea surface temperature anomalies averaged for (a) March–May (year +1) and (b) June–August (year +1), and c–d) same for TRMM precipitation and ERA5 850 hPa wind. Stippling indicates regression coefficients statistically significant at the 95% level based on a two-tailed bootstrap test. The analysis covers the period 1998–2018.	57
4.2	a–b) Linear regression of the December–February multimodel mean Niño3.4 index (year 0) onto multimodel mean CMIP6 sea surface temperature anomalies averaged for (a) March–May (year +1) and (b) June–August (year +1), and c–d) same for CMIP6 multimodel mean precipitation. Stippling indicates regression coefficients statistically significant at the 95% level based on a two-tailed bootstrap test. The analysis covers the period 1998–2018.	58
4.3	Scatter plots of JJAS Niño3.4 index versus ISM rainfall anomaly (mm day^{-1}) for each of the 20 CMIP6 models under historical simulations (1901–2014). Blue, red, and grey dots represent La Niña ($\text{Niño3.4} < -0.5$), El Niño ($\text{Niño3.4} > 0.5$), and neutral years, respectively. The Pearson correlation coefficient (r) and corresponding p -value are shown in the title of each panel, with * denoting statistical significance at the 95% confidence level ($p < 0.05$). Vertical dashed blue and red lines indicate the La Niña and El Niño thresholds, respectively, and the horizontal dashed grey line marks the zero rainfall anomaly.	60
4.4	Bar chart of Pearson correlation coefficients between the JJAS Niño3.4 index and ISM rainfall anomaly for each of the 20 CMIP6 historical simulations. Steel blue bars indicate models with statistically significant correlations ($p < 0.05$) and grey bars indicate models that are not statistically significant. The red dashed line denotes the observational estimate derived from ORAS5 Niño3.4 and IMD rainfall over the period 1980–2018 ($r = -0.23$).	61
4.5	LPS tracks over IO during a) flood years b) drought years and LPS track density during c) flood years and d) drought using ERA5.	65

4.6	Scatter plot of JJAS rainfall anomalies (TRMM) and LPS track density anomalies (ERA5) after removing the influence of the DJF Niño3.4 index from both variables. Each point represents an individual year. The regression line (blue) indicates the overall positive tendency. The partial correlation coefficient and corresponding p-value are shown in the figure title (Partial Corr = 0.46, p = 0.040)	66
4.7	LPS tracks over IO during flood years and drought years for historical and SSP585 scenarios using CMIP6 models	67
4.8	Multi model mean of LPS tracks over IO during flood years and drought years for historical and SSP585 scenarios	68
4.9	Multi model mean of LPS track density over IO during flood years and drought years for historical and SSP585 scenarios	68
4.10	Multi-model mean LPS track density difference (Flood-Drought) for (a) historical and (b) SSP585 scenarios. Shaded regions indicate the magnitude of the difference, while hatched areas denote regions where the differences are statistically significant at the 95% confidence level based on bootstrap resampling across models.	69
5.1	JJAS mean rainfall departure (in percentage) from IMD gridded rainfall data over Central India (75 °E – 85 °E and 19 °N – 26 °N) during 1930 to 2014	78
5.2	Histogram of JJAS percentage of departure of rainfall anomalies and number of years with extreme excess and extreme deficit threshold during the time period of 1930-2023 from IMD Rainfall data.	79
5.3	JJAS mean rainfall departure (in percentage) in CMIP6 Models over Central India (75 °E – 85 °E and 19 °N – 26 °N) for Historical during 1930 to 2014.	80
5.4	JJAS mean rainfall departure (in percentage) in CMIP6 Models over Central India (75 °E – 85 °E and 19 °N – 26 °N) for SSP126 during 2015 to 2099.	81
5.5	JJAS mean rainfall departure (in percentage) in CMIP6 Models over Central India (75 °E – 85 °E and 19 °N – 26 °N) for SSP245 during 2015 to 2099	82
5.6	JJAS mean rainfall departure (in percentage) in CMIP6 Models over Central India (75 °E – 85 °E and 19 °N – 26 °N) for SSP585 during 2015 to 2099	83
5.7	Box-whisker plot of the number of extreme excess (EE) and extreme deficit (ED) years across CMIP6 models under historical, SSP126, SSP245, and SSP585 scenarios. The boxes represent the interquartile range (25th–75th percentile), the red line denotes the median, the whiskers extend to 1.5 times the interquartile range, and open circles indicate outliers.	85

5.8	Box-whisker plot of the return periods (in years) of extreme excess (EE) and extreme deficit (ED) monsoon events across CMIP6 models under historical, SSP126, SSP245, and SSP585 scenarios. The boxes represent the interquartile range (25th–75th percentile), the red line denotes the median, the whiskers extend to 1.5 times the interquartile range, and open circles indicate outliers.	87
5.9	a-b) Multi model LPS track density composite for extreme excess and extreme deficits for the historical scenario (1930-2014), c) difference between extreme excess and extreme deficit multi model composite of LPS. Unit- Tracks per square degree per year.	88
5.10	Multimodel mean composite for a) extreme excess years JJAS precipitation, b) extreme deficit years JJAS precipitation, c) Difference between extreme excess and extreme deficit composite, using CMIP6 historical simulations during the time period of 1930-2014. Hatching in panel (c) indicates regions where the difference is statistically significant at the 95% confidence level based on a bootstrap permutation test. The black box denotes the core monsoon zone (75-86°E, 19-26°N)	89
5.11	Multimodel mean composite for a) LPS-active years JJAS precipitation, b) LPS-less-active years JJAS, c) difference between LPS-active years and LPS-less-active years precipitation using CMIP6 historical simulations during the time period of 1930-2014. Hatching in panel (c) indicates regions where the difference is statistically significant at the 95% confidence level based on a bootstrap permutation test. The black box denotes the core monsoon zone (75-86°E, 19-26°N)	90
5.12	a) Difference between SSP585 and historical extreme excess multi-model LPS track density composite, b) Same for extreme deficit. Unit- Tracks per square degree per year.	91
5.13	Frequency of Niño3.4 index in different intensity intervals in historical and SSP585 simulations across all models	93
5.14	Probability of occurrences of extreme excess and extreme deficit as a function of Niño3.4 strength in historical simulations.	93
5.15	Probability of occurrences extreme excess and extreme deficit as a function of Niño3.4 strength in SSP585 simulations.	94

List of Tables

1.1	Thesis structure	12
2.1	List of CMIP6 Models with Native Grid Resolutions	20
5.1	EE and ED mean thresholds for IMD rainfall data and CMIP6 models	84
5.2	Number of extreme excess (EE) and extreme deficit (ED) years for IMD and CMIP6 models under historical and future scenarios.	86
5.3	Return period (years) of extreme excess (EE) and extreme deficit (ED) events for IMD and CMIP6 models under historical and future scenarios.	88

Abbreviations

BoB	Bay of Bengal
CMIP6	Coupled Model Intercomparison Project Phase 6
ECMWF	European Centre for Medium-Range Weather Forecasts
ENSO	El Niño Southern Oscillation
EE	Extreme Excess
ED	Extreme Deficit
IMD	India Meteorological Department
IO	Indian Ocean
IOD	Indian Ocean Dipole
ISM	Indian Summer Monsoon
ISMR	Indian Summer Monsoon Rainfall
LPS	Low Pressure Systems
NOAA	National Oceanographic and Atmospheric Administration
NIO	North Indian Ocean
OHT	Ocean Heat Transport
ORAS5	Ocean Reanalysis System 5
SIO	Southern Indian Ocean
SLP	Sea Level Pressure
SST	Sea Surface Temperature
TRMM	Tropical Rainfall Measuring Mission
TE	Transfer Entropy

Chapter 1

Introduction

1.1 Background

1.1.1 Interannual variability of Indian Summer Monsoon

The interannual variability of the Indian Summer Monsoon (ISM) significantly impacts the livelihoods of millions across the Indian subcontinent. Agriculture, particularly rice farming, is strongly influenced by monsoon rainfall fluctuations [*DeFries et al.*, 2016], and the broader Indian economy has long been closely tied to the performance of the ISM [*Gadgil and Gadgil*, 2006; *Zaveri et al.*, 2016]. Rainfall variability also governs groundwater recharge patterns, with distinct responses observed in different regions of India [*Asoka et al.*, 2018].

The ISM is well known for its quasi-biennial character: the likelihood of more than two consecutive drought or flood years is low [*Parthasarathy and Mooley*, 1978]. Early studies noted that this interannual variability is tightly coupled to the Southern Oscillation (SO) [*Pant and Parthasarathy*, 1981], and subsequent work established the broader tropospheric biennial oscillation (TBO) as a key bridge between the SO and ISM rainfall [*Ropelewski et al.*, 1992]. The TBO refers to a coupled ocean-atmosphere mode characterized by a tendency for the monsoon-ENSO system to alternate between stronger and weaker phases on a near-biennial (~ 2 -year) timescale, arising from feedbacks between tropical convection, ocean dynamics, and land-atmosphere processes [*Meehl*, 1997]. Because low-frequency oscillations can

confer longer predictability to the tropical atmosphere [*Charney et al.*, 1981], considerable effort has gone into understanding how El Niño-Southern Oscillation (ENSO) modulates monsoon rainfall.

The ISM Rainfall shows considerable variability across different timescales, including intraseasonal, interannual, and decadal periods (Figure 1.1) [*Goswami et al.*, 1999; *Gadgil and Gadgil*, 2006; *Turner and Annamalai*, 2012; *Goswami et al.*, 2015; *Preethi et al.*, 2017; *Srivastava et al.*, 2017]. Although interannual variations in ISM rainfall account for only 10% of the long-term average, extremes in the seasonal mean ISM rainfall lead to significant events such as floods and droughts [*Shukla and Mooley*, 1987]. Slowly varying boundary forcings, such as sea surface temperatures (SST) in the Indo-Pacific region, Eurasian snow cover or extent, and soil moisture variability, are key factors influencing the interannual variability of ISM [*Charney and Shukla*, 1981; *Webster et al.*, 1998; *Krishnamurthy and Kinter III*, 2003]. *Goswami and Mohan* [2001] highlighted that a common mode of spatial variability governs both the intraseasonal and interannual variations of the Indian monsoon, and changes in the intraseasonal oscillations drive the interannual variability of the seasonal mean of the ISM.

Internal processes introduce an additional, atmosphere-driven source of year-to-year variability. The quasi-biennial oscillation (QBO) emerges from the interplay between intraseasonal oscillations and the annual cycle [*Goswami*, 1998], and numerical experiments suggest that such internal dynamics can modulate mean monsoon circulation even under fixed boundary conditions [*Harzallah and Sadourny*, 1995; *Stern and Miyakoda*, 1995]. Although the seasonal-mean monsoon rainfall contains a strong intraseasonal component, its net contribution tends to cancel out in pronounced flood or drought years [*Krishnamurthy and Shukla*, 2000]. Nevertheless, the persistence of

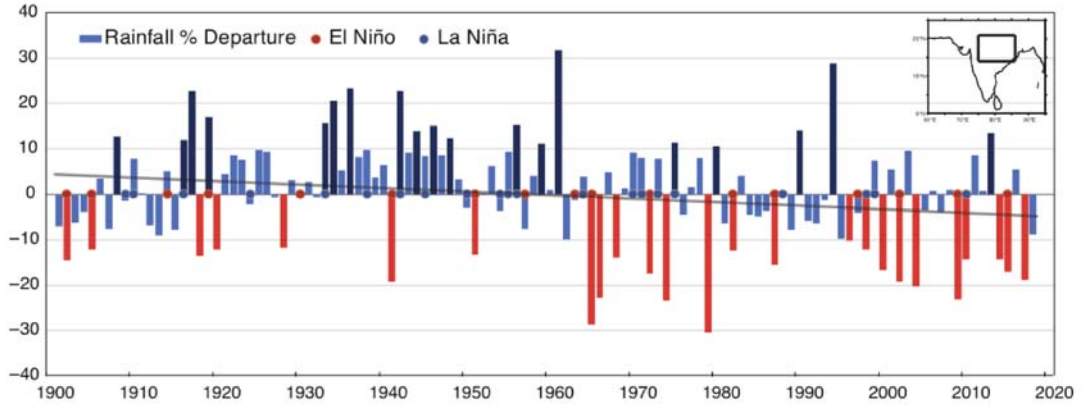


FIGURE 1.1: Summer monsoon (June–September) rainfall departure (in %) over Central India ($75\text{--}85^\circ\text{E}$, $19\text{--}26^\circ\text{N}$) for the period 1901–2018. Flood years with rainfall departure exceeding $+10\%$ are shown in dark blue and drought years with departure below -10% are shown in red. El Niño and La Niña conditions during the same season are indicated by red and blue dots, respectively. The grey line represents a long-term smoothed average. Rainfall data are from the Indian Meteorological Department [Singh *et al.*, 2019]

SST anomalies remains essential for maintaining the biennial mechanism that links successive seasons [Meehl, 1993].

The Indian Ocean Dipole (IOD) introduces additional complexity to this system, as demonstrated by Saji *et al.* [1999]. Positive IOD events, characterized by anomalous cooling (warming) in the eastern (western) equatorial Indian Ocean, can enhance monsoon rainfall independent of ENSO forcing. However, as shown by Ashok *et al.* [2003], the relationship between IOD and ENSO is not independent; their co-occurrence can either amplify or offset monsoon rainfall anomalies depending on their relative phase. This leads to a non-additive response in the monsoon system, complicating simple attribution of variability to a single driver. Recent work by Pillai *et al.* [2024] has further revealed how North Tropical Atlantic SST anomalies can influence monsoon behavior through teleconnections to the Indian Ocean, highlighting the multi-basin nature of monsoon drivers.

Projections from various studies indicate a potential increase in the ISM Rainfall by

the end of the century [*Katzenberger et al.*, 2021, 2022; *Gupta et al.*, 2020b; *Moon and Ha*, 2020; *Rajbanshi and Das*, 2021]. The Extreme temperature events are becoming more frequent in India, emerging as a significant health risk [*Seneviratne et al.*, 2021]. Temperatures are expected to increase by 4°C–5°C by the end of this century, as reported by *Koteswara Rao et al.* [2022] and *Kumar et al.* [2023]. Many studies have identified rising surface temperatures as the cause of this enhanced precipitation [*Almazroui et al.*, 2021; *Watterson et al.*, 2021; *Patel and Kuttippurath*, 2023].

Mishra et al. [2020] utilized an ensemble of climate simulations for historical (1971–2000) and future (2006–2100) periods to examine the coupling between El Niño and the Indian monsoon. Their findings indicate that under continued greenhouse warming, the frequency of concurrent hot and dry extremes is expected to increase by a factor of 1.5 during the 21st century. A departure exceeding +10% in rainfall anomalies classified as a flood, while a departure below -10% is considered a drought in Indian monsoon context [*Singh et al.*, 2019; *Vishnu et al.*, 2022]. *Preethi et al.* [2019], using Coupled Model Intercomparison Project Phase 5 (CMIP5) simulations, reported an increase in both the intensity and frequency of ISM droughts in near- and mid-future scenarios (2010–2059). The annual maximum consecutive 5-day precipitation in the Asian monsoon regions is expected to increase in future scenarios, thereby raising the risk of extreme flooding, according to *Almazroui et al.* [2021]. Using CMIP5 simulations, *Jena and Azad* [2021] projected a 16% increase in the probability of drought occurrence, while flood events are expected to decrease by 11% in the future under projected global warming. Recent studies highlight contrasting trends in the occurrence and intensity of hydrological extremes over the Indian region in the coming decades. *George et al.* [2025] project an increasing trend in drought frequency in the near future, transitioning to dominance of flood events in the far

future. Additionally, the analysis indicates that while the intensity of droughts is expected to escalate in the far future, flood intensity may decrease during the same period.

1.1.2 Role of Ocean–Atmosphere Coupling in the Regulation of SST and ISM Variability

The Asian–Australian monsoon represents an interconnected ocean–atmosphere–land system, whose strength is controlled by negative feedback interactions among the land, ocean, and atmosphere [[Webster et al., 1998, 2002](#); [Loschnigg and Webster, 2000](#)]. Indian Ocean SST is a prominent factor which controls the Indian summer precipitation and their empirical relationship extensively investigated in the earlier studies. For example, correlation as high as +0.8 between equatorial Indian Ocean SSTs in the winter before wet monsoon season and the Indian rainfall is reported by [Sadhuram \[1997\]](#); [Harzallah and Sadourny \[1997\]](#); [Clark et al. \[2000\]](#). Moreover, [Clark et al. \[2000\]](#) developed a combined Indian Ocean SST index that maintains an correlation of 0.68 for the time-span of 1945 to 1994 without considering ENSO influence.

The regulation of SST, however, differs across basins. In the Pacific, variability arises from a balance between local thermodynamic processes and large-scale atmospheric circulation driven by SST gradients, whereas in the Indian Ocean (IO), SSTs are strongly influenced by cross-equatorial oceanic advection and variations in upper-ocean heat storage [[Loschnigg and Webster, 2000](#)]. Unlike in the Pacific, convection does not immediately follow warm SST anomalies in the IO during spring and early summer; instead, [Loschnigg and Webster \[2000\]](#) showed that cross-equatorial heat

transport is the primary mechanism controlling SST in the northern IO and regulating the regional heat balance. The cross-equatorial ocean heat transport from the northern to the southern IO is a crucial component of the ISM. The southern hemisphere atmosphere transports latent heat during the northern summer monsoon [[Hastenrath and Lamb, 1980](#)]. Moreover, the moisture evaporated from southern IO is carried to the north across the equator, which in turn precipitates. In a later study, [Hastenrath and Greischar \[1993\]](#) found out that this southward heat transport to southern IO and northward cross-equatorial latent heat export balances each other.

The ISM is argued to be a self-regulated coupled ocean-atmosphere system [[Webster et al., 2002](#); [Loschnigg and Webster, 2000](#)]. Self-regulation means that the interannual fluctuations in the ISM rainfall are modulated by the coupling between the ocean and the atmosphere over the IO. At the core of this argument is the southward cross-equatorial Ekman transport from the North Indian Ocean (NIO) to the south, driven by the low-level southwesterly low-level monsoon winds. According to [Webster et al. \[2002\]](#), an anomalously strong monsoon results in a stronger cross-equatorial ocean heat transport (OHT), which in turn would lead to an anomalous oceanic cooling (warming) in the north (south)(Figure 1.2. This can lead to a weakening of the meridional temperature gradient in the following summer, leading to an anomalously weak monsoon. At the peak of the ISM season, the magnitude of OHT over the IO is about 1.5 to 2 PW [[Webster et al., 2002](#)]. The seasonal reversal of the Ekman transport is essential to maintaining the Indian Ocean's heat balance as demonstrated by [[Loschnigg and Webster, 2000](#)] and [[Wacongne and Pacanowski, 1996](#)]. [Webster et al. \[2002\]](#) modified [Meehl \[1994\]](#) biennial monsoon theory by incorporating OHT and Indian Ocean Dipole(IOD). The IO southward heat transport during boreal summer can be explained by the Ekman flux [[Levitus, 1987](#)]. According to hydrographic measurements, the IO transports heat of about 1.5

petawatts (PW) at 32°S [*Lumpkin and Speer, 2007*]. IO meridional heat transport demonstrates considerable variability across different time scales, including both shorter-term variations, such as intraseasonal fluctuations spanning approximately 10 days, and longer-term variations that occur over interannual timescales, lasting several years [*Chirokova and Webster, 2006*]. *Lee and Marotzke [1998]* investigated IO meridional overturning heat transport and found that seasonal reversal of transport occurring near 10°S and 10°N two monsoon seasons. *Lutsko et al. [2019]* analysed the impact of OHT over ISM using an atmospheric model and OHT delineation is achieved through by coupling a slab ocean model. Their sensitivity experiment without OHT gives a weak monsoon and on the other hand, a gradual increase of OHT in the experiments improved monsoon performance in the model.

1.1.3 Role of Teleconnections in ISM Variability

El Niño–Southern Oscillation (ENSO) is one of the most influential large-scale drivers of interannual monsoon variability. Historically, El Niño events have been associated with weak ISM years and droughts, while La Niña events tend to enhance monsoon rainfall [*Kumar et al., 2006*]. Evidence for a robust ENSO-monsoon link spans both observations and modelling. *Shukla and Paolino [1983]* argued that SO indices could serve as long-range predictors of ISM droughts, while *Meehl [1987]* showed that extreme SO events systematically coincide with drought and flood years over Asia. Large SST anomalies in both the Indian and Pacific Oceans display a clear biennial signature linked to ENSO phases [*Kiladis and van Loon, 1988*]. Mechanistically, Niño-3 SST anomalies that develop in the preceding winter can pre-condition the following summer monsoon via the Walker circulation [*Kawamura, 1998; Soman and Slingo, 1997*]. The importance of this remote control is underscored by modelling experiments showing that land-atmosphere feedbacks associated with soil

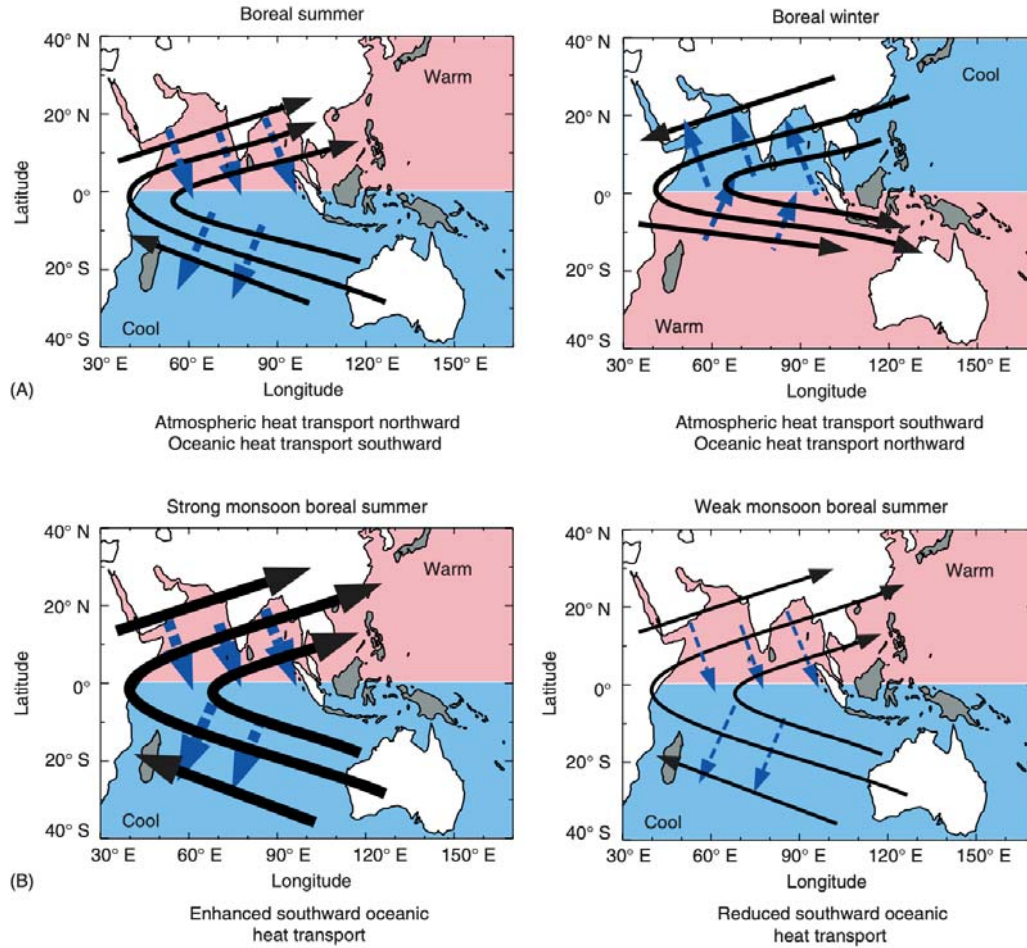


FIGURE 1.2: Schematic of a regulatory framework for the monsoon annual cycle. The left and right panels illustrate climatological lower-tropospheric winds (solid black lines) during summer and winter, respectively. Blue dashed arrows indicate Ekman mass transport, which is deflected to the right of the winds in the Northern Hemisphere and to the left in the Southern Hemisphere. Owing to the prevailing sea surface temperature gradient, heat is transferred from the summer hemisphere to the winter hemisphere in both seasons. Panel B depicts summer surface winds during strong and weak monsoon years. In strong monsoon years, enhanced Ekman transport leads to rapid cooling of the northern Indian Ocean, while in weak years, the cooling is comparatively weaker. Since strong monsoons are typically preceded by anomalously warm Indian Ocean SSTs, a strong year is often followed by a weak year, and vice versa. (*Webster et al. [2003]*; Published 2003 by the Encyclopedia of atmospheric sciences)

moisture, surface heat fluxes, and evapotranspiration alone cannot overturn ENSO's influence on monsoon circulation anomalies [[Shen et al., 1998](#)]. Recent palaeoclimate reconstructions confirm that ENSO has remained the dominant driver of ISM inter-annual variability for at least the past five centuries [[Shi and Wang, 2019](#)], and new analyses highlight how equatorial Rossby-wave adjustments and Walker-circulation changes modulate the ISM period during ENSO events [[Hu et al., 2022](#)]. However, recent studies suggest that ENSO's influence on ISM extremes is becoming more complex and less predictable under climate change. According to climate model projections, El Niño events in the Pacific Ocean are expected to become more frequent while maintaining a stable inverse relationship with the monsoon. This trend may contribute to an increase in monsoon droughts in the future [[Cai et al., 2014b](#); [Azad and Rajeevan, 2016](#)]. Moreover, the teleconnection between ENSO and the Indian monsoon has weakened since the late 1970s, possibly due to changes in the background tropical SST gradient and the Walker circulation [[Annamalai et al., 2005](#); [Krishnaswamy et al., 2015](#)].

1.1.4 Role of Synoptic-Scale Variability in ISM Variability

Low-pressure systems (LPS) associated with the Indian monsoon are synoptic-scale cyclonic vortices that originate within the quasi-stationary monsoon trough. These systems typically travel west-northwestward during the summer monsoon season (June–September) and persist for approximately 3 to 5 days [[Mooley, 1973](#); [Godbole, 1977](#); [Saha et al., 1981](#); [Hunt and Parker, 2016](#)]. Floods are associated with a stronger meridional pressure gradient over the north Indian Ocean, a reduced northward seasonal shift of the monsoon trough, an increased frequency of active spells, and a higher occurrence of monsoon depressions with longer westward tracks [[Sikka, 2006](#); [Ajayamohan et al., 2010](#); [Hurley and Boos, 2015](#)]. In contrast, droughts are

linked to a weaker meridional pressure gradient, a more pronounced northward shift of the monsoon trough, a greater number of break spells, and fewer monsoon depressions with shorter westward tracks [*Bhalme and Mooley, 1980; Goswami and Mohan, 2001; Vishnu et al., 2020*]. *Ajayamohan et al. [2010]* demonstrated that the increase in extreme rainfall events (ERE) over central India from 1951 to 2003 is strongly associated with a rise in synoptic activity, particularly driven by an increasing frequency of weak LPS. Although stronger systems such as depressions and cyclonic storms have shown a declining trend, the number of weak LPS has increased significantly, making them the primary contributors to the observed rise in ERE. Importantly, over 60% of ERE in central India were spatially linked to LPS. The formation of LPS in BoB and central India has crucial role in defining the flood and drought events of ISM.

1.2 Motivation and Research Gaps

This thesis aims to address key research gaps in understanding the interannual variability of the Indian Summer Monsoon (ISM). Despite longstanding interest in the hypothesis that the monsoon behaves as a self-regulating coupled ocean–atmosphere system, this concept has not been rigorously tested using reanalysis datasets. Moreover, the extreme fluctuations in ISM variability, especially in connection with large-scale teleconnections and sub-seasonal internal variability, remain underexplored within a coupled model framework. Future projections also offer limited clarity on how extreme interannual fluctuations of the ISM may evolve under global warming.

1.3 Objectives of the thesis

1. To understand the role of ocean – atmosphere coupling over the Indian Ocean in ISM interannual variability using observations.
2. To examine the roles of teleconnections and synoptic variability in ISM interannual variability using CMIP6 historical simulations.
3. To investigate the extreme interannual variability of the ISM under future warming scenarios.

1.4 Structure of the thesis

This thesis is presented as a compilation of six chapters as illustrated in Table 1.1. It comprises three main working chapters 3, 4 and 5, which were finalized during the duration of the degree; out of these three chapters, 2 are research articles and an overview of their current status is provided in the list of publications.

The thesis begins with a literature review (Chapter 1), which provides the background and motivation for the research, as well as the key questions addressed in the thesis. It includes a review of the scientific literature, identifies knowledge gaps, and outlines how this study will address these gaps. Finally, it discusses the objectives and scope of the thesis and introduces a framework for the subsequent chapters.

Chapter 2 provides a detailed explanation of the datasets and methodology that will be used in the following three main working chapters.

In Chapter 3, the first working chapter describes the the role of ocean – atmosphere coupling over the Indian Ocean in ISM interannual variability using observations.

CHAPTER 1	INTRODUCTION
CHAPTER 2	DATA AND METHODOLOGY
CHAPTER 3	INDIAN SUMMER MONSOON INTERANNUAL VARIABILITY: ROLE OF OCEAN-ATMOSPHERE COUPLING IN OBSERVATIONS.
CHAPTER 4	INDIAN SUMMER MONSOON INTERANNUAL VARIABILITY: ROLE OF TELECONNECTION AND SYNOPTIC VARIABILITY IN CMIP6 HISTORICAL PROJECTIONS.
CHAPTER 5	THE EXTREME FLUCTUATIONS OF THE INDIAN SUMMER MONSOON INTERANNUAL VARIABILITY IN CMIP6 FUTURE SIMULATIONS.
CHAPTER 6	CONCLUSIONS AND SCOPE OF FUTURE WORK

TABLE 1.1: Thesis structure

Chapter 4, the second working chapter, will delve into the roles of teleconnections and synoptic variability in ISM interannual variability using CMIP6 historical simulations.

Finally, Chapter 5, the third and last working chapter of the thesis, will examine the extreme interannual variability of the ISM under future warming scenarios.

The conclusion of the thesis and the future scope will be discussed in Chapter 6.

Chapter 2

Data and Methods

2.1 Observation data

The thesis makes use of several observational datasets, namely precipitation and sea surface temperature.

2.1.1 Precipitation data

Precipitation datasets from the India Meteorological Department (IMD) and the Tropical Rainfall Measuring Mission (TRMM) are utilized in this thesis. The following section provides a detailed account of each dataset.

2.1.1.1 IMD data

The India Meteorological Department (IMD) provides a daily gridded precipitation dataset [*Pai et al., 2014*] at a spatial resolution of $0.25^\circ \times 0.25^\circ$. The dataset records rainfall in millimeters (mm) and spans 122 years, covering the period from 1901 to 2023. It is arranged on a grid of 135×129 points, beginning at 6.5°N and 66.5°E , with subsequent points extending systematically to 38.5°N and 100.0°E . Each yearly file contains 365 entries for non-leap years and 366 for leap years. The IMD daily rainfall dataset is accessible at https://www.imdpune.gov.in/cmpg/Griddata/Rainfall_25_NetCDF.html.

2.1.1.2 TRMM data

The Tropical Rainfall Measuring Mission (TRMM), a joint initiative of the National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploration Agency (JAXA), was launched in November 1997. The satellite carried multiple instruments, including the TRMM Microwave Imager, Visible and Infrared Radiometer, Precipitation Radar, Lightning Imaging Sensor, and the Cloud and Earth Radiant Energy Sensor. Data collected by these instruments have been used to develop several retrieval algorithms, among which the TRMM Multi-satellite Precipitation Analysis (TMPA) is the most widely employed. The TMPA algorithm integrates information from ground-based rain gauges with satellite-derived infrared and microwave measurements to produce high-quality precipitation estimates. The TRMM 3B42 Version 7 product, generated using this algorithm, is available at https://disc.gsfc.nasa.gov/datasets/TRMM_3B42_Daily_7/summary. This dataset provides precipitation estimates at a spatial resolution of $0.25^\circ \times 0.25^\circ$ and a temporal resolution of three hours, covering the period 1998–2019 within the latitudinal belt 50°S – 50°N . In this thesis, the TRMM TMPA 3B42 V7 product [*Huffman et al.*, 2016] is employed.

2.1.2 Sea Surface Temperature data

2.1.2.1 Daily SST data

Daily SST data with a spatial resolution of $0.25^\circ \times 0.25^\circ$, and it is the combination of ocean temperature observations from satellite and in situ platforms (i.e., ships and buoys) [*Reynolds et al.*, 2007]. It is also known as NOAA’s Optimum Interpolation Sea Surface Temperature (OISST).

2.2 Reanalysis data

Reanalysis datasets provide a comprehensive and consistent representation of the Earth’s atmosphere, ocean, and land surface by assimilating a wide range of historical observations into modern numerical weather prediction and climate models. Atmospheric reanalyses integrate data from satellites, radiosondes, aircraft, ships, and ground-based stations to generate spatially and temporally continuous fields of variables such as winds, temperature, pressure, and humidity. Ocean reanalyses, in contrast, assimilate in situ and satellite-based oceanic observations including sea surface temperature, salinity, ocean currents, and sea level into ocean general circulation models to reconstruct the historical state of the ocean. While reanalyses provide physically consistent datasets, they are subject to important limitations. Ocean observations are sparse and unevenly distributed, particularly prior to the Argo era, leading to uncertainties in subsurface temperature, salinity, and circulation fields. Differences in model physics, atmospheric forcing, and data assimilation methods can introduce systematic biases across products. These uncertainties are especially relevant for derived quantities such as ocean heat transport (OHT), and therefore results based on reanalysis products should be interpreted with appropriate caution. To improve robustness, this study employs multiple ocean reanalyses (ORAS5 and SODA) for comparison. Together, atmospheric and ocean reanalyses provide consistent, physically based datasets that are invaluable for investigating coupled climate processes, variability, and long-term trends. Prominent examples include ERA5 (ECMWF), MERRA-2 (NASA), and JRA-55 (JMA) for the atmosphere, and products such as ORAS5 (ECMWF) and GODAS (NOAA) for the ocean, which are widely employed for climate diagnostics, model evaluation, and understanding large-scale phenomena such as monsoons, ENSO, and decadal variability. In the present study, ERA5 and NCEP–NCAR are employed as atmospheric

reanalyses, while ORAS5 and SODA are utilized as ocean reanalyses. Both daily and monthly means from these datasets are analyzed in the thesis.

2.2.1 ORAS5

This study uses European Centre for Medium range Weather Forecasting (ECMWF) Ocean Reanalysis System 5 (ORAS5) [[Zuo et al., 2015](#)] to analyse the OHT. ORAS5 is based on the NEMO ocean model and incorporates observations through the NEMOVAR data assimilation framework, which applies a three-dimensional variational approach. The system assimilates a range of ocean and sea-ice observations, including subsurface temperature and salinity profiles, sea level anomalies, and sea-ice concentration, to produce a dynamically consistent reconstruction of the ocean state. The dataset is generated as an ensemble system, although a single member is typically used for analysis. It is forced by atmospheric reanalysis products, ensuring consistency in surface fluxes, and is further constrained by observations such as sea surface temperature, salinity, and global mean sea level variations. ORAS5 provides continuous spatial and temporal coverage, even in regions with limited observations, through the combined use of model dynamics and data assimilation. Compared to earlier versions, ORAS5 has improved horizontal resolution (0.25°), allowing better representation of mesoscale features, along with enhanced vertical resolution near the surface, which is important for air-sea interactions. Despite these improvements, uncertainties remain due to observational sparsity and model-dependent biases, particularly in subsurface fields and derived quantities such as OHT. In this study, potential temperature and meridional velocity from ORAS5 are used to estimate OHT over the period 1980–2018. Compared to the predecessor ORAS4, significant improvements have been made to the ocean model resolution

of ORAS5. Specifically, the horizontal resolution has been increased to an eddy-permitting resolution of 0.25 degrees, allowing for a more detailed representation of oceanic eddies and smaller-scale features. This enhancement enables a more accurate depiction of the ocean’s dynamics and improves the model’s ability to capture fine-scale processes. Furthermore, ORAS5 incorporates a near-surface resolution of 1 meter in the vertical dimension. This refinement enables a more precise representation of the upper layers of the ocean, which are crucial for understanding air-sea interactions and capturing the intricate processes occurring near the ocean surface. Additionally, ORAS5 features a prognostic thermodynamic-dynamic sea-ice model. Potential temperature and meridional velocity are used for OHT calculation from ORAS5. The study period spans from 1980 to 2018.

2.2.2 SODA

The Simple Ocean Data Assimilation (SODA) reanalysis is designed to reconstruct the historical evolution of the ocean by combining model dynamics with available observations. It is developed as a research-oriented product using widely adopted community ocean modelling frameworks, with resolution chosen to capture the dominant, data-resolvable ocean processes. The objective is to produce a physically consistent estimate of ocean variability that agrees with observations within their uncertainty limits, while providing unbiased representations of long-term changes. In this study, we use SODA version 3 [[Carton et al., 2018](#)], which represents a substantial improvement over earlier versions. It is based on the GFDL MOM5 ocean model coupled with a dynamic sea-ice component, and operates at an eddy-permitting horizontal resolution of approximately 0.25° with enhanced vertical structure. The system incorporates an updated data assimilation approach, including bias correction methods that improve the representation of long-term trends such as ocean

heat content. SODA3 is forced by atmospheric reanalysis fields (e.g., MERRA-2) and provides multi-decadal coverage, here spanning 1980–2015. The dataset is available at multiple temporal resolutions and grid configurations, allowing flexibility for climate diagnostics. As with other ocean reanalyses, uncertainties arise from limitations in observational coverage and model assumptions, and therefore SODA is used alongside ORAS5 to assess the robustness of the results.

2.2.3 ERA5

ERA5 is the latest global atmospheric reanalysis produced by the ECMWF using its Integrated Forecast System (IFS) [[Hersbach et al., 2020](#)]. It has a spatial resolution of $0.25^\circ \times 0.25^\circ$ at an hourly temporal scale. It is generated through a four-dimensional variational (4D-Var) data assimilation approach, which combines a wide range of observations with short-term model forecasts to provide a dynamically consistent estimate of the atmospheric state. The model has a high vertical resolution with 137 levels extending up to the upper atmosphere, and outputs are available both on model levels and on standard pressure and other derived levels. In addition to three-dimensional atmospheric variables, ERA5 also provides a comprehensive set of surface and single-level fields, including precipitation, radiation, and vertically integrated quantities. The atmospheric model is coupled with a land surface scheme (HTESSEL) and a wave model (WAM), enabling consistent representation of land–atmosphere interactions and ocean surface conditions. The dataset includes a high-resolution realization (31 km, hourly) along with a lower-resolution ensemble that provides an estimate of uncertainty arising from the data assimilation process. ERA5 offers data at sub-daily and monthly timescales, based on a combination of analyses and short-range forecasts initialized twice daily. This makes it particularly well suited for studying atmospheric variability and extremes.

2.2.4 NCEP-NCAR

The NCEP–NCAR reanalysis is a long-term global atmospheric dataset produced by the National Centers for Environmental Prediction (NCEP) and the National Center for Atmospheric Research (NCAR) [*Kalnay et al., 2018*]. Covering the period from 1948 to the present, it provides gridded data at daily to monthly resolutions and has been widely used for climate diagnostics, variability studies, and model evaluation. It is produced using a fixed atmospheric general circulation model based on the NCEP spectral model, together with a three-dimensional variational data assimilation system. The use of a constant model and assimilation framework ensures temporal consistency, which is important for long-term climate studies. The system assimilates a wide range of observations, including surface measurements, radiosondes, aircraft, and satellite data, although the observing system evolves over time. It provides global atmospheric fields at relatively coarse spatial resolution, with outputs available at daily to monthly timescales. Compared to more recent reanalyses, NCEP–NCAR has limitations in terms of spatial resolution, model physics, and representation of satellite data. Nevertheless, its long temporal coverage from 1948 onwards makes it valuable for studying historical climate variability and for comparison with newer datasets.

2.3 Climate model data

The Coupled Model Intercomparison Project Phase 6 (CMIP6) provides a comprehensive suite of climate model simulations developed by leading research centers worldwide. These models couple atmospheric, oceanic, land, and sea ice components to simulate past, present, and future climate conditions under standardized

experimental protocols. CMIP6 includes historical simulations as well as future projections based on Shared Socioeconomic Pathways (SSPs), which represent different greenhouse gas emission scenarios. In this thesis, the coupled model simulations as part of the coupled model inter-comparison project phase six (CMIP6; [Eyring *et al.*, 2016]) are used to examine the dynamics associated with dry air intrusion and its effect on ISM. In the present study, historical and future warming scenario (SSP 585) simulations from the CMIP6 are analysed. One realisation (r1i1p1f1) per model at its native grid was used. It is available at the Earth System Grid Federation (ESGF) data portal <https://aims2.llnl.gov/search/cmip6>. An overview of the models, their modelling centres, and their native spatial resolutions is provided in Table 2.1.

TABLE 2.1: List of CMIP6 Models with Native Grid Resolutions

Sl. No.	Modelling Centre	Model	Land (km)	Atmosphere (km)	Ocean (km)
1	National Center for Atmospheric Sciences	CESM2- WACCM	100	100	100
2	Max Planck Institute for Meteorology	MPI-ESM1- 2-LR	250	250	250
3	Norwegian Climate Center	NorESM2- LM	250	250	100
4	JAMSTEC / AORI, University of Tokyo	MIROC6	250	250	100

TABLE 2.1: (Continued)

Sl. No.	Modelling Centre	Model	Land (km)	Atmosphere (km)	Ocean (km)
5	AEEred Wegener Institute	AWI-CM-1-1- MR	100	100	25
6	Academia Sinica, Taipei	TaiESM1	100	100	100
7	First Institute of Oceanography	FIO-ESM-2-0	100	100	100
8	Chinese Academy of Meteorological Sciences	CAMS- CSM1-0	100	100	100
9	Canadian Centre for Climate Modelling and Analysis	CanESM5	500	500	100
10	LASG, Institute of Atmospheric Physics, CAS	CAS-ESM2-0	100	100	100
11	Tsinghua University	CIESM	100	100	50
12	CMCC, Italy	CMCC-CM2- SR5	100	100	100
13	CMCC, Italy	CMCC- ESM2	100	100	100

TABLE 2.1: (Continued)

Sl. No.	Modelling Centre	Model	Land (km)	Atmosphere (km)	Ocean (km)
14	LASG, Institute of Atmospheric Physics, CAS	FGOALS-f3- L	100	100	100
15	LASG, Institute of Atmospheric Physics, CAS	FGOALS-g3	250	250	100
16	NOAA GFDL	GFDL-ESM4	100	100	50
17	Indian Institute of Tropical Meteorology	IITM-ESM	250	250	100
18	Institute of Numerical Mathematics	INM-CM5-0	100	100	50
19	Institut Pierre Simon Laplace	IPSL-CM6A- LR	250	250	100
20	KMA/NIMS, Korea	KACE-1-0-G	250	250	100
21	Korea Institute of Ocean Science	KIOST-ESM	250	250	100
22	Meteorological Research Institute, Japan	MRI-ESM2-0	100	100	100

TABLE 2.1: (Continued)

Sl. No.	Modelling Centre	Model	Land (km)	Atmosphere (km)	Ocean (km)
23	Nanjing Univ. of Information Science	NESM3	250	250	100
24	CSIRO, Australia	ACCESS- CM2	250	250	100
25	CSIRO, Australia	ACCESS- ESM1-5	250	250	100

2.4 Methodology

2.4.1 Calculation of Ocean heat transport

Ocean heat transport (OHT) in the Indian Ocean is typically calculated by integrating the meridional heat flux across longitude and depth at a given latitude. Following [Chirokova and Webster \[2006\]](#), the formulation can be expressed as

$$Q(\phi) = \rho c_p \int \int v(x, \phi, z) \theta(x, \phi, z) dx dz, \quad (2.1)$$

where ρ is the seawater density, c_p the specific heat capacity, v the meridional velocity, θ the potential temperature (defined as the temperature a water parcel would have if adiabatically referenced to the surface), x longitude, ϕ latitude, and z depth. This framework assumes mass conservation within the basin and directly

links anomalous cross-equatorial OHT with the modulation of the Indian summer monsoon through variations in northward or southward heat transport. [Chirokova and Webster \[2006\]](#) showed that enhanced northward OHT anomalies are associated with stronger monsoon rainfall, while reduced transport corresponds to deficient monsoon years.

Building on this classical approach, [McMonigal and Larson \[2022\]](#) calculated the meridional heat transport across the Indian Ocean (MHT_{IO}) by integrating the product of meridional velocity and potential temperature over the full ocean depth and zonal extent of the basin:

$$\text{MHT}_{IO}(\phi) = \rho c_p \int \int v(x, \phi, z) \theta(x, \phi, z) dx dz, \quad (2.2)$$

where θ represents potential temperature. In this formulation, the Indonesian Throughflow (ITF), a key interocean exchange that transports warm Pacific water into the Indian Ocean through the Indonesian seas [[Gordon, 2005](#); [Sprintall et al., 2014](#)], introduces a net volume transport that violates strict mass conservation. To address this, the calculation is performed relative to a reference temperature of 0°C , following the method of [Trenberth and Zhang \[2019\]](#) and others. Although the absolute values of transport depend on the choice of reference temperature, anomalies relative to the monthly climatology are largely insensitive to this choice and therefore remain robust indicators of interannual variability.

[McMonigal and Larson \[2022\]](#) further demonstrated that the mean MHT_{IO} simulated by coupled models compares well with estimates from reanalyses and observations, showing a southward maximum of about 2 PW near the ITF inflow. Importantly, the variance in MHT_{IO} is dominated by interannual timescales, highlighting

the role of OHT anomalies in modulating ENSO–monsoon teleconnections.

Thus, while the formulation of *Chirokova and Webster* [2006] emphasizes the climatological link between cross-equatorial OHT and the Indian monsoon, the modified approach of *McMonigal and Larson* [2022] provides a more practical framework for model diagnostics, particularly in the presence of volume transport through straits such as the ITF, and underscores the importance of considering OHT anomalies rather than absolute values in understanding interannual variability.

2.4.2 Identification of flood and drought years

The flood (drought) years of ISM are identified as the years in which JJAS mean precipitation over Central India exceeds (falls below) 10% of climatological mean precipitation [*Singh et al.*, 2019]. The remaining years are considered as normal monsoon years. This classification is used to examine large-scale ocean-atmosphere interactions, particularly to analyse changes in ocean heat transport during flood and drought years. The relatively moderate threshold ensures a sufficient number of events for constructing robust composites.

2.4.3 EOF analysis

Standard Empirical Orthogonal Function (EOF; also known as eigenvector or principal component) analysis produces patterns and time series that are orthogonal to each other. The patterns obtained depend on the specific domain and time period being analyzed [*Kutzbach*, 1967]. The EOF representation is considered optimal because it allows for the maximum variance to be explained by selecting the eigenvectors associated with the largest eigenvalues of the covariance matrix. EOF analysis

is applied to the longitude–depth sections of JJAS mean anomalies of θ , v , and their product (as a proxy for ocean heat transport), averaged over 5°S–5°N in the Indian Ocean, to identify dominant modes of interannual variability.

2.4.4 Transfer Entropy

The transfer entropy (TE), a metric used to quantify the information transfer between two variables [*Kaiser and Schreiber, 2002; Schreiber, 2000*]. Unlike correlation or mutual information, which capture symmetric associations, TE detects asymmetry and can identify the extent to which the past states of one process improve the prediction of another. Mathematically, it is based on conditional probabilities and measures the reduction in uncertainty of a target variable when the history of a source variable is taken into account, beyond the target’s own past. This makes it particularly valuable for studying nonlinear and dynamic interactions in complex systems such as climate, where it has been applied to investigate teleconnections, causal dependencies, and feedback mechanisms between atmospheric and oceanic processes.

For two stochastic processes, X (target) and Y (source), the transfer entropy from Y to X is defined as

$$TE_{Y \rightarrow X} = \sum p(x_{t+1}, x_t^{(k)}, y_t^{(l)}) \log \left(\frac{p(x_{t+1} | x_t^{(k)}, y_t^{(l)})}{p(x_{t+1} | x_t^{(k)})} \right) \quad (2.3)$$

where $x_t^{(k)}$ and $y_t^{(l)}$ denote the past k and l states (lags) of the target and source variables, respectively, and $p(\cdot)$ represents joint and conditional probability distributions. This formulation quantifies the reduction in uncertainty of the future state x_{t+1} when the past of Y is included, beyond the information already contained in

the past of X . A non-zero value of $TE_{Y \rightarrow X}$ indicates a directional influence from Y to X .

In this study, TE is used to examine the causal relationship between OHT and SST over the southern Indian Ocean (SIO). The OHT time series, averaged over 5°S – 5°N , is treated as the source variable (Y), while SST over the SIO is treated as the target variable (X).

To investigate the temporal influence of OHT on SST, TE is computed using a lagged framework. Specifically, the SST time series is shifted progressively from lag 0 (t_0) to +24 months ($t+24$), while the OHT time series is kept fixed. This approach allows assessment of whether past variations in OHT provide additional predictive information for future SST evolution at different lead times.

The analysis is performed using monthly data, and a first-order Markov assumption is adopted (i.e., $k = l = 1$), such that only the immediate past states of OHT and SST are considered.

2.4.5 Identification of extreme excess and extreme deficit years

To identify more intense and rare events, a percentile-based threshold is applied. Extreme excess (deficit) years are defined using the 90th percentile of the percentage deviation of seasonal rainfall anomalies from the long-term mean over Central India (75 – 85°E , 19 – 26°N), based on historical simulations and future projections from CMIP6 models. This approach is specifically used to isolate the tails of the rainfall distribution and assess changes in extremes under different climate scenarios. A more detailed description of this methodology is provided in Chapter 5.

2.4.6 Generalized extreme value distribution

The Generalized Extreme Value (GEV) distribution is a probability distribution commonly used in extreme value theory to model the statistical behavior of block maxima (or minima) drawn from a sequence of observations. It unifies three types of extreme value distributions-Gumbel, Fréchet, and Weibull into a single parametric family, characterized by the location, scale, and shape parameters. The location parameter defines the central tendency, the scale parameter controls the dispersion, and the shape parameter determines the tail behavior, distinguishing between heavy-tailed, light-tailed, and bounded extremes. Owing to its flexibility, the GEV distribution is widely applied in hydrology, climatology, and environmental sciences to estimate return levels and return periods of rare events such as floods, droughts, and extreme temperatures. The return period of extreme excess (EE) and extreme deficit (ED) years is estimated using a generalized extreme value (GEV) distribution [Von Storch and Zwiers, 2002]. The GEV distribution is fitted to the annual maxima and minima of JJAS precipitation anomalies, representing extreme excess and deficit events, respectively. The distribution is characterized by three parameters: location (μ), scale (σ), and shape (ξ), which are estimated using the maximum likelihood method.

The return level for a specific return period is derived from the inverse cumulative distribution function of the GEV, expressed as:

$$x_T = \mu + \frac{\sigma}{\xi} \left[\left(-\ln \left(1 - \frac{1}{T} \right) \right)^{-\xi} - 1 \right], \quad \text{for } \xi \neq 0, \quad (2.4)$$

where ($\xi = 0$) corresponds to the Gumbel distribution and the return level simplifies to:

$$x_T = \mu - \sigma \ln \left(-\ln \left(1 - \frac{1}{T} \right) \right). \quad (2.5)$$

For each threshold corresponding to LF and LD events, the return periods are calculated by inverting the GEV cumulative distribution:

$$T = \frac{1}{1 - F(x)}, \quad (2.6)$$

2.4.7 LPS tracking algorithm

We used the tracking technique of [Praveen et al. \[2015\]](#) to follow the paths of LPS in the ERA-5 reanalysis data and CMIP6 models. Using gridded daily sea level pressure (SLP) data, this technique finds closed isobars at intervals of 1 hPa to detect and track LPS. The technique is based on closed-contour identification of sea-level pressure, with modifications to account for regional features such as summer heat lows and the monsoon trough. Following Hanley and Caballero (2012), local pressure minima are identified, and spurious heat lows are excluded using a threshold pressure-gradient criterion scaled to dataset resolution. Closed contours at 1-hPa intervals are then constructed, and pressure depth is calculated from the local minimum to the outermost contour. While this criterion effectively filters out thermally driven heat lows, it may also exclude weaker or developing LPS, and this limitation is considered when interpreting the results. Tracking is performed by linking successive positions of the detected centers within a defined search radius that adapts to system speed and land-sea contrasts. Tracks are terminated if no system is found within 24 hours, and only systems with lifetimes exceeding two days are retained. The algorithm is applied to reanalysis and CMIP6 data over the Bay of Bengal and adjoining regions during the monsoon season (June–September), consistent with the IMD classification of LPS intensities.

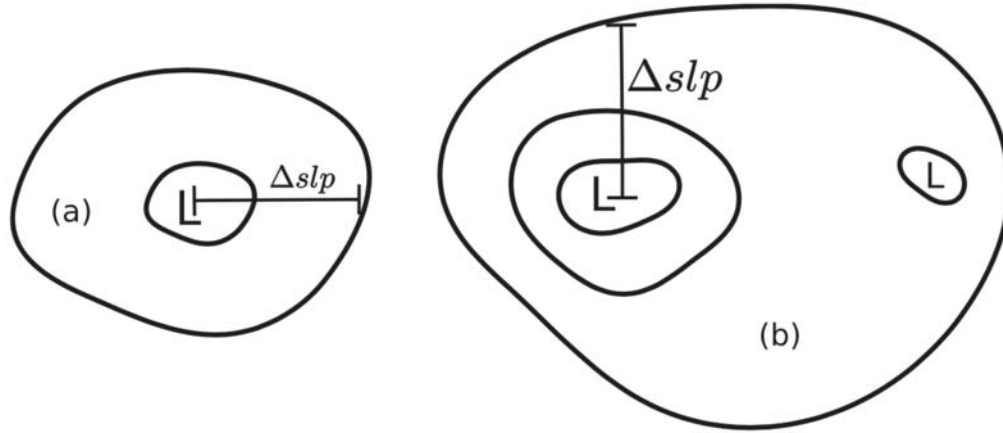


FIGURE 2.1: Schematic illustrating the identification of the LPS center and the computation of the pressure gradient for (a) a single-center system and (b) a multicenter system. (*Praveen et al. [2015]*; published in *Journal of Climate*)

2.4.8 Calculation of Niño 3.4 index

Niño 3.4 index is calculated using SST anomalies from the ORAS5 ocean reanalysis, averaged over 5°N – 5°S , 170°W – 120°W , with a 5-month running mean applied.

2.4.9 Statistical significance test

Statistical significance of regression coefficients is assessed using a non-parametric block bootstrap approach. In this method, the data are resampled in blocks to preserve temporal autocorrelation, and regression coefficients are recomputed over 1000 realizations. Confidence intervals are estimated from the resulting distributions, and coefficients are considered significant at the 95% level when the interval does not include zero.”

Chapter 3

Indian Summer Monsoon Interannual Variability: Role of Ocean-Atmosphere Coupling in Observations

3.1 Introduction

In this chapter, we examine the summer cross-equatorial ocean heat transport (OHT) in the Indian Ocean (IO) using reanalysis datasets and investigate its relationship with IO sea surface temperature (SST) and the interannual variability of the Indian summer monsoon (ISM), with particular emphasis on its biennial behavior. We specifically test the hypothesis that OHT serves as a key internal regulator of ISM variability. The southward OHT during boreal summer influences the northern IO heat balance and, in turn, modulates regional SST [*Loschnigg and Webster, 2000*]. Earlier studies [*Meehl, 1987, 1997*] highlighted the link between monsoon variability and pre-monsoon SST conditions, a relationship further supported by subsequent research [*Hastenrath, 1987; Harzallah and Sadourny, 1997; Clark et al., 2000*], which demonstrated strong correlations between IO SST anomalies in winter–spring and the intensity of the following monsoon. Building on this framework, we assess the influence of OHT on subsequent-year SST and ISM variability to clarify its role in regulating interannual monsoon fluctuations. In addition, we examine the behavior of OHT during extreme ISM phases, such as floods and droughts, to explore whether

cross-equatorial heat transport plays a role in shaping monsoon extremes. By disentangling the contributions of OHT and internal atmospheric variability, this study aims to provide a more complete understanding of the physical processes underlying ISM variability.

3.2 Datasets and Methodology

A comprehensive description of the datasets and methods is provided in Chapter 2; hence, it is not reiterated here for conciseness.

3.2.1 Datasets overview

This study uses European Centre for Medium range Weather Forecasting (ECMWF) Ocean Reanalysis System 5 (ORAS5) ([[Zuo et al., 2015](#)]; Section 2.2.1) for the ocean potential temperature and meridional velocity and SST.

The atmospheric variables such as zonal and meridional wind components from the fifth generation ECMWF reanalysis (ERA5) are used ([[Hersbach et al., 2020](#)]; Section 2.2.3). NCEP-NCAR reanalysis data used for the calculation of the zonal mean meridional stream function ([[Kalnay et al., 2018](#)]; Section 2.2.4).

Two different datasets are used for precipitation. Tropical Rainfall Measuring Mission (TRMM) (0.25x0.25, 1998-2018) daily data was used to analyse the rainfall over the IO ([[Huffman et al., 2016](#)]; Section 2.1.1.2) and Indian Meteorological Department(IMD) New High Spatial Resolution (0.25x0.25 degree) daily gridded rainfall data (1980-2018) for the Central India for the calculation drought-flood index ([[Pai et al., 2014](#)]; Section 2.1.1.1).

3.2.2 Methods

In our study, the method used to compute OHT over the Indian Ocean (40°E to 120°E and 40°S to 30°N) at different latitudes involves integrating the product of meridional velocity and potential temperature over the depth up to 2000 m across the basin. This integration provides an estimate of the heat transport in the north-south direction (meridional) at each latitude. It is important to note that this calculation does not uphold mass conservation due to the influence of volume transport through the Indonesian Throughflow (ITF), and it is referenced to a baseline temperature of 0°C [McMonigal and Larson, 2022]. Nevertheless, our analysis primarily focuses on anomalies relative to the monthly climatology. This approach reduces the dependence on the arbitrarily chosen reference temperature, as highlighted in the work of Trenberth and Zhang [2019] and Zhang *et al.* [2019].

$$OHT = \rho C_p \int \int (\theta - \theta_t) * v dx dz \quad (3.1)$$

where ρ is density, θ is potential temperature, θ_t is reference temperature, and v is meridional velocity. The reference temperature is considered zero.

The statistical significance of the analysis was determined by applying a two-tailed t-test.

The transfer entropy (TE), a metric used to quantify the information transfer between two variables [Kaiser and Schreiber, 2002; Schreiber, 2000] is computed between the OHT time series (averaged over 5°S to 5°N) and the SST across the southern Indian Ocean (SIO) (40°S–EQ, 40°E–120°E) at varying time lags.

The mass stream function for the Hadley Cell can be expressed as:

$$\psi(\phi, p) = 2\pi a \cos(\phi) \int_p^{p_s} \frac{v(\phi, p')}{g} dp', \quad (3.2)$$

where:

- $\psi(\phi, p)$: Meridional mass stream function (kg/s)
- a : Earth's radius (6.371×10^6 m)
- ϕ : Latitude
- p : Pressure level (Pa)
- p_s : Surface pressure (Pa)
- $v(\phi, p')$: Meridional wind (m/s)
- g : Gravitational acceleration (9.81 m/s^2).

3.3 Results and Discussion

3.3.1 Summer Cross-Equatorial Indian Ocean Heat Transport

The meridional OHT is calculated using Eq 3.1 as the integral product of the potential temperature and the meridional velocity, following *Chirokova and Webster [2006]*. The southward cross-equatorial heat transport in the IO is stronger in the boreal summer. Fig. 3.1 a shows the OHT as a function of latitude during June-September (JJAS). The OHT is mostly southward across all latitude bands over the tropical IO during JJAS, with a maximum value of slightly more than 1.5 PW between the equator and 10°S. The OHT values between 20°S and 20°N, range from 0.5 to -1.6 PW. These values are in line with the estimates of *Webster et al. [2002]* and *Chirokova and Webster [2006]*. Fig.3.1 b shows the OHT time series averaged

over 5°S and 5°N for the time period of 1980-2014. The time series reveals that mean cross-equatorial heat transport is southward in the boreal summer season in the IO.

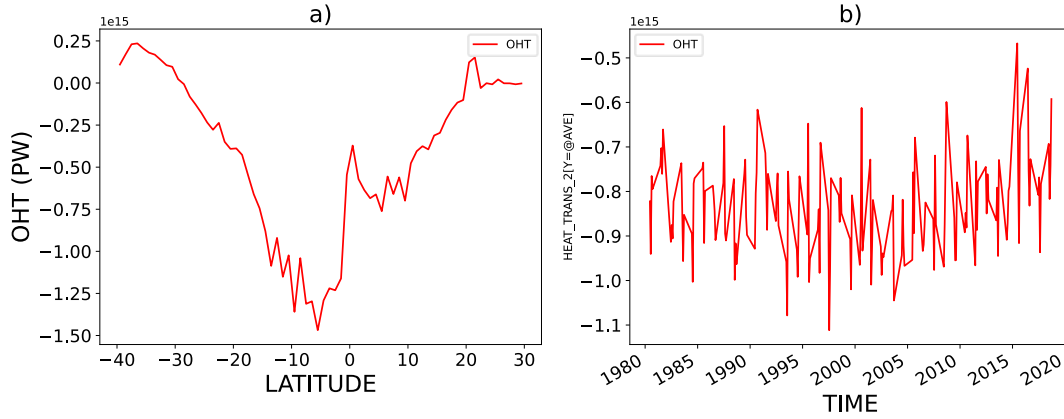


FIGURE 3.1: (a) June-September meridional ocean heat transport climatology over the Indian Ocean, (b) Time series of JJAS OHT averaged over 5°S to 5°N. The climatology is computed for the 1980–2018 period.

3.3.2 Understanding the factors contribute to the variability of Indian Ocean meridional heat transport

The longitude-depth cross-section of potential temperature (θ), meridional velocity (v) of ocean water, and their product are shown in Fig. 3.2. We construct a time series by averaging the OHT between 5°S and 5°N. The analysis shown in Fig. 3.1 already suggests that maximum OHT values are in between 5°S to 10°S. The highest values of θ and v are observed within the top 100 m, and thus, maximum OHT must also be confined to this layer Fig. 3.2. This is clear from the product of v and θ .

To understand the interannual variability in OHT, we performed an empirical orthogonal function (EOF) analysis on the longitude-height section of the JJAS mean θ , v and product of θ and v (θv) anomalies, averaged over 5°S to 5°N (Fig. 3.3). A

dipole-like pattern is observed in the EOF1 of θ anomalies over depth. The EOF1 of the v and θv also shows a similar EOF1 mode, which suggests that v controls the variability in the OHT. The leading mode of θ captures 41.9% variance, which indicating that this mode explains bulk of the interannual variability in the sea water temperature. Further, the opposing sign of the variability in the east and west of the IO is indicative of IOD-like variability. However, the EOF1 patterns of v and θv do not have a coherent structure like that of θ in the region west of 80 °E. By "coherent structure", we refer to a spatially continuous and organized pattern, while the EOF1 of v and θv appears fragmented and lacks such spatial organization. It is worth noting that EOF decompositions can be sensitive to the choice of domain boundaries, and strong western boundary current variability could potentially dominate the leading modes without producing a coherent basin-wide pattern. To examine this possibility, the analysis was repeated with the western boundary shifted from 40°E to 50°E. The EOF structures of v and θv remain spatially fragmented even in the reduced domain, suggesting that the absence of a coherent pattern is not simply an artefact of the domain choice but reflects the genuinely heterogeneous spatial character of OHT variability in the IO. In light of this, the lack of a coherent EOF mode in v and θv is not interpreted as indicative of weak interannual variability per se, but rather as a reflection of the spatially heterogeneous nature of OHT variability, which does not project strongly onto a single large-scale mode. This spatial incoherence, particularly west of 80°E, raises questions about the supposed basin-wide role of OHT in driving the interannual variability of the ISM as argued by [Webster et al. \[2002\]](#) and [Chirokova and Webster \[2006\]](#).

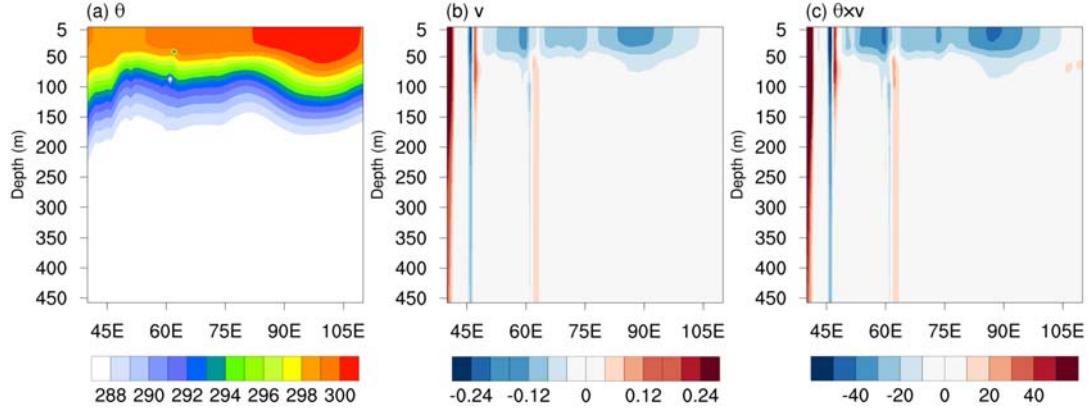


FIGURE 3.2: Longitude-depth cross-section of JJAS mean a) potential temperature (θ , units: K), b) meridional velocity (v , units: m s^{-1}), and c) product of θ and v ($\theta \times v$ units: K m s^{-1}) averaged over 5°S to 5°N

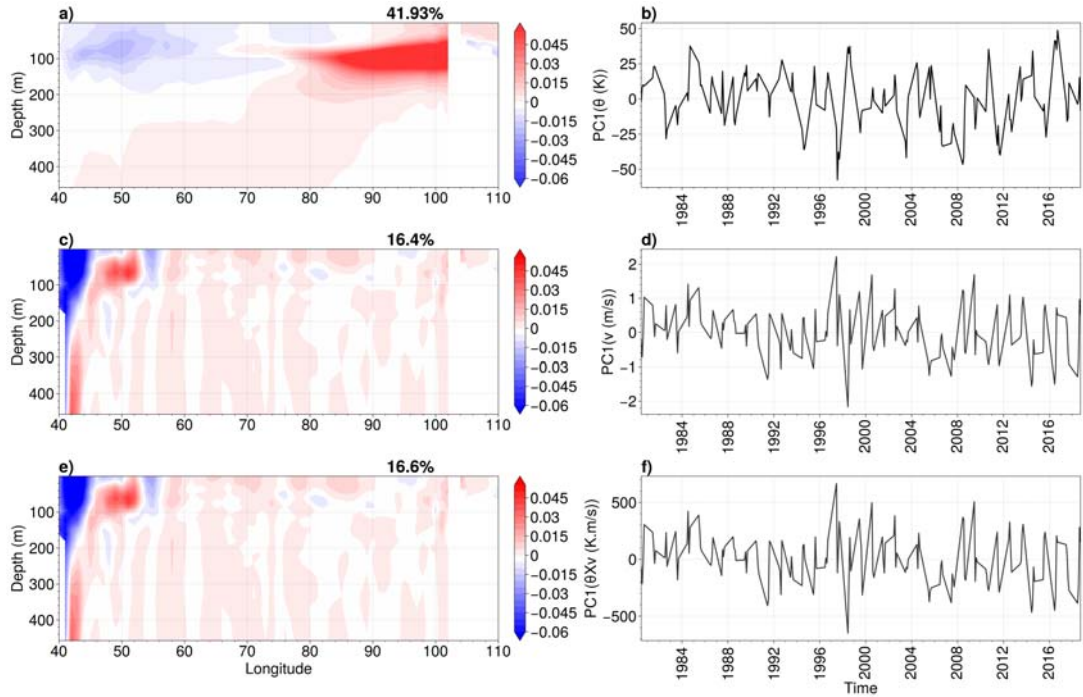


FIGURE 3.3: a,c,e – EOF 1 of θ , v and product of θ and v respectively; b,d,f- PC1 of θ , v and product of θ and v respectively for JJAS averaged over 5°S to 5°N

3.3.3 The role of summer Indian Ocean heat transport in the subsequent year monsoon and SST pattern

The strong annual cycle of cross-equatorial heat transport evident in our analysis is also supported by previous studies [*Chirokova and Webster, 2006; Lee and Marotzke, 1998*]. To understand the effect of OHT on ISM variability, a linear regression of JJAS mean OHT timeseries averaged over 5°N to 5°S is performed on IO SST, wind vectors at 850 hPa, and precipitation anomalies in the same year (year 0) and following year (year +1). This analysis is restricted to 1998-2018 due to constrained TRMM precipitation data availability. For consistency the regression on SST and wind is also done on same period. The argument of OHT playing a central role in regulating ISM is based on its plausible influence on IO SST variability. The regression of SST for different seasons with the JJAS mean OHT is shown in Fig. 3.4. The regression pattern shows a muted relationship between OHT and SST except for a positive regression pattern in the eastern part of the South Indian Ocean for September – November (SON) and December – February (DJF) seasons of year 0 (Figs. 3.4 a and b). However, none of the positive regression values are statistically significant. The regression coefficients become weaker for the March – May (MAM) and June – August (JJA) SSTs of the year+1 (Fig. 3.4 c and d). Statistically significant negative regression pattern in the southern central IO during MAM(+1) and JJAS(+1) is not consistent with the idea that increased southward OHT causes an increase in SST. This weakening of the OHT influence on SST beyond six months casts more doubt on the role of OHT in regulating the interannual variability of ISM. To assess the robustness of these results, the same regression analysis was repeated using the SODA reanalysis (Fig. 3.5). The SODA-based regression patterns are broadly consistent with those derived from ORAS5, showing similarly muted and largely statistically insignificant OHT–SST relationships during SON and DJF

of year 0. In the subsequent MAM(+1) and JJA(+1) seasons, SODA likewise yields weak regression coefficients with no coherent statistically significant positive signal over the NIO that would support a constructive OHT–SST–ISM linkage. The close agreement between these two independent ocean reanalysis products confirms that the identified OHT–SST relationships are not an artefact of a particular dataset. Taken together, the evidence from both ORAS5 and SODA indicates that the influence of OHT on IO SST weakens substantially beyond a lead time of six months, casting further doubt on the role of cross-equatorial OHT in regulating the interannual variability of the ISM.

A similar regression of OHT on wind vectors and precipitation was also done (Fig. 3.6). Most of these regression coefficients were also not statistically significant. The effect of JJAS mean OHT on precipitation and low-level winds weakened substantially by the following boreal spring and summer (Figs. 3.6 c and d) similar to that in the case of SSTs. The OHT time series is also regressed onto the volume-mean temperature anomalies over the SIO for the same seasons (Figs. 3.7), and this reveals statistically insignificant relationship between JJAS OHT and seasonal volume-mean temperature anomalies.

[Gupta et al. \[2020a\]](#) recently utilized TE to examine the exchange of information between pollutants and meteorological variables. [Srujan et al. \[2022\]](#) demonstrated a causal link between Rossby wave variance in the West Pacific and the development of downstream low-pressure systems (LPS) over the Bay of Bengal (BoB) using TE. A high TE value reflects a strong transfer of information. TE reveals the flow of information from the memory of one variable to another [[Gupta et al., 2020a](#)] and captures both the memory and the direction of information transfer, offering an advantage over mutual information. To understand the causal relationship between cross-equatorial OHT and SST, TE is computed between the OHT

time series (averaged over 5°S to 5°N) and the SST across the SIO at varying time lags (Fig. 3.8). To investigate the potential predictive relationship between OHT and SST, TE is determined by holding the OHT time series constant while shifting the SST time series from time lag first month (t_0) to 24th month ($t+24$). The TE values between OHT and SST are relatively small and it indicates that the influence of cross-equatorial OHT is less significant in the evolution of SST over SIO. [Srujan et al. \[2022\]](#) reported large TE values on the order of 10^9 between mean sea level pressure and Rossby-filtered outgoing longwave radiation, whereas our analysis shows significantly smaller TE values between OHT and SST. There is evidence of a non-zero causal relationship between OHT and SST; however, the values are extremely small, making them insufficient to interpret as a meaningful relationship. For the calculation of OHT, we are integrating ocean temperature and meridional velocity over the volume of entire IO and it gives apparently high values of 1 to 2 PW. However, at individual locations, the OHT value might be too small to make significant changes.

The opposing relationship between OHT and SST contradicts the role of OHT in modulation of the heat balance and the regulation of amplitude of SST as proposed by previous studies [[Loschnigg and Webster, 2000](#); [Webster et al., 2002](#); [Chirokova and Webster, 2006](#)]. This further indicates that the interannual variability in ISM is not regulated by the ocean-atmosphere coupling over the IO as envisaged by [Webster et al. \[2002\]](#). Adding to this [Lutsko et al. \[2019\]](#) examined the relationship between OHT and the monsoon within the same season, rather than focusing on interannual variability. Their idealized simulations showed that an increase in OHT led to a decrease in SST south of the continent during summer. This, in turn, increased the moist static energy over the continent, enhancing the land-ocean thermal contrast

and ultimately resulting in stronger precipitation within the same year. These findings highlight the crucial role of strong southward OHT in creating and maintaining conditions conducive to a robust monsoon, but not to the interannual variability. The discrepancy between these model-based findings and our observational results may stem from several factors. Idealized or slab ocean models often exaggerate certain feedbacks due to their simplified physical representations. Model biases, especially in the simulation of SST–OHT interactions or vertical ocean structure, may further complicate the interpretation. Additionally, spatial averaging or coarse resolution can obscure key regional processes that are more accurately captured in observational datasets.

To understand how Hadley cell circulation responds to cross-equatorial OHT, we have applied similar linear regression of OHT time series into the zonal mean meridional stream function anomalies for different seasons in year 0 and year +1 (Fig. 3.9). Hadley cell can be explained by the zonal mean of meridional stream function. The less statistical significant regression coefficients between OHT and stream function in all seasons indicates OHT influence is not conveyed into the mean circulation over the IO. This also lead to the assumption that OHT not regulating the interannual variability of ISM.

3.3.4 The boreal summer OHT during drought and flood years of ISM

Although our results show that OHT is found not playing any role in the interannual variability in ISM, it is interesting to examine the differences in the OHT in contrasting monsoon seasons. Here we identify eight cases of flood and drought monsoon years during 1980 – 2018 period and do a composite difference of JJAS mean OHT.

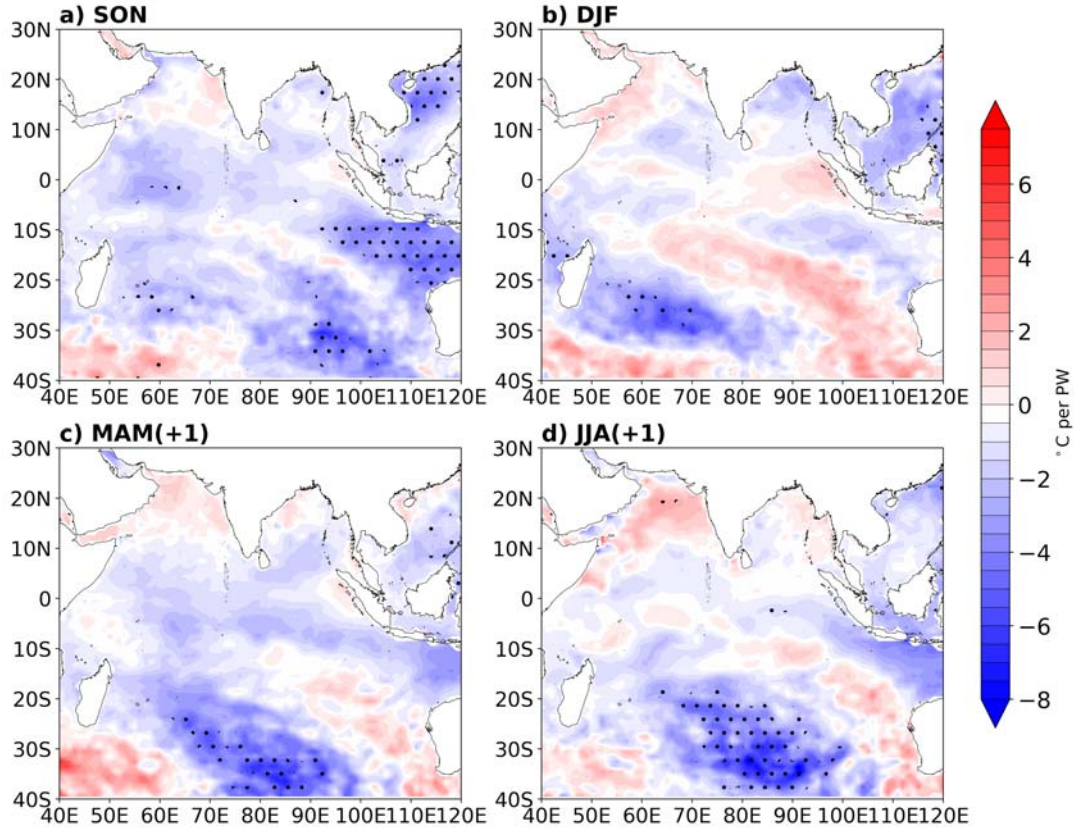


FIGURE 3.4: The linear regression of JJAS mean OHT averaged over 5°N to 5°S on sea surface temperatures anomalies averaged for (a) SON, (b) DJF, (c) MAM(+1) and (d) JJA(+1). The stippling indicates statistically significant regression coefficients at 95% level as revealed by a two-tailed bootstrap significance test. The 1998–2018 time period is considered for this analysis. To maintain consistency with our interpretation and to avoid confusion regarding the sign of heat transport, we have multiplied all regression coefficients by -1

The flood (drought) years of ISM are identified as the years in which JJAS mean precipitation over Central India exceeds (falls below) 10% of climatological mean precipitation [Singh *et al.*, 2019] (Fig. 3.10). The remaining years are considered as normal monsoon years. The composite mean time series of JJAS mean OHT over the IO for normal, flood, and drought years look similar (Fig. 3.11a). The difference plots of flood and drought composites from normal composite are shown in Fig. 3.11b. This analysis also suggests that the difference in OHT between flood and drought years is weak. The maximum magnitude of the OHT is about 1.5 PW,

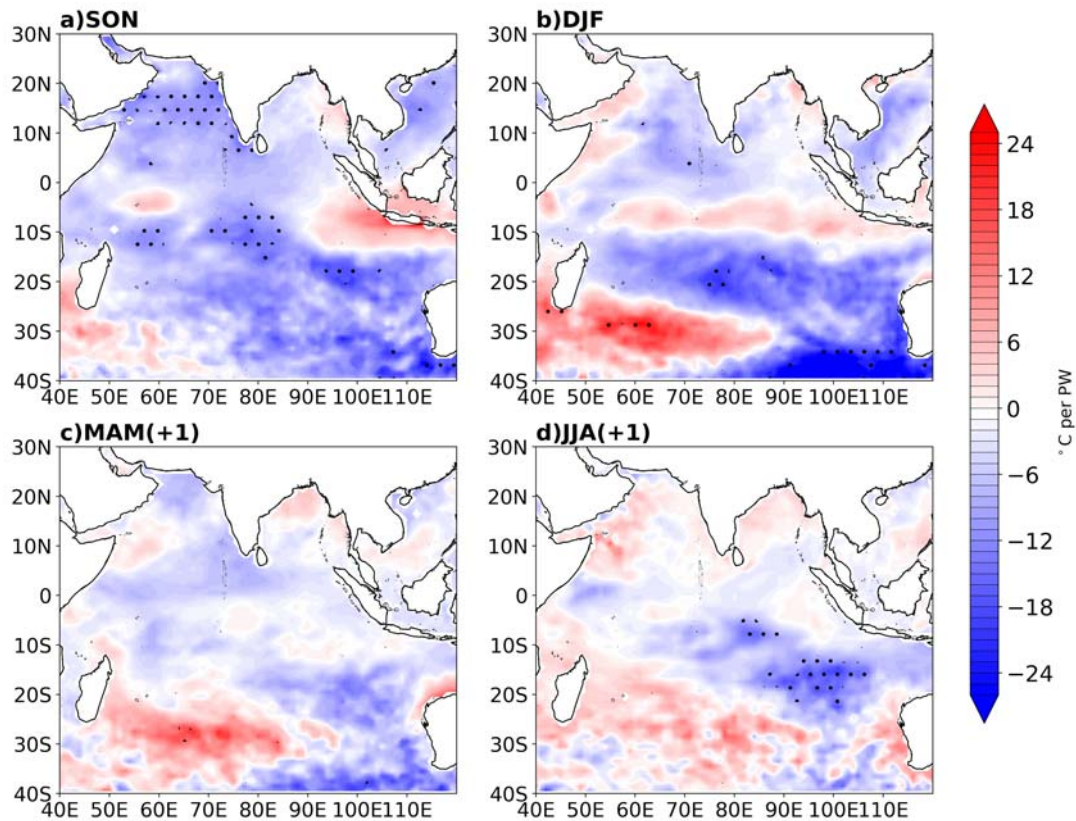


FIGURE 3.5: The linear regression of JJAS mean OHT using SODA reanalysis averaged over 5°N to 5°S on sea surface temperatures anomalies averaged for (a) SON, (b) DJF, (c) MAM(+1) and (d) JJA(+1). The stippling indicates statistically significant regression coefficients at 95% level as revealed by a two-tailed bootstrap significance test. The 1998–2018 time period is considered for this analysis. To maintain consistency with our interpretation and to avoid confusion regarding the sign of heat transport, we have multiplied all regression coefficients by -1

whereas the maximum difference in the OHT between normal and drought years is about 0.06 PW. Similar differences are seen between normal and flood years as well. The difference in OHT between flood and drought years averaged between equator and 30 °S is found to be about 0.012 PW, which is about 1.7% of the OHT in normal monsoon years. Thus, it is clear that the OHT difference between two extremes of ISM is much smaller in magnitude. While these analyses show that the OHT does not play a role in the interannual variability of ISM, the muted difference in OHT between flood and drought monsoons is an interesting phenomenon that warrants

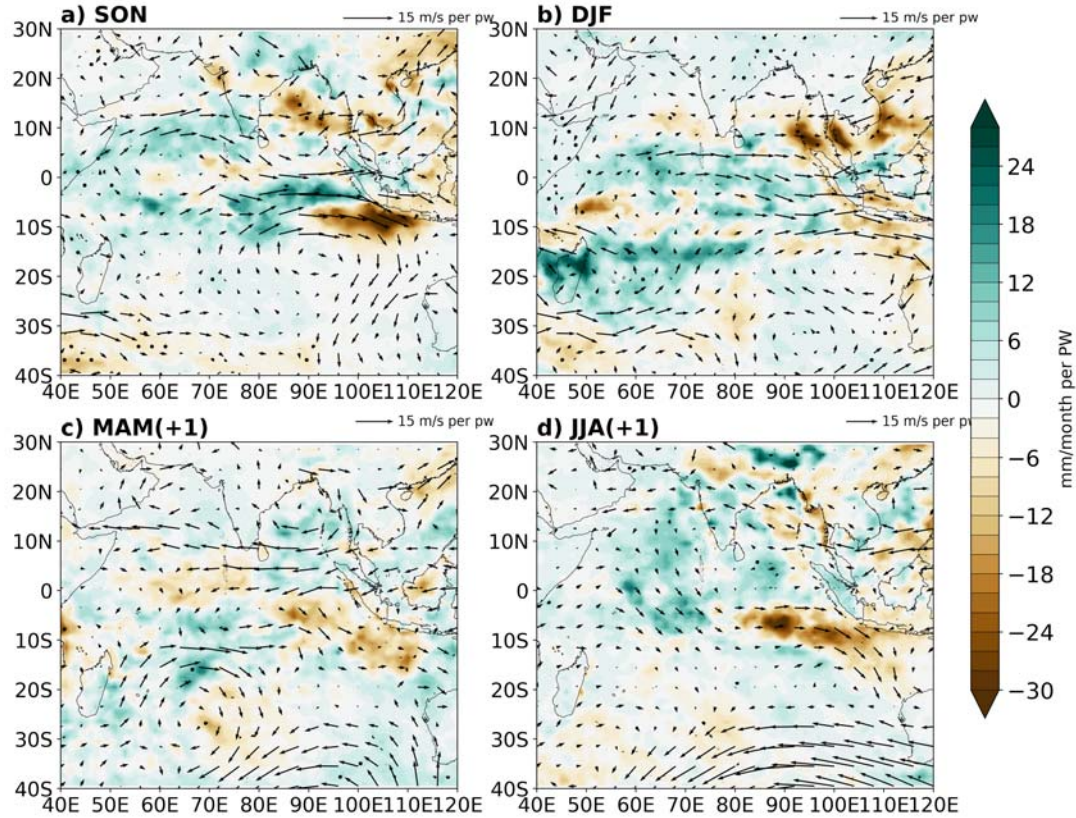


FIGURE 3.6: The linear regression of JJAS mean OHT averaged over 5°N to 5°S on precipitation and 850hpa wind anomalies averaged for (a) SON, (b) DJF, (c) MAM(+1) and (d) JJA(+1). The stippling indicates statistically significant regression coefficients at 95% level as revealed by a two-tailed bootstrap significance test. The 1998–2018 time period is considered for this analysis. To maintain consistency with our interpretation and to avoid confusion regarding the sign of heat transport, we have multiplied all regression coefficients by -1

further investigation. The small OHT differences observed in flood/drought composites may be due to the dominant influence of ENSO on ISM variability, which could mask subtler oceanic signals [Kumar *et al.*, 2006; Goswami *et al.*, 1999]. Additionally, compensating atmospheric feedbacks, such as changes in wind and cloud patterns, may dampen SST responses to OHT anomalies [Luo *et al.*, 2012].

The cross-equatorial OHT in the IO during summer is an Ekman response to the strong southwesterly monsoon winds. Therefore, the changes in the low-level monsoon flow can help us understand the OHT variability. Flood, drought and normal

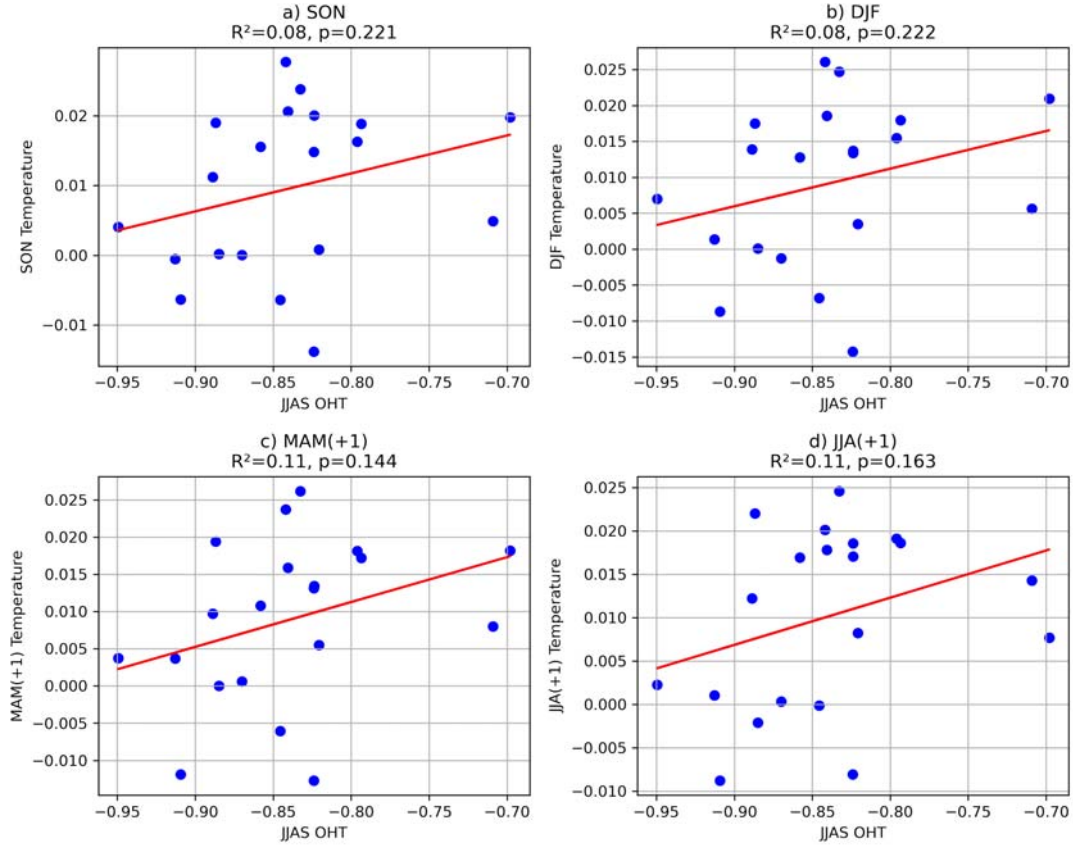


FIGURE 3.7: The linear regression of JJAS mean Indian Ocean OHT averaged over 5°N to 5°S on southern Indian Ocean (40°S–0°, 40°E–120°E) volume-mean temperature anomalies during a) SON, b) DJF, c) MAM(+1), and d) JJA(+1) for the period 1998–2018. Each panel shows the scatter plot of seasonal mean temperature anomalies against JJAS OHT with a linear regression fit (red line). Coefficients of determination (R^2) and p-values are indicated in each panel.

composites for monsoon low-level winds over the IO are shown in Fig. 3.12. The strong low-level flow over the Arabian Sea, the monsoon low-level jet, is a characteristic feature of ISM (Fig. 3.12a). The maximum wind speed in the normal composite is about 18 m s^{-1} . This strong low-level southwesterly flow is responsible for the cross-equatorial OHT in the IO. The difference in the low-level winds between the drought and normal years shows a weakening of the wind speeds over the Arabian Sea by about 1 m s^{-1} (Fig. 3.12 b). In flood years, the southwesterly monsoon flow is stronger over the Arabian Sea, Bay of Bengal, and continental India (Fig. 3.12 c).

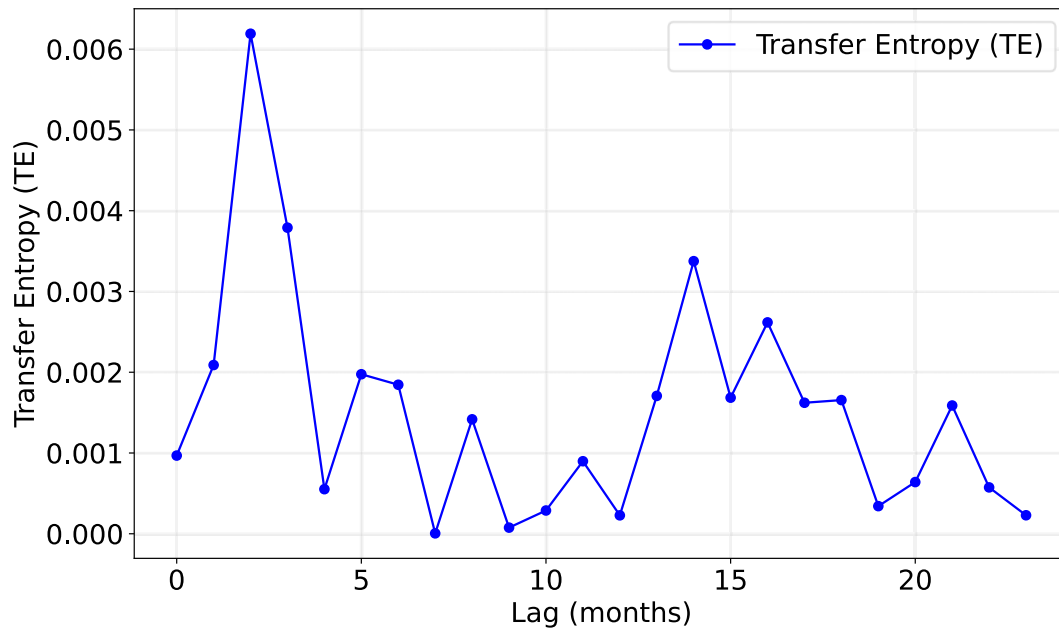


FIGURE 3.8: The Transfer Entropy (TE) between the OHT time series (averaged over 5°S to 5°N) and the SST across the southern Indian Ocean (40°S–EQ, 40°E–120°E) at varying time lags from t_0 to $t+24$

The maximum decrease (increase) in the wind speed in the flood (drought) composite is about 1.2 m s^{-1} only (Figs. 3.12 b and c). These analyses suggest that the changes in the seasonal mean wind speed in the anomalous monsoon years are about 6-7% of the mean wind speed in normal monsoon years. Also, the weakening of the low-level southwesterly flow in the drought years is confined to the southern part of the Arabian Sea and the eastern part of the South Indian Ocean close to the equator. The eastward component of the flow over the Bay of Bengal appears to be strengthened in the drought year composite. In the flood composite, the low-level monsoon circulation is strengthened over the Arabian Sea and the Bay of Bengal. However, the flow weakened over a section of the Indian Ocean over $65^\circ\text{E} - 80^\circ\text{E}$ and $5^\circ\text{S} - 5^\circ\text{N}$. The analysis reveals that wind speed variability is much smaller than precipitation variability. Between 1980 and 2018, the seasonal mean precipitation anomalies over central India and the 850 hPa wind speed anomalies over the Arabian Sea exhibit a correlation of 0.47. This moderate correlation suggests that

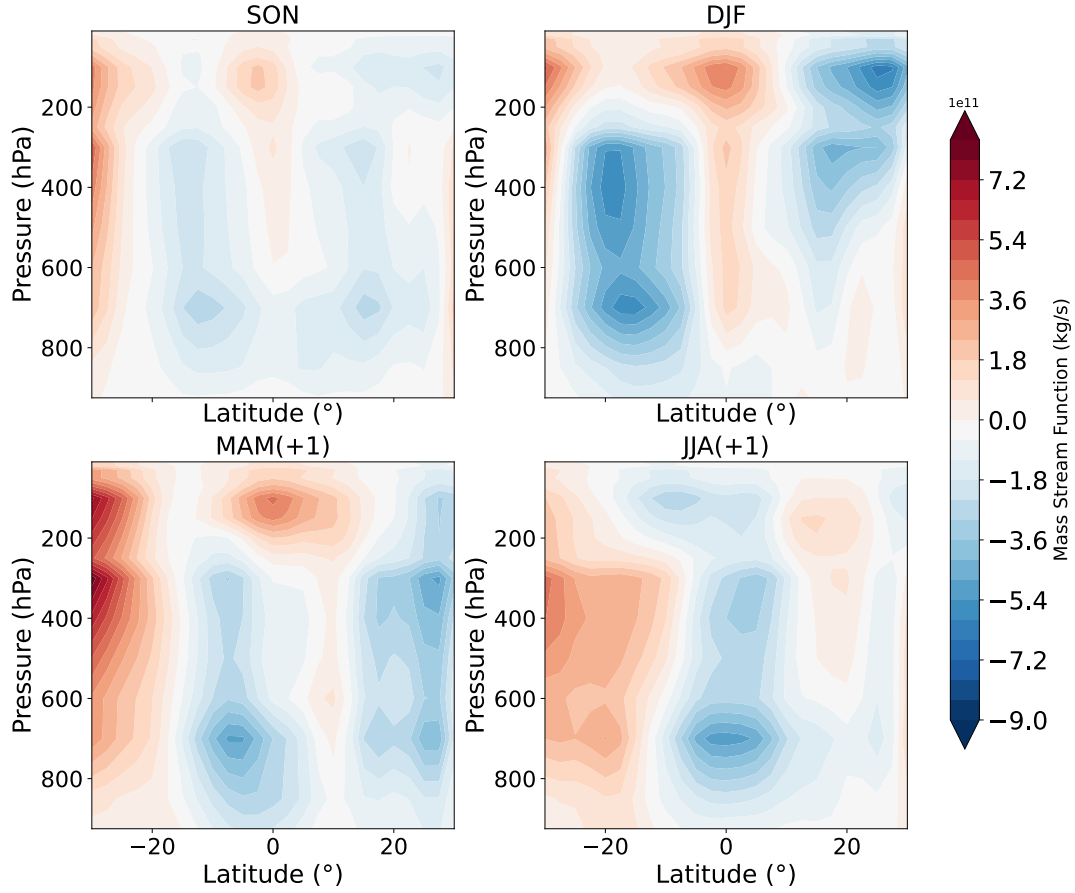


FIGURE 3.9: The linear regression of JJAS mean OHT averaged over 5°N to 5°S on zonal mean meridional stream function anomalies averaged for (a) SON, (b) DJF, (c) MAM(+1) and (d) JJA(+1). The stippling indicates statistically significant regression coefficients at 95% level as revealed by a two-tailed bootstrap significance test. The 1998–2018 time period is considered for this analysis.

the majority of precipitation variability arises from factors other than atmospheric circulation. The relatively weak interannual variability in the low-level monsoon flow aligns with the similarly subdued variability in OHT. In addition, the opposing changes in the low-level wind pattern in different parts of the IO can induce contradictory changes in the OHT, which can be the reason for a muted change in the OHT between drought and flood monsoons. The drought composite shows an enhanced low-level flow from the northern Arabian Sea and West Asia towards continental India. This is particularly noteworthy, as this pattern resembles the dry air advection suggested by [Singh and Sandeep \[2022\]](#). The decreased moisture transport coupled

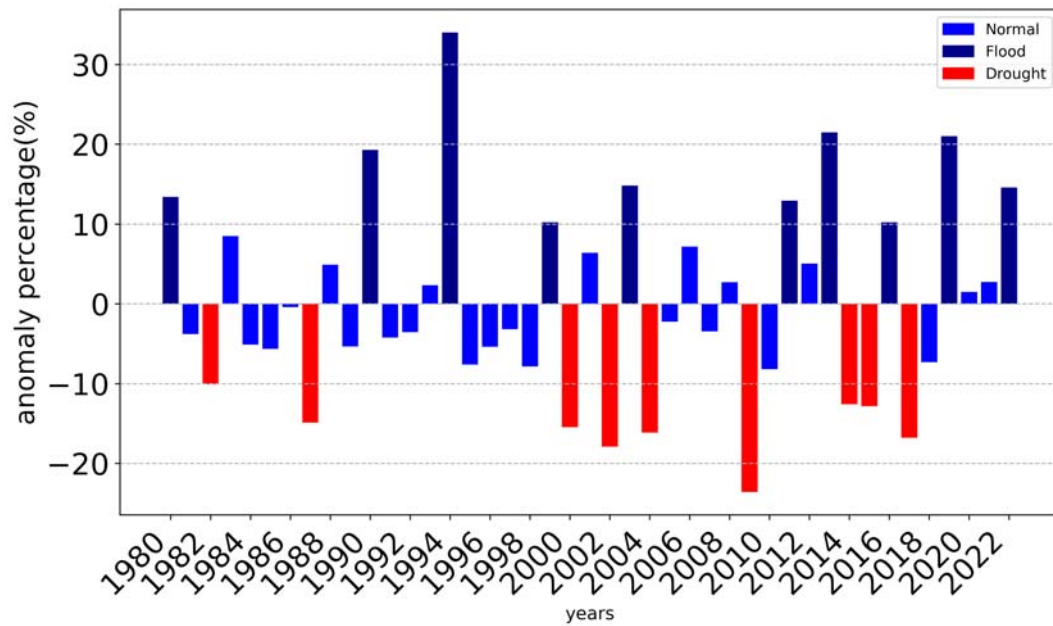


FIGURE 3.10: JJAS mean rainfall departure (in percentage) over Central India (75 °E – 85 °E and 19 °N – 26 °N)

with the dry air intrusion can lead to large deficits in ISM rainfall over continental India. The dry air intrusion over continental India during summer monsoon is also suggested to be a contributor to the interannual variability of rainfall over Northwest India [*Singh and Sandeep, 2024*].

Furthermore, we also examined the flood and drought composites of the Hadley circulation, along with their differences (Figs. 3.13). The analysis revealed no substantial differences between the flood and drought composites of the Hadley cell. The interannual variability in precipitation not reflect in the hadley cell or zonal mean meridional stream function. Similar to OHT, these results reveal that Hadley cell circulation does not play a significant role in the interannual variability of ISM.

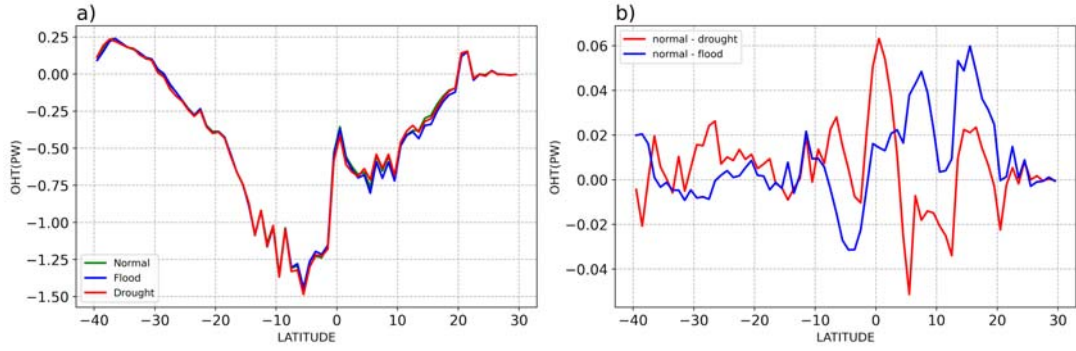


FIGURE 3.11: a) JJAS mean OHT composite of flood, drought and normal monsoon years and b) difference of flood and drought OHT composite from normal

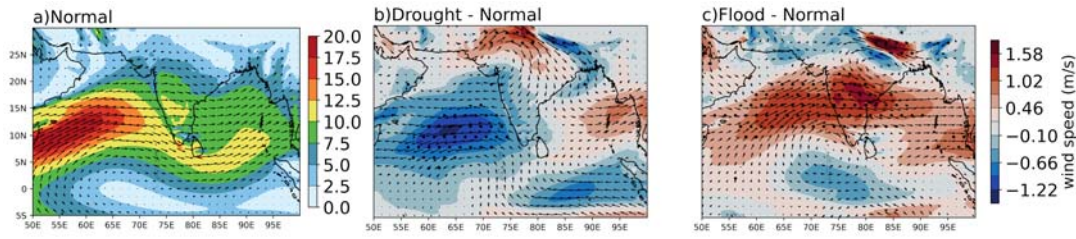


FIGURE 3.12: The JJAS mean composite of 850 hPa wind speed composite, for (a) normal years, and (b) difference between drought and normal years, and (c) difference between flood and normal years. The stippling indicates statistically significant regression coefficients at 95% level as revealed by a two-tailed *t*-test

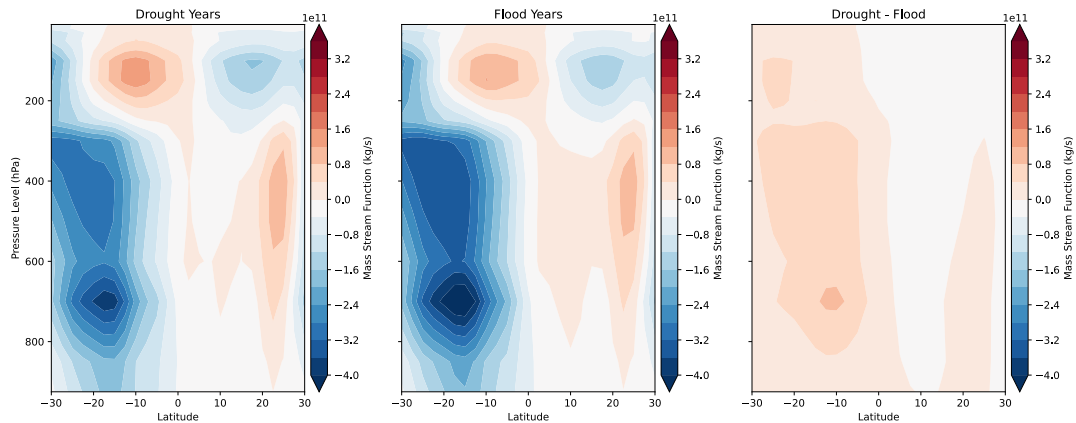


FIGURE 3.13: a-b) Drought and flood composite of zonal mean meridional stream-function, b) Difference between drought and flood composite

3.4 Summary and Conclusions

The interannual variability in ISM rainfall shows a quasi-biennial nature, with more than two consecutive droughts or floods a rare occurrence. This led to a claim that the ISM is a self-regulated coupled-ocean atmosphere system, in which the cross-equatorial ocean heat transport (OHT) over the Indian Ocean (IO) by the ISM winds is assumed to have a crucial role [[Webster et al., 2002](#); [Chirokova and Webster, 2006](#)]. A long ocean "memory" is needed to support this mechanism of self-regulated monsoon interannual variability, as the warm/cold oceanic anomalies must persist for one year. The ability of OHT to modulate the heat balance of IO is important for achieving this self regulation. However, a direct analysis on the relationship between the summer OHT, oceanic temperature anomalies in the following seasons, and the subsequent ISM was lacking in the literature. So main focus of this paper confined to testing the hypothesis proposed by [Webster et al. \[2002\]](#) and [Chirokova and Webster \[2006\]](#) using reanalysis data.

Here, we computed the OHT for all summer monsoon seasons in the 1980–2018 period. Furthermore, we examined the influence of this summer OHT on the following seasons' SST, low-level wind vectors, and precipitation. Our focus of this study is understanding how OHT in year 0 affects the ISM in year +1. These analyses revealed that the effect of OHT on SST and other meteorological fields does not last beyond following winter season. Moreover, the low transfer entropy values between OHT and SST further confirm the absence of a strong or sustained causal influence of cross-equatorial OHT on SST evolution over the South Indian Ocean. Thus, the OHT variability cannot contribute to the interannual variability of ISM. The difference in seasonal mean precipitation over central India between drought and flood monsoons is approximately 20%, whereas the corresponding difference in

OHT is less than 2%. Further analysis shows that the difference in low-level monsoon wind speed between flood and drought monsoons is also much smaller than the precipitation difference. This aligns with the weaker interannual variability in OHT, which is primarily governed by Ekman transport. Therefore, we conclude that interannual variability in ISM rainfall is not a self-regulated mechanism through the ocean-atmosphere coupling over the Indian Ocean. Nevertheless, we acknowledge, as a caveat that, while the weak regression coefficients generally indicate a weak relationship between OHT and ISM precipitation on interannual scale, it does not fully capture the complex non-linear nature of interactions between climate variables. The OHT may still have an indirect effect on ISM rainfall through modification of other processes that in turn may affect ISM.

[Webster et al. \[2002\]](#) explicitly studied the role of the IOD in the self-regulation of the ISM. However, in our regression coefficients of SST during SON and DJF (Figure 3.4), there is no statistically significant IOD-like pattern evident, which is notable given that IOD typically peaks in the post-monsoon season.

This study specifically examines the impact of ocean heat transport (OHT) on the interannual variability of ISM, while the influence of sub-seasonal variability, such as LPS activity, warrants further exploration in future research. Our analysis of low-level monsoon circulation suggest an increased advection from the northern Arabian Sea and the West Asian desert region towards the continental India. This might be another contributor to the ISM rainfall variability as suggested by earlier studies [[Singh and Sandeep, 2022, 2024](#)]. Thus, both internal and external factors contribute to the interannual variability of ISM rainfall. The cross-equatorial ocean heat transport, as argued earlier, is not one of those factors.

Chapter 4

ISM Interannual Variability: Role of Teleconnections and Synoptic Variability in CMIP6 Historical Projections

4.1 Introduction

Given the subdued influence of cross-equatorial OHT on ISM variability, we proceed to examine ENSO, which has long been recognized as a key factor modulating interannual variations in the monsoon. The effect of the ENSO on ISM rainfall variability has been widely studied [[Webster et al., 1998](#); [Kumar et al., 1999, 2006](#)]. Most of the literature on the influence of ENSO on monsoon examined the ENSO-monsoon relationship in the same calendar year. In line with the OHT analysis, we examined the impact of ENSO using a similar approach to investigate its relationship with monsoon rainfall in the subsequent year. Further we explored the role of synoptic activity such as low pressure systems (LPS) in the interannual variability of ISM. The monsoon LPSs are the precipitating vortices embedded in the large-scale monsoon circulation. These systems can be found in all monsoon regions, with a predominant presence over Indian region during summer. With a life span of 3-7 days, the LPSs contribute to the synoptic scale rainfall variability of ISM. During boreal summer, about 10-14 LPSs form over the Bay of Bengal and the Gangetic plains and follow a northwestward trajectory along the continental India. These systems contribute more than 50% of the ISM rainfall over the central India [[Praveen](#)

et al., 2015]. Therefore, the variability in LPS activity can lead to ISM rainfall variability. The LPSs are often found to be clustered to the active phase of monsoon intraseasonal oscillations and thus play a major role in the scale interaction over the Indian region [*Srujan and Sandeep*, 2024]. Often these scale interactions contribute to the interannual variability of monsoon rainfall [*Suhas et al.*, 2012].

4.2 Datasets and Methodology

The dataset and methods are detailed in chapter 2 and do not repeat the description for brevity.

4.2.1 Datasets overview

ORAS5 is used for SST to calculate Niño3.4 index ([*Zuo et al.*, 2015]; Section 2.2.1). Tropical Rainfall Measuring Mission (TRMM) (0.25x0.25, 1998-2018) daily data was used to analyse the rainfall over the IO ([*Huffman et al.*, 2016]; Section 2.1.1.2). ERA5 used for the daily sea-level pressure data.

Daily gridded sea level pressure data are available for only 18 CMIP6 models listed in Table 2.1 and are used to track LPS during JJAS, while SST data from 20 models (based on availability) are analyzed to study the El Niño–Southern Oscillation (ENSO).

4.2.2 Methodology

We used the tracking technique of *Praveen et al.* [2015] to follow the paths of LPS in the ERA-5 reanalysis data. Using gridded daily sea level pressure (SLP) data,

this technique finds closed isobars at intervals of 1 hPa to detect and track LPS. Additionally, this technique uses the pressure depth (Δ SLP) to classify the LPS depending on their intensity category.

Niño 3.4 index is calculated using SST anomalies averaged over 5°N–5°S, 170°W–120°W, with a 5-month running mean applied.

4.3 Results and Discussion

4.3.1 Relationship Between ENSO and ISM of the Following Summer in Observations

In line with the OHT analysis, we also performed a regression using the Niño3.4 index following a similar approach, to explore its relationship with the monsoon rainfall in the following year using reanalysis data. To understand the influence of ENSO on the SST over the IO, we performed a linear regression of DJF mean Niño3.4 index on the following MAM and JJA mean SSTs (Fig. 4.1 a and b). The positive regression patterns over the NIO indicate that a warm (cold) ENSO can lead to warm (cold) SST anomalies over the NIO in the following spring and summer seasons. The regression patterns over the SIO is rather weak, with patches of both positive and negative regression coefficients. The positive SST anomalies over the NIO following a warm ENSO event reflect a remote oceanic response to ENSO forcing; however, the net influence on the subsequent ISM is mediated by the spatial structure of SST gradients across the Indian Ocean basin and the associated modulation of atmospheric circulation, moisture transport, and land–sea thermal contrast.

The JJA mean wind vectors show a weak relationship with the Niño3.4 SST anomalies of the previous winter, while the precipitation shows a positive correlation with it over most of continental India (Figs. 4.1 c and d). Nevertheless, the regression patterns of precipitation is also statistically not significant over the continental India. This indicates that the effect of ENSO in the year 0 on the summer monsoon of year+1 is rather weak. This is consistent with the previous studies that showed weak positive correlations between ENSO and ISM at lead/lag of one year and a strong negative correlation in the same calendar year [*Kirtman and Shukla, 2000*]. This suggests that even the effect of Niño3.4 SST anomalies in the winter of year 0 on the ISM of year+1 diminishes substantially. Thus, a simple explanation of the interannual fluctuations of ISM rainfall in the range of $\pm 10\%$ through the ocean atmosphere coupling is difficult. We did not examine the complicated mechanisms such as the tropospheric biennial oscillation which might be better suited to explain the interannual variability of ISM [*Meehl, 1993*].

4.3.2 Relationship Between ENSO and ISM of Following Summer in CMIP6 Historical Simulations

To understand how the ENSO relationship with the ISM of following year, same regression analysis carried using CMIP6 models. The multimodel mean of Niño3.4 index during DJF (Year 0) is regressed into the following MAM and JJA (year+1) multimodel mean SST and precipitation (Figure 4.2). The regression patterns reveal a strong basin-wide warming response over both the northern and southern IO, which persists from spring into summer. Unlike the reanalysis, which showed weaker and patchier regression in the southern IO, the CMIP6 multimodel mean indicates a more spatially coherent warming signal across the basin. This suggests that the models tend to amplify the ENSO-related warming over the IO in the year following

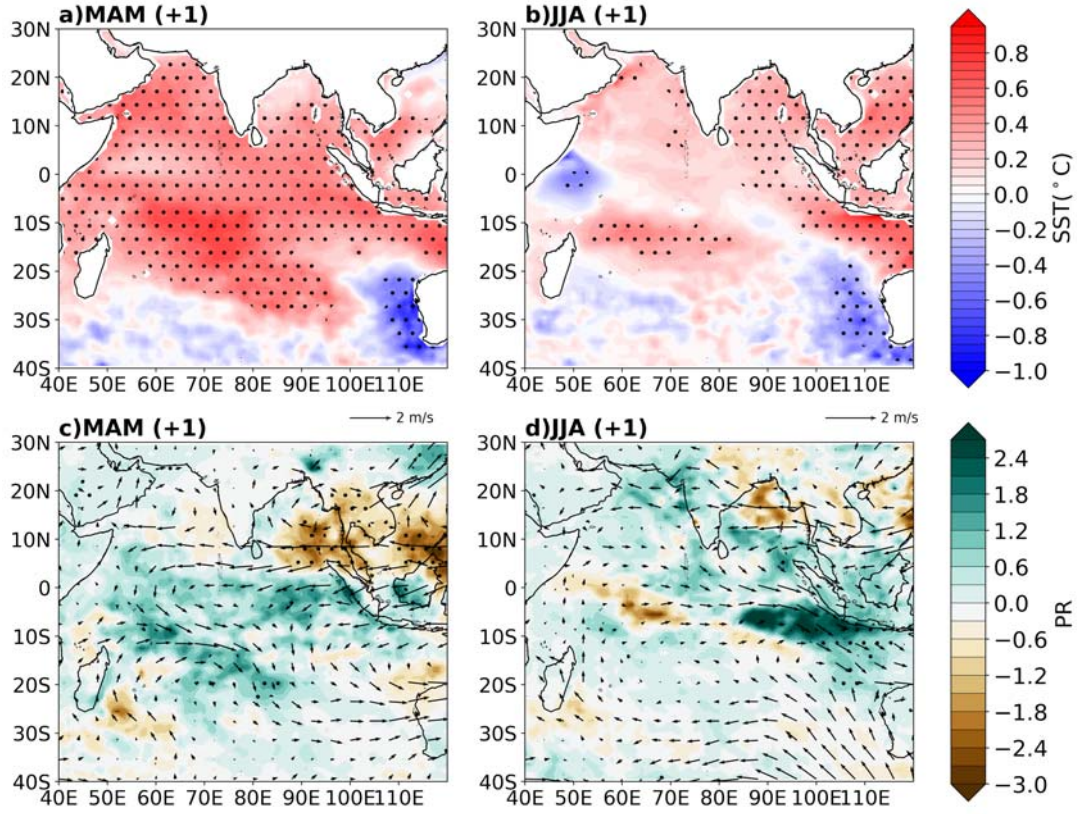


FIGURE 4.1: a–b) Linear regression of the December–February mean Niño3.4 index (year 0) onto ORAS5 sea surface temperature anomalies averaged for (a) March–May (year +1) and (b) June–August (year +1), and c–d) same for TRMM precipitation and ERA5 850 hPa wind. Stippling indicates regression coefficients statistically significant at the 95% level based on a two-tailed bootstrap test. The analysis covers the period 1998–2018.

an ENSO event, thereby preconditioning the ocean surface for a stronger basin-wide SST anomaly. The JJA precipitation (Figs. 4.2c and d) show limited and mostly insignificant relationships with the preceding winter Niño3.4 anomalies. While weak positive rainfall regression is seen over parts of continental India, the signal is not statistically significant, and the associated wind anomalies remain weak across the IO basin. This highlights that, similar to the reanalysis, the impact of ENSO on the ISM rainfall at a one-year lag is not robust in CMIP6 models. Overall, CMIP6 models capture the broad structure of ENSO’s delayed influence on IO SSTs more strongly than reanalysis but reproduce only weak and

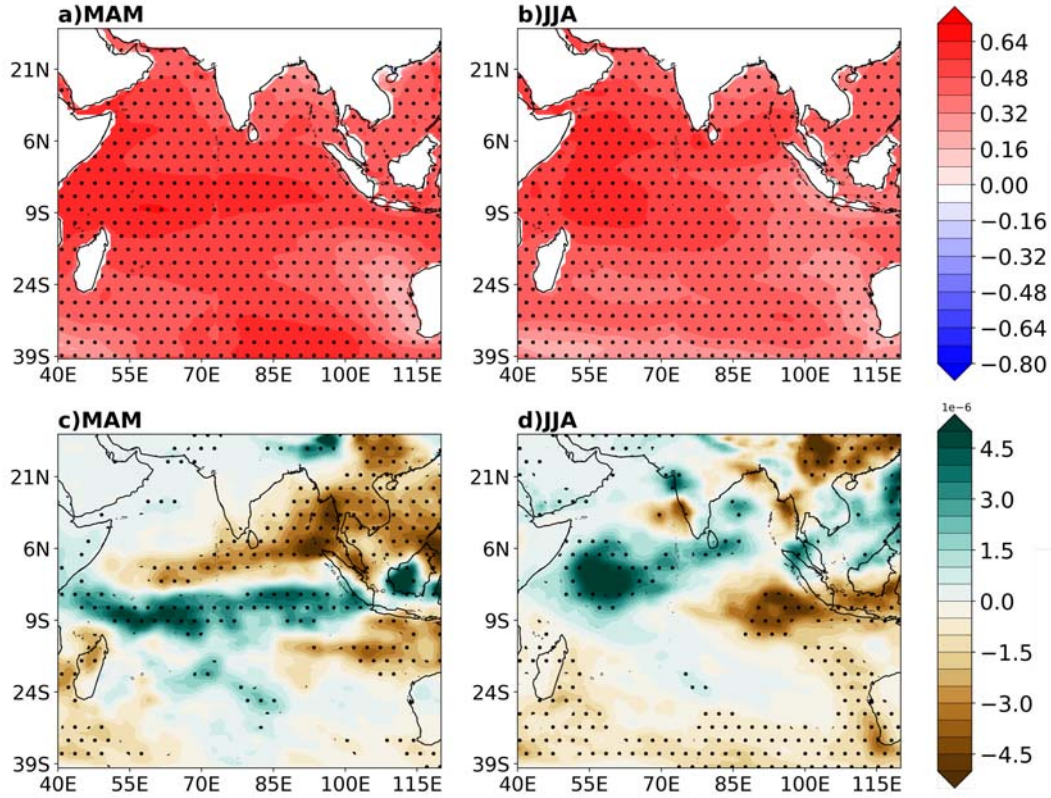


FIGURE 4.2: a–b) Linear regression of the December–February multimodel mean Niño3.4 index (year 0) onto multimodel mean CMIP6 sea surface temperature anomalies averaged for (a) March–May (year +1) and (b) June–August (year +1), and c–d) same for CMIP6 multimodel mean precipitation. Stippling indicates regression coefficients statistically significant at the 95% level based on a two-tailed bootstrap test. The analysis covers the period 1998–2018.

insignificant links to monsoon rainfall and circulation in the following year. This supports the notion that the one-year lagged ENSO–ISM teleconnection is not a dominant mode in either observations or models.

To understand in detail how the relationship between ENSO and ISM rainfall anomalies is represented in CMIP6 models, we examined the scatter plot between the Niño3.4 index and ISM rainfall anomalies for all 20 models (Fig. 4.3). The distribution of points reveals a predominantly negative association across the ensemble, indicating that warm ENSO events (El Niño) generally coincide with below-normal

ISM rainfall, while cold ENSO events (La Niña) are associated with enhanced rainfall. This negative ENSO–ISM teleconnection, long established in observations, is therefore broadly captured by the CMIP6 multimodel ensemble. To quantify how robustly this relationship is represented, the Pearson correlation coefficient between the Niño3.4 index and ISM rainfall anomaly was computed for each model, and the results are summarised in Fig. 4.4. Out of 20 models, 17 exhibit a statistically significant negative correlation at the 95% confidence level ($p < 0.05$). Three models INM-CM5-0 ($r = -0.18$), CAS-ESM2-0 ($r = 0.12$), and FIO-ESM-2-0 ($r = 0.15$), fail to reproduce a significant negative ENSO–ISM relationship, with CAS-ESM2-0 and FIO-ESM-2-0 even showing a weak positive association, indicating a fundamentally different or absent ENSO teleconnection in these models. The observational estimate based on ORAS5 Niño3.4 and IMD rainfall over 1980–2018 yields $r = -0.23$ ($p = 0.156$), which, while negative in sign, does not reach statistical significance over this relatively short record. Notably, the majority of CMIP6 models tend to simulate a stronger ENSO–ISM correlation than observed, likely reflecting an overestimation of ENSO amplitude or an overly strong monsoon sensitivity to ENSO forcing in these models. Taken together, the CMIP6 ensemble broadly confirms the negative influence of ENSO on ISM rainfall, but the substantial inter-model spread ranging from statistically significant negative correlations to near-zero or positive values highlights persistent uncertainty in simulating the strength of this teleconnection. This is consistent with earlier studies reporting that while most climate models reproduce the sign of the ENSO-ISM relationship, they differ widely in its magnitude due to biases in ENSO dynamics, the Indian Ocean response, and monsoon circulation feedbacks

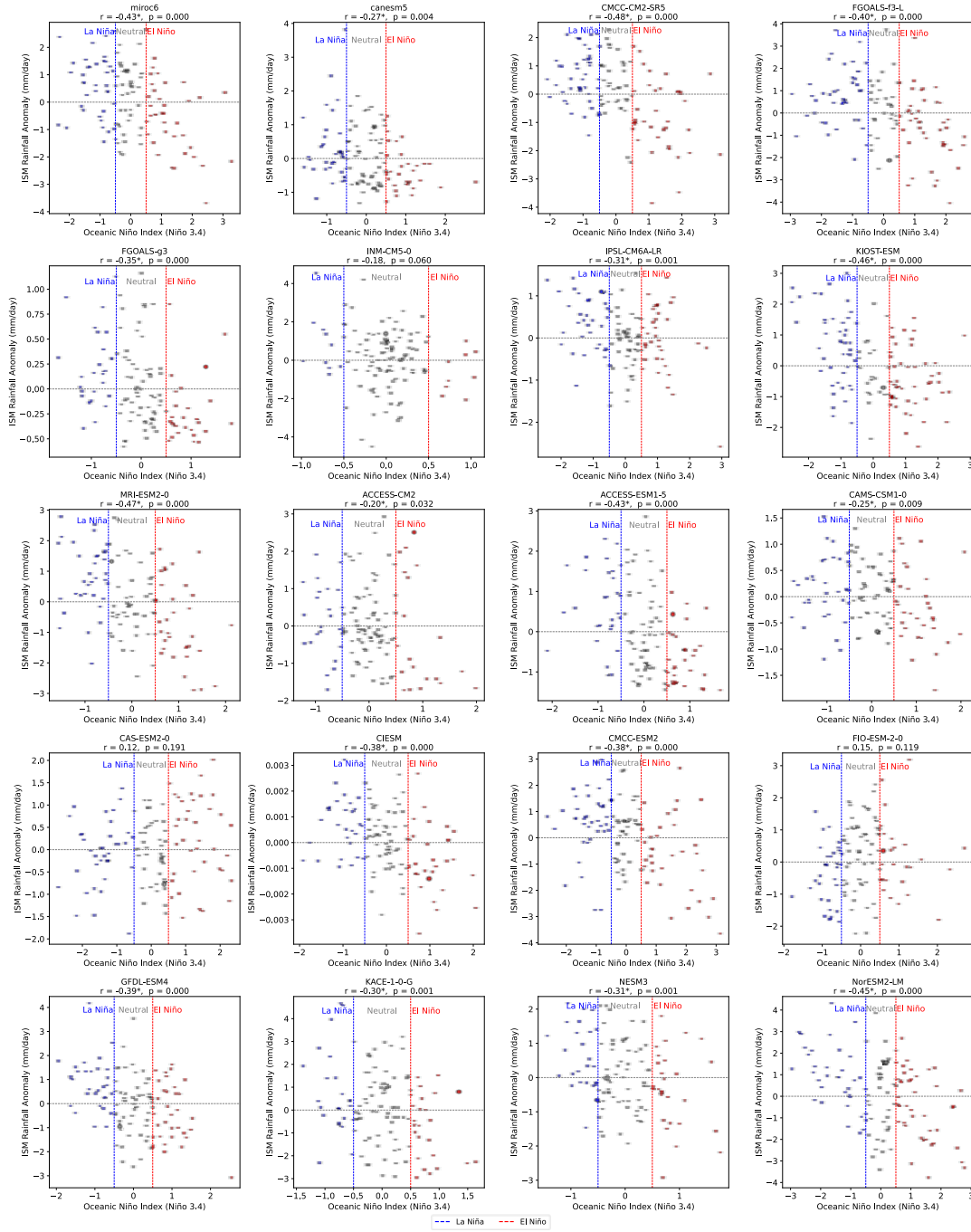


FIGURE 4.3: Scatter plots of JJAS Niño3.4 index versus ISM rainfall anomaly (mm day^{-1}) for each of the 20 CMIP6 models under historical simulations (1901–2014). Blue, red, and grey dots represent La Niña ($\text{Niño}3.4 < -0.5$), El Niño ($\text{Niño}3.4 > 0.5$), and neutral years, respectively. The Pearson correlation coefficient (r) and corresponding p -value are shown in the title of each panel, with * denoting statistical significance at the 95% confidence level ($p < 0.05$). Vertical dashed blue and red lines indicate the La Niña and El Niño thresholds, respectively, and the horizontal dashed grey line marks the zero rainfall anomaly.

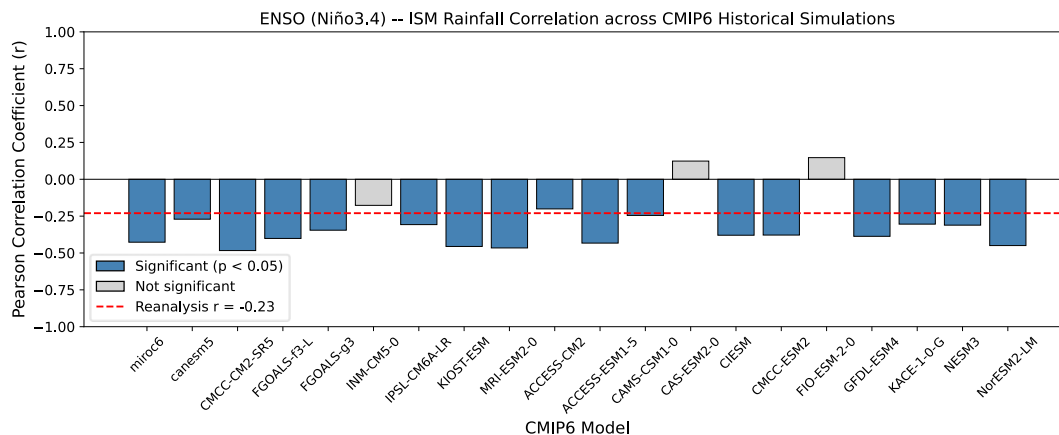


FIGURE 4.4: Bar chart of Pearson correlation coefficients between the JJAS Niño3.4 index and ISM rainfall anomaly for each of the 20 CMIP6 historical simulations. Steel blue bars indicate models with statistically significant correlations ($p < 0.05$) and grey bars indicate models that are not statistically significant. The red dashed line denotes the observational estimate derived from ORAS5 Niño3.4 and IMD rainfall over the period 1980-2018 ($r = -0.23$).

4.3.3 LPS and Interannual Variability of the ISM

Here, we examined the LPS activity for seven flood and drought years. The trajectories and track density per square degree per year of all LPSs formed in these excess and deficit monsoon years are shown in Figs. 4.5 a and b and c and d, respectively. A total of 57 LPSs formed in the seven flood monsoon years examined here. These LPSs contributed a total of 360 days of synoptic activity, with an average of 51 days of synoptic activity per flood monsoon season. On the contrary, only 41 LPSs were formed in the seven drought monsoon years. This shows that, on average the drought monsoon years have seen two LPSs less than the flood monsoon years. In terms of the days of LPS activity, the drought monsoon years have experienced an average of 40 LPS days per summer. Furthermore, the LPS trajectories in the flood monsoon seasons show a coherent northwestward propagation, while those in the drought years show a prominent eastward propagation as well. The eastward propagation of LPSs can further reduce the rainfall over the core monsoon region of Central India. The track density show that during flood years LPS tracks are denser

than drought years. Thus, it is clear that the internal variability also contributes to the intraseasonal variability of ISM. However, the internal processes such as LPS genesis might also be influenced by the large-scale climate drivers like ENSO.

Since ENSO and LPS activity are not entirely independent, part of the apparent LPS-rainfall relationship could arise from ENSO modulation. To examine this, a partial correlation analysis was performed by removing the influence of the DJF Niño3.4 index from both the JJAS TRMM rainfall and ERA5-based LPS track density timeseries. Even after removing the ENSO signal, a statistically significant positive relationship between LPS track density and JJAS precipitation is retained (partial correlation = 0.46, $p = 0.040$; Fig. 4.6), demonstrating that LPS activity carries independent information about ISM interannual variability that cannot be explained by ENSO alone.

Here, we examined the LPS activity during flood and drought years using 14 CMIP6 models for the historical and SSP585 scenarios (Fig. 4.7). Consistent with the reanalysis-based results, the trajectories and track density reveal notable differences between flood and drought years. In most models, flood years are associated with a higher frequency of LPSs and longer durations of synoptic activity compared to drought years. For example, several models such as MPI-ESM1-2-LR, NESM3, and AWI-CM-1-1-LR simulate more than 30 LPSs and extended LPS days during flood years, whereas the corresponding drought years show fewer events and reduced activity. Conversely, some models (e.g., CESM2-WACCM and IITM-ESM) exhibit more LPSs during drought years, highlighting the inter-model spread in simulating LPS–monsoon interactions. To provide a more robust, model-aggregated perspective, multi-model mean LPS tracks and track density maps for flood and drought years under both historical and SSP585 scenarios are presented in Figs. 4.8 and 4.9. These multi-model mean representations reduce individual model biases and

highlight the common spatial characteristics of LPS activity. The results show that, during flood years, LPSs tend to follow a more coherent northwestward propagation from the Bay of Bengal into the Indian subcontinent, favouring enhanced rainfall over Central India. In contrast, during drought years, LPS activity is comparatively weaker, with reduced northwestward penetration and a tendency for tracks to remain confined to the eastern region, thereby limiting rainfall contributions over the core monsoon zone. It is noted, however, that a quantitative comparison of inter-model and interannual variances reveals that inter-model variance (301.27) is approximately 2.7 times larger than the mean interannual variance (110.04), accounting for around 73% of the total variance. This indicates that the diversity seen across models is primarily structural in origin rather than a reflection of internal climate variability, and represents an important source of uncertainty in the LPS-based projections discussed here.

To further quantify and assess the statistical robustness of these differences, Fig. 4.10 presents the MMM LPS track density difference (flood minus drought) for the historical (Fig. 4.10a) and SSP585 (Fig. 4.10b) scenarios, with hatching indicating regions of statistical significance at the 95% confidence level based on a bootstrap resampling test. In the historical period, a prominent positive anomaly in LPS track density is evident over Central India and the northern Bay of Bengal (approximately 15°N–25°N, 80°E–95°E), indicating that flood years are systematically associated with greater LPS activity in this region. Critically, this positive anomaly is statistically significant, confirming that the flood–drought contrast in LPS behaviour is not attributable to internal variability or sampling uncertainty. Under the SSP585 future scenario, this pattern is not only retained but becomes spatially more extensive and of greater magnitude, with the region of significant positive anomaly expanding further westward and northward over the Indian subcontinent.

This amplification suggests that warming may intensify the role of LPS activity in differentiating flood and drought monsoons, although the inter-model spread in the magnitude of these changes introduces uncertainty in the precise spatial extent of the projected signal.

Using experiments with General Circulation Models (GCMs) on seasonal mean prediction and predictability, [Goswami and Xavier \[2005\]](#) shown that internal low-frequency variability may account for a significant amount (approximately 50% or more) of the observed interannual variability in the Indian summer monsoon. It is difficult to establish a cause-effect relationship between internal variability and interannual variability. There are studies that suggest that stronger LPS activity was associated with flood monsoon years in the past [[Krishnan et al., 2006](#)]. The link between LPS activity over the Bay of Bengal and the westward propagating atmospheric disturbances from the Western North Pacific is known [[Krishnamurti et al., 1977](#); [Srujan et al., 2022](#); [Vishnupriya et al., 2022](#)]. It may be possible that the low-frequency coupled ocean-atmosphere variability like tropospheric biennial oscillation modulates the LPS genesis over the Bay of Bengal by influencing this teleconnection. This will be explored in a future study.

4.4 Summary and Conclusions

The roles of ENSO as well as monsoon synoptic activity in the interannual variability of ISM have been investigated. Our analyses revealed that the ENSO significantly influences the evolution of SST anomalies over the North Indian Ocean in the following spring and summer. However, this strong correlation does not imply a causality, especially in the backdrop of a weak relation between the Niño3.4 SST anomalies of the year 0 winter and the ISM circulation and precipitation in year+1. This is

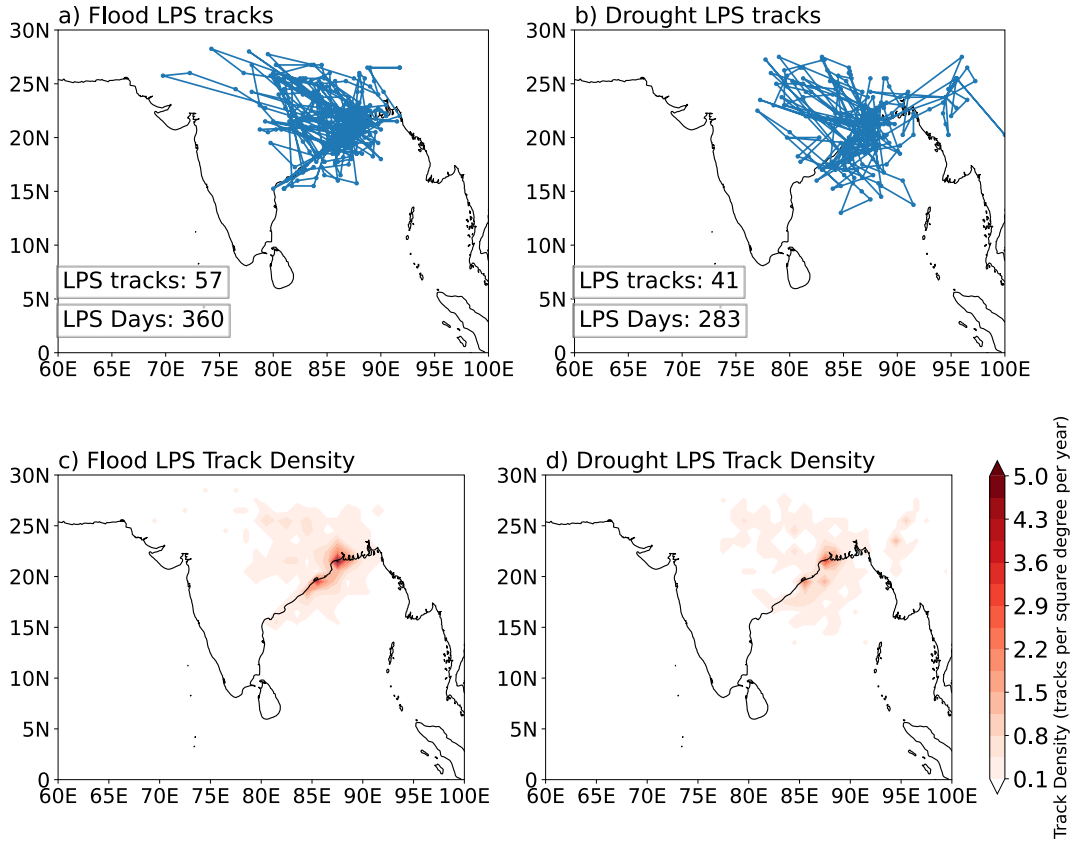


FIGURE 4.5: LPS tracks over IO during a)flood years b) drought years and LPS track density during c)flood years and d)drought using ERA5.

particularly relevant in light of the Indo-Western Pacific Ocean Capacitor (IPOC) mechanism proposed by [Xie et al. \[2016\]](#), which highlights a delayed ENSO influence on the southwest Indian Ocean (SWIO) through oceanic Rossby wave propagation and associated SST anomalies. While our regression patterns show a warming signal over the SWIO consistent with this framework, the associated atmospheric response over the Indian region, especially in terms of rainfall and low-level winds is weak or inconsistent. Similarly, it is worth noting that [Izumo et al. \[2008\]](#) showed that ENSO-related anomalies during the preceding winter can influence monsoon rainfall along the west coast of India, particularly through mechanisms involving western Arabian Sea upwelling. This suggests that although ENSO-related SST memory in the Indian Ocean is present, its capacity to modulate the subsequent summer monsoon

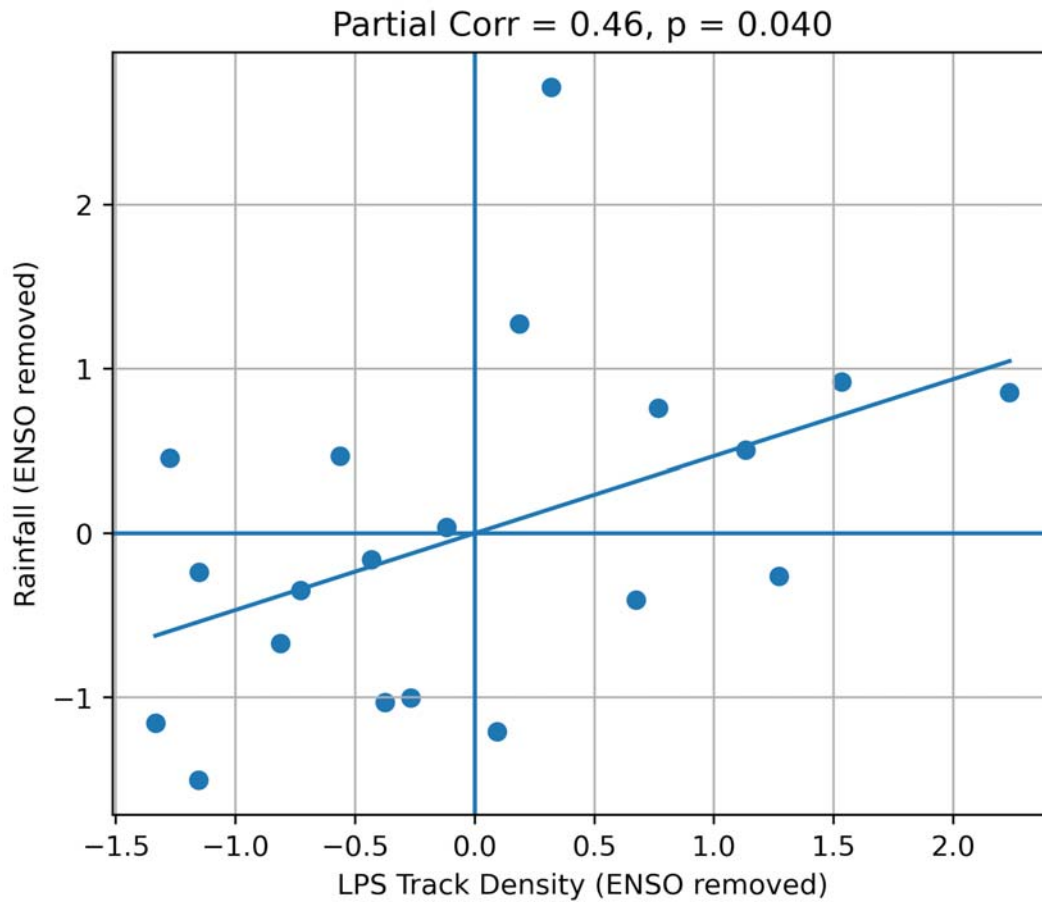


FIGURE 4.6: Scatter plot of JJAS rainfall anomalies (TRMM) and LPS track density anomalies (ERA5) after removing the influence of the DJF Niño3.4 index from both variables. Each point represents an individual year. The regression line (blue) indicates the overall positive tendency. The partial correlation coefficient and corresponding p-value are shown in the figure title (Partial Corr = 0.46, p = 0.040)

may be limited or masked by competing internal variability. It also highlights that the ENSO–monsoon teleconnection may exhibit spatial heterogeneity, with stronger lagged effects over specific regions. Therefore, it remains difficult to attribute interannual ISM rainfall fluctuations in the $\pm 10\%$ range solely to ocean–atmosphere coupling, underscoring the likely importance of internal atmospheric processes such as low-pressure system activity.

Other than the external drivers such as the ENSO, the internal monsoonal processes

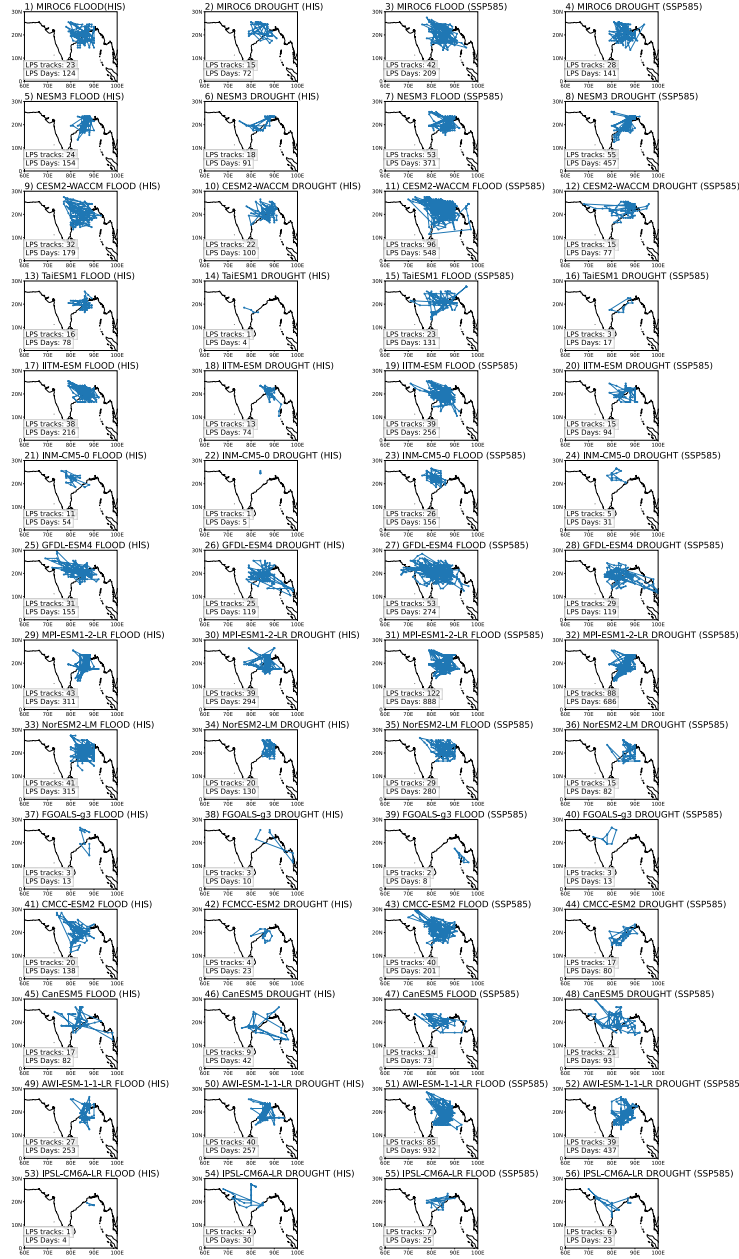


FIGURE 4.7: LPS tracks over IO during flood years and drought years for historical and SSP585 scenarios using CMIP6 models

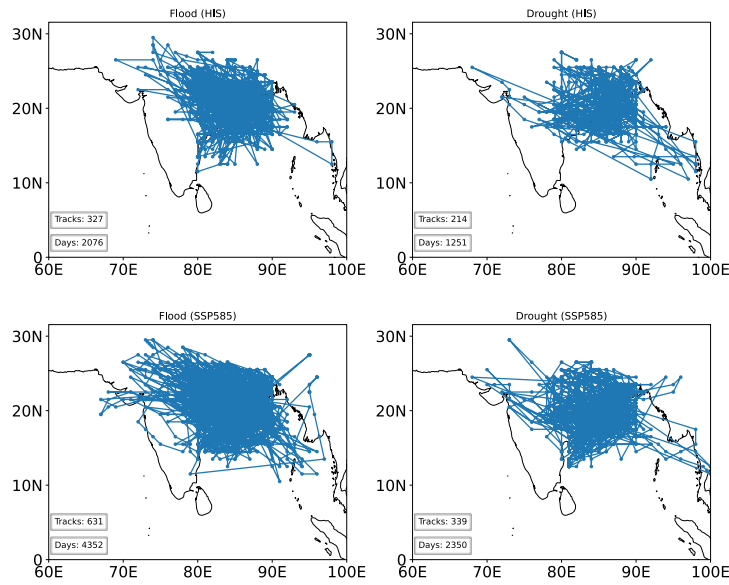


FIGURE 4.8: Multi model mean of LPS tracks over IO during flood years and drought years for historical and SSP585 scenarios

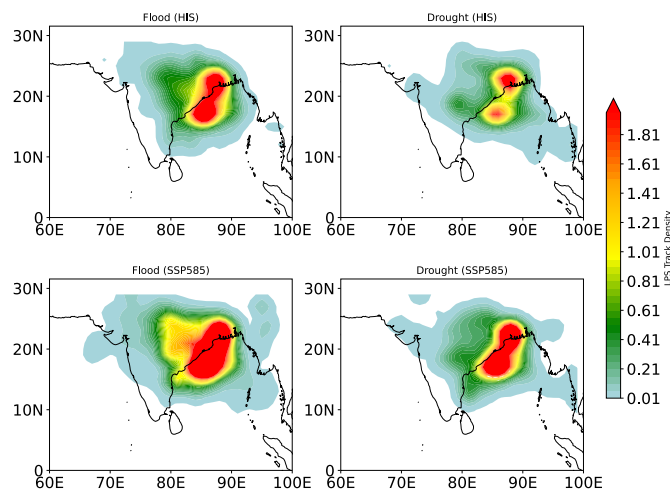


FIGURE 4.9: Multi model mean of LPS track density over IO during flood years and drought years for historical and SSP585 scenarios

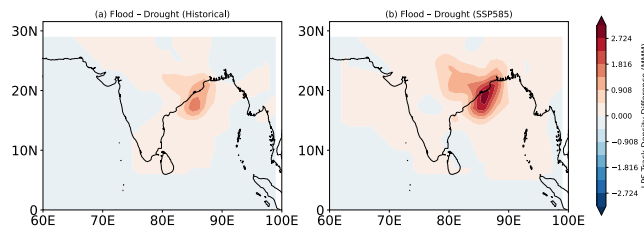


FIGURE 4.10: Multi-model mean LPS track density difference (Flood-Drought) for (a) historical and (b) SSP585 scenarios. Shaded regions indicate the magnitude of the difference, while hatched areas denote regions where the differences are statistically significant at the 95% confidence level based on bootstrap resampling across models.

such as the low-pressure system activity can also contribute to the interannual variability of ISM. Our analysis showed that, during drought monsoon years, on average the LPS genesis decreased by two storms per summer season. Also, the propagation of LPSs over continental India was incoherent in drought monsoon seasons compared to the flood monsoon seasons. These variabilities in LPS activity can substantially contribute to the ISM rainfall variability. Our analysis of low-level monsoon circulation suggest an increased advection from the northern Arabian Sea and the West Asian desert region towards the continental India. This might be another contributor to the ISM rainfall variability as suggested by earlier studies [[Singh and Sandeep, 2022, 2024](#)]. Thus, both internal and external factors contribute to the interannual variability of ISM rainfall. [Krishnan et al. \[2011\]](#) highlighted that monsoon LPS events, when coinciding with a positive Indian Ocean Dipole (IOD), enhance monsoon activity over the Indian subcontinent. As LPS are a component of sub-seasonal variability, understanding how sub-seasonal variability impacts the interannual variability of ISM remains an important area for future research.

Chapter 5

The Extreme Fluctuations of the ISM Interannual Variability in CMIP6 Future Simulations

5.1 Introduction

Despite numerous studies projecting changes in monsoon mean rainfall and short-duration extremes, the future behavior of extreme excess (EE) and extreme deficit (ED) rainfall events remains underexplored. Previous research often emphasizes mean or moderate anomalies, whereas events that exceed $\pm 10\%$ of seasonal mean rainfall, which carry the greatest socio-economic impacts, have received comparatively little attention. The uncertainty surrounding the occurrence and frequency of these extreme events in different future scenarios show EDs significant implications for the robustness of future climate risk assessments and the formulation of effective adaptation and mitigation strategies. This study focuses on the occurrence, frequency, and return periods of EE and ED under historical and future scenarios using Coupled Model Intercomparison Project Phase 6 (CMIP6) data. We further investigate the role of LPS and ENSO in modulating these extremes under changing climate conditions.

5.2 Datasets and Methodology

5.2.1 Datasets overview

The analysis utilizes monthly rainfall data from 25 CMIP6 models, selected based on their availability within the emission scenarios considered. The study examines historical simulations spanning 1930–2014, as well as future projections under SSP126, SSP245, and SSP585 scenarios [Van Vuuren *et al.*, 2014; O’Neill *et al.*, 2017] for the period 2015–2099. The Indian Meteorological Department yearly gridded rainfall data ($0.25^\circ \times 0.25^\circ$) [Pai *et al.*, 2014] used as a observation to validate models. For effective comparison, all models are regridded to a $0.25^\circ \times 0.25^\circ$ resolution to align with the observational dataset using bilinear interpolation. For each model and summer season, the mean monsoon rainfall is calculated by averaging the monthly rainfall data from June to September (JJAS) over central India (75°E – 85°E , 19°N – 26°N). To ensure uniformity, only one ensemble member (r1i1p1f1, when available) is utilized for each model, regardless of the availability of additional ensemble members. An overview of the modelling centres and their native spatial resolutions are provided in Table 2.1.

Daily gridded sea level pressure data is available for only 18 CMIP6 models from this list 2.1 and is used to track LPS during JJAS, while SST data from 20 models in this list (based on availability) is analyzed to study El Niño Southern Oscillation (ENSO).

5.2.2 Methods

Based on previous studies, excess and deficit events in the ISM are identified by calculating the percentage departure from the mean of JJAS precipitation. In

this study, we focus on EE and ED events. To determine these, we calculate thresholds based on the 90th percentile (Figure 5.2) of the percentage deviation of seasonal rainfall anomalies from the long-term mean averaged over central India (75–85°E, 19–26°N), using historical all-forcing runs and future climate projections from CMIP6 models. Specifically, the years in which the seasonal mean rainfall anomaly exceeds 90th percentile on the positive (negative) side are considered EE (ED) years. The thresholds derived for the historical scenario are consistently applied to future scenarios.

The return period of EEs and EDs is calculated using a generalized extreme value distribution (GEV) [Von Storch and Zwiers, 2002]. The GEV distribution is fitted to the annual maxima and minima of JJAS precipitation anomalies for floods and droughts, respectively. The probability distribution is parameterized by the location (μ), scale (σ), and shape (ξ) parameters, which are estimated using the maximum likelihood estimation method.

The return level for a specific return period is derived from the inverse cumulative distribution function of the GEV, expressed as:

$$x_T = \mu + \frac{\sigma}{\xi} \left[\left(-\ln \left(1 - \frac{1}{T} \right) \right)^{-\xi} - 1 \right], \quad \text{for } \xi \neq 0, \quad (5.1)$$

where ($\xi = 0$) corresponds to the Gumbel distribution and the return level simplifies to:

$$x_T = \mu - \sigma \ln \left(-\ln \left(1 - \frac{1}{T} \right) \right). \quad (5.2)$$

For each threshold corresponding to EE and ED events, the return periods are calculated by inverting the GEV cumulative distribution:

$$T = \frac{1}{1 - F(x)}, \quad (5.3)$$

This methodology ensures a consistent and robust determination of the recurrence intervals of extreme flood and drought events under both historical and future scenarios.

We used the tracking technique of [Praveen et al. \[2015\]](#) to follow the paths of LPS in the ERA-5 reanalysis data. Using gridded daily sea level pressure (SLP) data, this technique finds closed isobars at intervals of 1 hPa to detect and track LPS. Additionally, this technique uses the pressure depth (Δ SLP) to classify the LPS depending on their intensity category.

Niño 3.4 index is calculated using SST anomalies averaged over 5°N–5°S, 170°W–120°W, with a 5-month running mean applied.

5.3 Results and Discussion

5.3.1 Number and Return Period of EE and ED years over central India in Different CMIP6 Scenarios

The percentage deviation of summer monsoon (June–September) rainfall over central India (75–85°E, 19–26°N) was computed for the period 1930–2014. Green bars represent EE events, red bars indicate ED events, and blue bars denote normal years (Fig. 5.1). The Fig. 5.1 illustrates the results from the IMD gridded rainfall dataset, which records 5 EE and 5 ED events from 1930 to 2023. The mean threshold used for EE is 18.5% and ED is -22.4% by calculating the mean of deviations exceeding above and falling below the threshold and it is showed as histogram of JJAS

percentage of departure of rainfall anomalies and number during the time period of 1930-2023 in Fig. 5.2. For historical scenarios, data from 1930 to 2014 is analyzed, while for future projections under the SSP585, SSP245, and SSP126 scenarios, data from 2015 to 2099 is considered. The historical mean-based thresholds are applied uniformly to each model's future scenario simulations. Figure 5.2 shows the results for 25 CMIP6 models under historical conditions, and Figs 5.3, 5.4, 5.5, extend this analysis to future scenarios. The mean thresholds for EE and ED for each model are included in table 5.1. The multimodel mean of CMIP6 models shows 4.4 EE and 4.8 ED events, closely aligning with observations.

Figure 5.7 presents box-whisker plots of EE and ED event counts under historical and future scenarios. Detailed model-wise counts are provided in table 5.2. Blue boxes represent historical simulations, while orange, yellow, and pink boxes correspond to SSP126, SSP245, and SSP585, respectively. The historical medians for both EE and ED are 5. Under SSP126, the EE median remains comparable to historical levels (5 years) but exhibits greater inter-model spread, while the ED median decreases slightly (4 years). In SSP245, the EE median increases to 6 years and the ED median declines to 3 years, with considerable variability across models. Under SSP585, the EE median increases to 7 years, accompanied by pronounced inter-model uncertainty, highlighting a higher likelihood of extreme wet events under high-emission conditions. The ED median under SSP585 (5 years) remains comparable to the historical level, though with a considerably larger inter-model spread relative to lower emission scenarios.

EE and ED counts show relatively low variability across models during the historical period, with narrow interquartile ranges and constrained whiskers. Under SSP126, a low-emission pathway, the EE distribution remains centered near historical levels but with greater variability, while the ED median decreases slightly. SSP245

exhibits a further increase in EE frequency and a broader interquartile range, highlighting growing model uncertainty. In contrast, the ED median declines, pointing to a shift toward more floods and fewer droughts under moderate warming. SSP585 shows the most pronounced changes: both EE and ED medians increase, accompanied by wide interquartile ranges and extended whiskers, reflecting not only higher event frequency but also substantial inter-model disagreement. This indicates that while extreme events are projected to become more common under high-emission conditions, their magnitude and occurrence remain highly uncertain.

A clearer separation in the trajectories of floods and droughts emerges across emission scenarios. EE frequency increases consistently with warming, supported by thermodynamic mechanisms such as Clausius–Clapeyron scaling, which enhances the moisture-holding capacity of the atmosphere and intensifies convective rainfall. In contrast, ED trends are more variable. SSP126 shows little change from the historical period. SSP245 indicates fewer, but potentially longer-lasting, droughts. SSP585 projects a clear increase in drought frequency. This divergence highlights differing sensitivities of hydrological extremes to warming, with floods responding more directly to thermodynamic forcing, while droughts are shaped by complex interactions involving soil moisture memory, land–atmosphere feedbacks, and sea surface temperature (SST) variability.

The return period of EE and ED are calculated for historical and future scenarios. Figure 5.8 compares the return period for EE and ED years under four scenarios—Historical, SSP126, SSP245, and SSP585. The return period of EE and ED in each model for different scenarios is depicted in table 5.3.

The historical simulations provide a reference for understanding natural variability in flood and drought occurrences. The median return period for EE years in historical simulations is 17.23 years, while that for ED years is 19.77 years. The return

periods for EE years show a progressive decline across future scenarios, indicating that EE will become more frequent as global warming intensifies. Under SSP126, which represents a low-emission trajectory, the median return period for EEs remains close to the historical value at 15.74 years and remains nearly unchanged at 17.20 years in SSP245, and further decreases to 12.15 years in SSP585. This finding supports projections that intensified precipitation extremes under high greenhouse gas concentrations will enhance moisture transport and convective activity, leading to more frequent extreme rainfall events [[Menon et al., 2013](#); [Katzenberger et al., 2022](#)].

For ED events, the historical median return period is 19.77 years, increasing slightly to 21.00 years under SSP126, which suggests that droughts may become only marginally less frequent in a low-emission future. Under SSP245, the median return period rises further to 28.56 years, indicating a noticeable reduction in drought frequency, likely reflecting the interplay between warming-driven drying and enhanced rainfall variability. In contrast, SSP585 shows a decline in the median return period to 16.86 years, pointing to more frequent droughts under high-emission conditions. This outcome aligns with projections that stronger warming enhances evapotranspiration and decreases soil moisture, thereby intensifying the recurrence and severity of drought events.

The analysis reveals a clear contrast between EE and ED trends under different emission scenarios. While EE show a more consistent reduction in return periods across all future scenarios, droughts exhibit a more complex pattern, with SSP245 indicating prolonged but less frequent droughts, while SSP585 projects a clear increase in drought frequency. The interquartile range and presence of outliers in higher-emission scenarios highlight significant model variability, suggesting that some regions may experience even more extreme shifts in flood and drought frequencies.

The findings underscore the increasing hydroclimatic volatility expected under climate change, particularly in monsoon-dependent regions where the balance between wet and dry extremes is already fragile.

This analysis highlights scenario-dependent shifts in the return periods of EE and drought years, revealing the increasing frequency of extreme events under higher emissions. The return period for EEs decreases progressively across scenarios, with SSP585 showing the most significant increase in flood frequency, as indicated by a median return period of 15.90 years compared to 24.59 years historically. In contrast, the return periods for ED years exhibit a nonlinear pattern, with SSP245 suggesting longer but less frequent droughts, while SSP585 projects a clear increase in drought frequency, reducing the return period to 23.19 years compared to 28.62 years historically. These results reinforce concerns about the intensification of hydroclimatic extremes in a warming world.

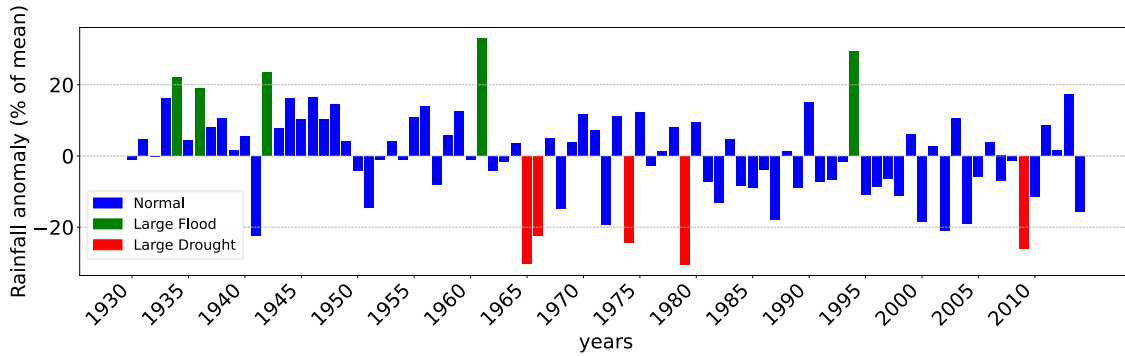


FIGURE 5.1: JJAS mean rainfall departure (in percentage) from IMD gridded rainfall data over Central India (75 °E – 85 °E and 19 °N – 26 °N) during 1930 to 2014

5.3.2 Relation between LPS and EE and ED years

Extreme rainfall events over central India are largely driven by synoptic-scale monsoon LPS, which frequently develop during the monsoon season [*Goswami et al.*,

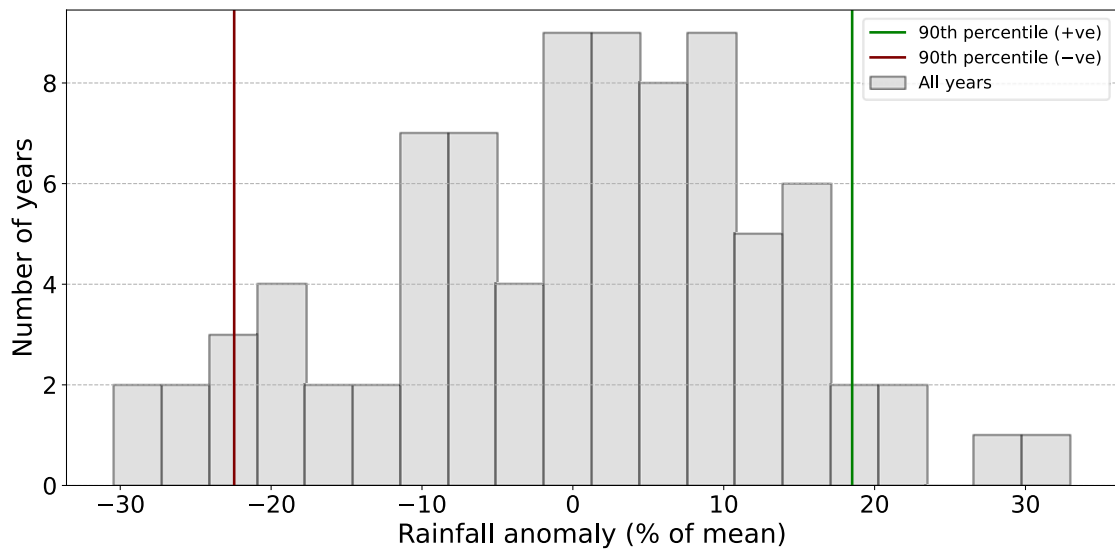


FIGURE 5.2: Histogram of JJAS percentage of departure of rainfall anomalies and number of years with extreme excess and extreme deficit threshold during the time period of 1930-2023 from IMD Rainfall data.

2006; Sikka, 2006]. Nearly 50% of the total monsoon season rainfall is attributed to these systems, making them a major contributor to seasonal precipitation [Yoon and Chen, 2005]. The increased frequency of extreme rainfall events in central India is linked to a simultaneous rise in synoptic-scale activity driven by LPS over the region [Ajayamohan *et al.*, 2010]. Ajayamohan *et al.* [2010] also quantify that the rise in weak monsoon lows contributes more significantly to synoptic activity than stronger monsoon storms and depressions. They further report that LPS-related extreme rainfall events increased by 22% between 1951 and 2003, while non-LPS-related events rose by only 2.5%.

The LPS activity during EE and ED years is analyzed to understand the role of monsoon sub-seasonal variability in driving EE and ED events. Figure 5.9 a and b shows the multimodel track density composites of LPS for EE and ED in the historical scenario. The historical EF composite exhibits 5 ± 0.36 LPS tracks per square degree per year, while the ED composite shows 3.7 ± 0.38 LPS tracks per square degree per year during the ISM period. Figure 5.9c) shows the difference between EE and ED

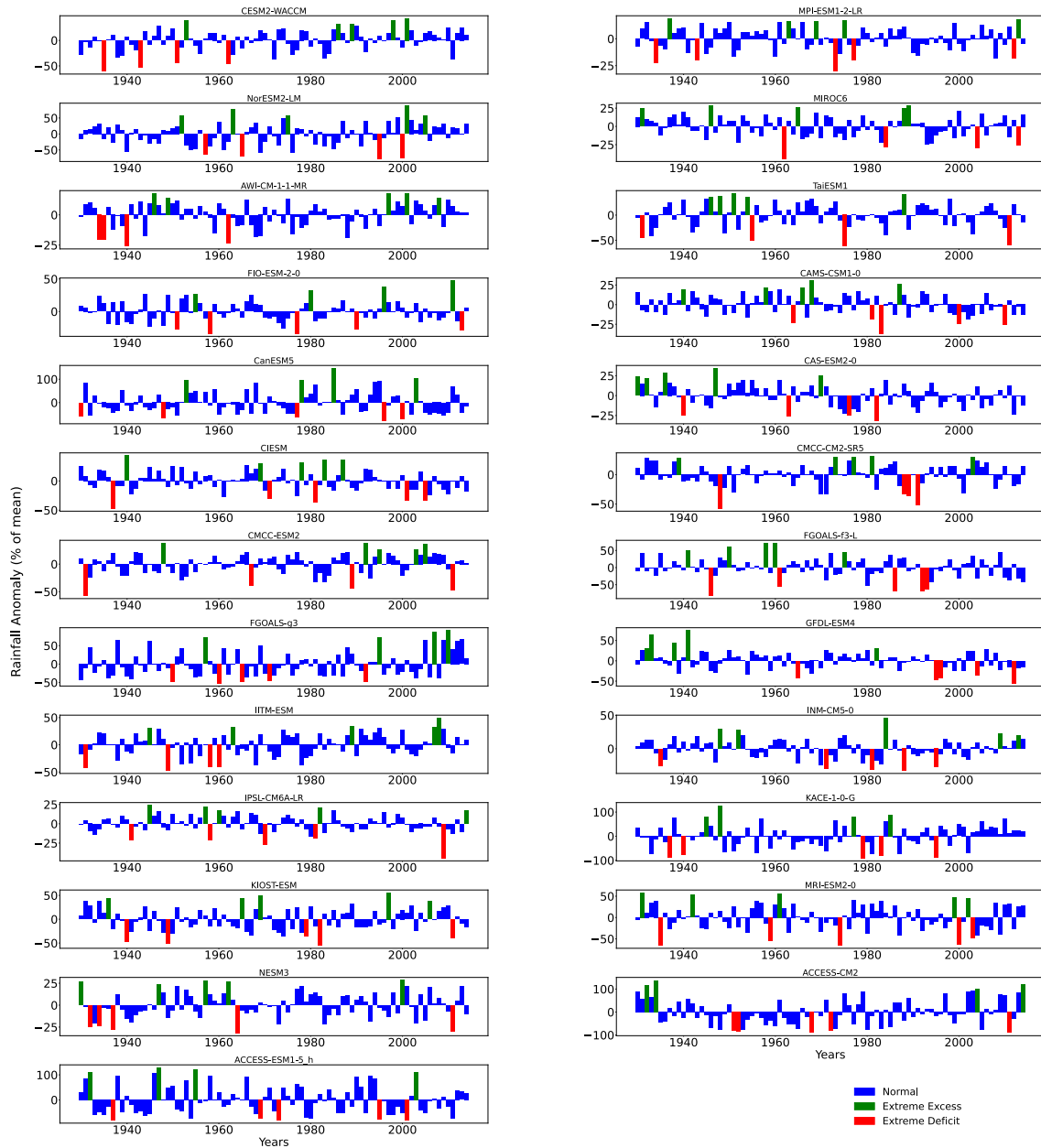


FIGURE 5.3: JJAS mean rainfall departure (in percentage) in CMIP6 Models over Central India (75 °E – 85 °E and 19 °N – 26 °N) for Historical during 1930 to 2014.



FIGURE 5.4: JJAS mean rainfall departure (in percentage) in CMIP6 Models over Central India (75 °E – 85 °E and 19 °N – 26 °N) for SSP126 during 2015 to 2099.

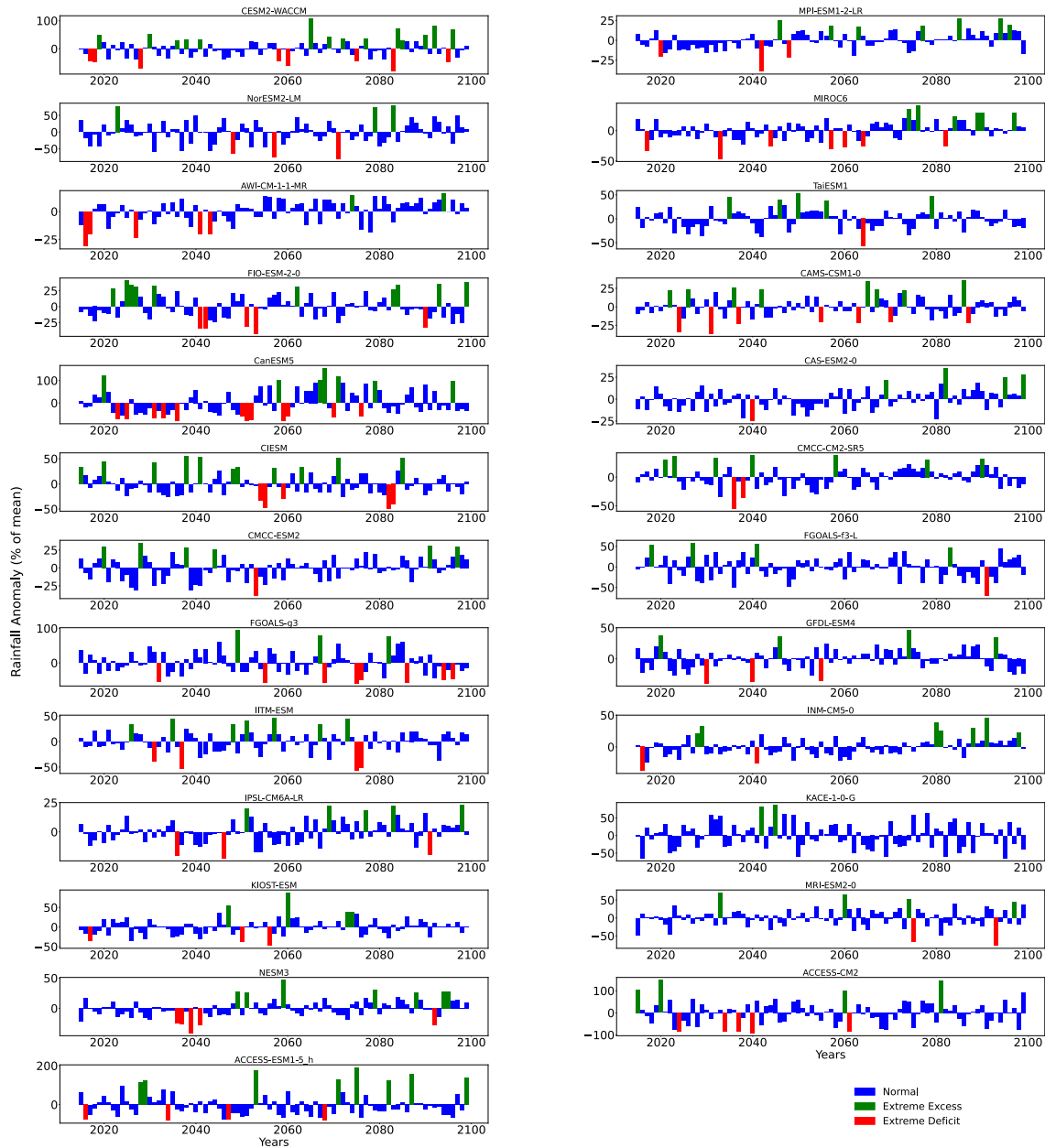


FIGURE 5.5: JJAS mean rainfall departure (in percentage) in CMIP6 Models over Central India (75 °E – 85 °E and 19 °N – 26 °N) for SSP245 during 2015 to 2099 .

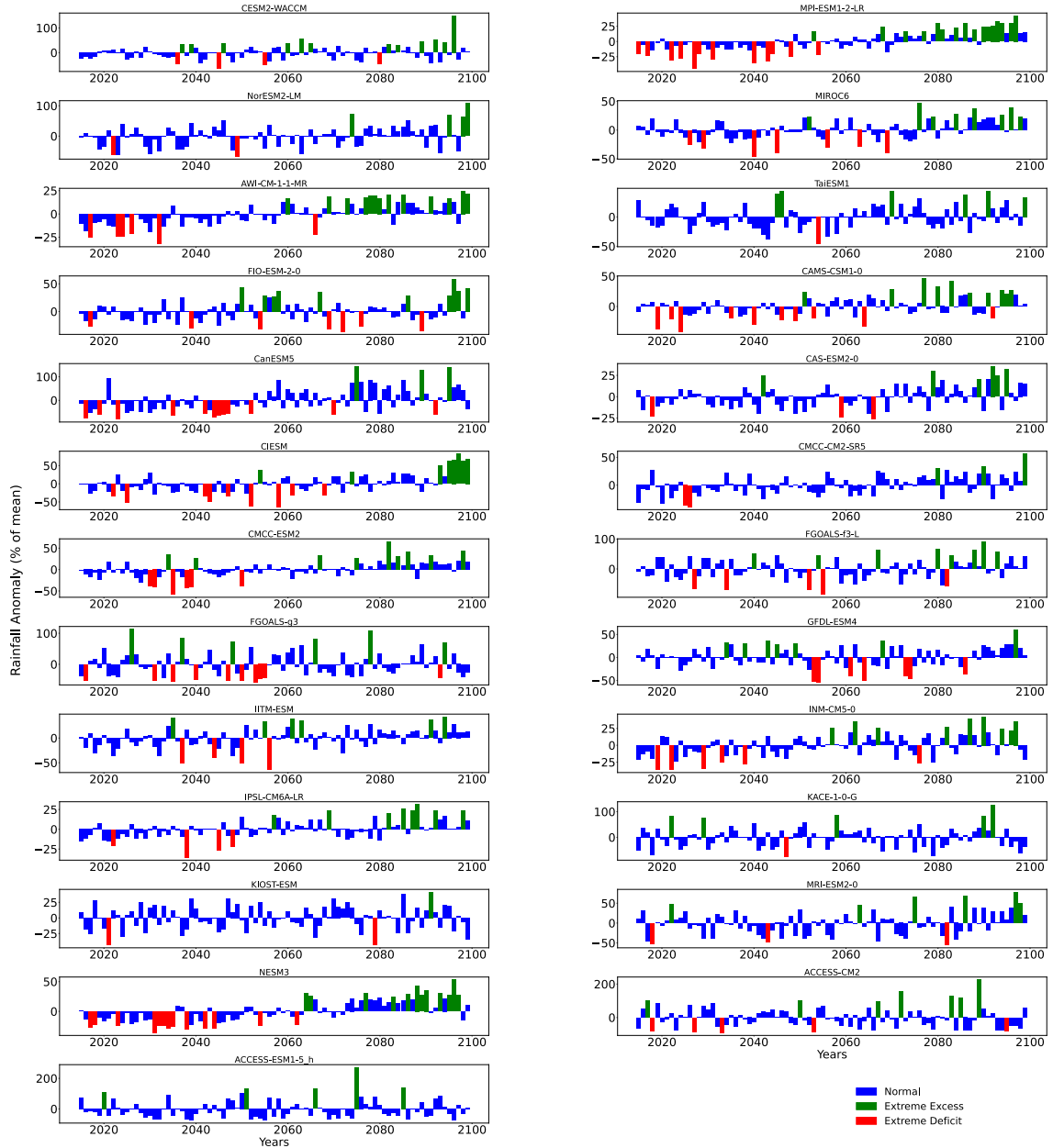


FIGURE 5.6: JJAS mean rainfall departure (in percentage) in CMIP6 Models over Central India (75 °E – 85 °E and 19 °N – 26 °N) for SSP585 during 2015 to 2099 .

TABLE 5.1: EE and ED mean thresholds for IMD rainfall data and CMIP6 models

Sl. No.	Model/Observation	EE Mean Threshold (%)	ED Mean Threshold (%)
1	IMD	18.50	-22.40
2	CESM2-WACCM	29.08	-41.16
3	MPI-ESM1-2-LR	16.05	-18.55
4	NorESM2-LM	54.65	-61.02
5	MIROC6	22.68	24.52
6	AWI-CM-1-1-MR	13.83	-19.13
7	TaiESM1	33.55	-42.89
8	FIO-ESM-2-0	26.54	-26.96
9	CAMS-CSM1-0	19.58	-18.57
10	CanESM5	93.25	-55.39
11	CAS-ESM2-0	20.47	-23.32
12	CIESM	29.84	-30.04
13	CMCC-CM2-SR5	28.16	-33.64
14	CMCC-ESM2	23.37	-35.05
15	FGOALS-f3-L	44.90	-54.06
16	FGOALS-g3	69.00	-43.42
17	GFDL-ESM4	29.42	-35.56
18	IITM-ESM	31.14	-38.44
19	INM-CM5-0	20.05	-24.95
20	IPSL-CM6A-LR	17.57	-17.58
21	KACE-1-0-G	77.64	-77.64
22	KIOST-ESM	38.26	-35.57
23	MRI-ESM2-0	43.43	-48.09
24	NESM3	23.81	-22.60
25	ACCESS-CM2	95.56	-80.66
26	ACCESS-ESM1-5	108.19	-76.20

composite and the moderate increase in LPS activity during EE years indicates that EEs over central India are supported by a higher number of LPS compared to EDs. Furthermore, EE years display a coherent northwestward propagation of LPS into the Indian land region, whereas ED years exhibit reduced northward propagation and a more prominent eastward propagation of LPS away from the Indian landmass. This finding is consistent with [Krishnamurthy and Ajayamohan \[2010\]](#), who reported that during flood monsoon years, LPS tracks extend as far as northwest India, while in drought years, they remain limited to central India. According to [Sandeep et al.](#)

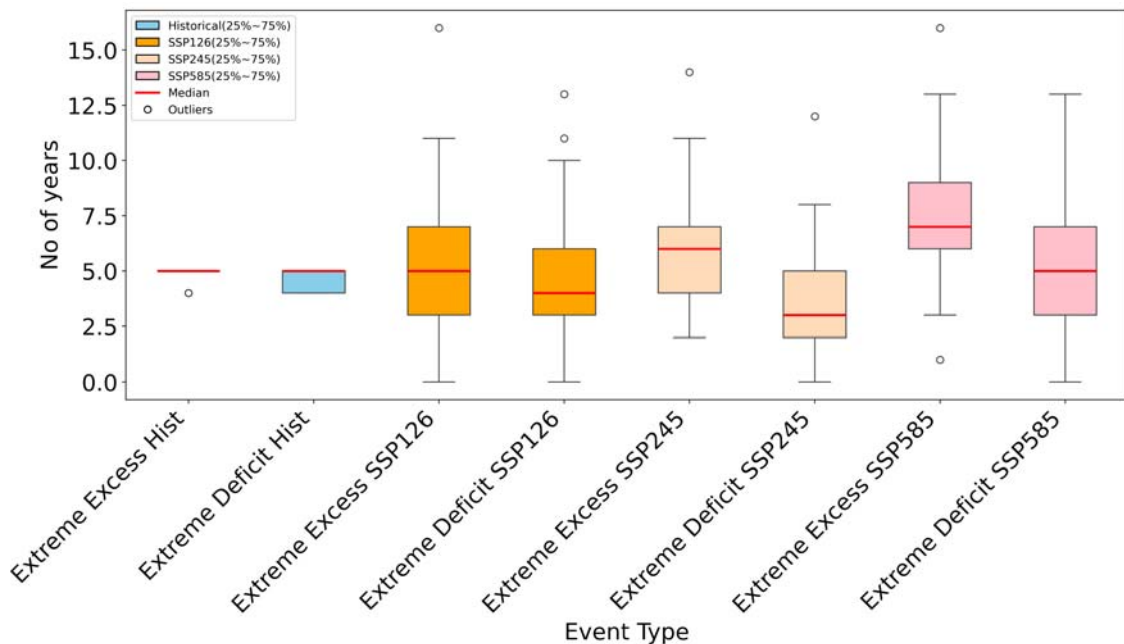


FIGURE 5.7: Box-whisker plot of the number of extreme excess (EE) and extreme deficit (ED) years across CMIP6 models under historical, SSP126, SSP245, and SSP585 scenarios. The boxes represent the interquartile range (25th–75th percentile), the red line denotes the median, the whiskers extend to 1.5 times the interquartile range, and open circles indicate outliers.

[2018], the poleward shift in LPS activity is linked to a rise in precipitation extremes over northern India. This reduced northward propagation and enhanced eastward propagation of LPS can be attributed as a key factor contributing to ED occurrences over central India.

we computed composites of JJAS mean rainfall for EE and ED years and their difference using CMIP6 historical simulations for the period of 1930–2014, which revealed that EE years exhibit significantly higher precipitation over central India - a region strongly influenced by LPS compared to ED years (Figure 5.10). Moreover, we analyzed JJAS precipitation composites for LPS-active and LPS-less-active years and their difference using the multimodel mean of CMIP6 historical simulations (Figure 5.11). To identify these years, we constructed a time series of LPS days during the monsoon season (June–September) based on a historical track dataset. A day was

TABLE 5.2: Number of extreme excess (EE) and extreme deficit (ED) years for IMD and CMIP6 models under historical and future scenarios.

Sl. No.	Model/Observation	Extreme Excess Years				Extreme Deficit Years			
		Hist.	SSP585	SSP245	SSP126	Hist.	SSP585	SSP245	SSP126
1	IMD	5				5			
2	CESM2-WACCM	5	12	14	16	4	4	8	11
3	MPI-ESM1-2-LR	5	16	7	7	5	12	3	4
4	NorESM2-LM	5	4	3	1	4	2	3	4
5	MIROC6	5	8	6	10	4	7	7	8
6	AWI-CM-1-1-MR	5	13	2	2	4	6	5	3
7	TaiESM1	5	6	5	5	4	1	1	1
8	FIO-ESM-2-0	4	10	10	5	5	7	5	3
9	CAMS-CSM1-0	5	10	8	6	5	10	7	5
10	CanESM5	4	3	7	8	5	12	12	13
11	CAS-ESM2-0	5	6	4	2	4	3	1	4
12	CIESM	5	8	11	8	5	9	5	10
13	CMCC-CM2-SR5	5	3	7	6	4	2	2	4
14	CMCC-ESM2	5	9	6	6	4	6	1	1
15	FGOALS-f3-L	5	8	4	3	5	5	1	2
16	FGOALS-g3	4	6	3	4	5	10	8	8
17	GFDL-ESM4	5	7	4	8	5	7	3	2
18	IITM-ESM	5	6	7	7	4	4	4	3
19	INM-CM5-0	5	9	7	11	5	6	2	3
20	IPSL-CM6A-LR	5	8	5	4	5	4	3	6
21	KACE-1-0-G	4	5	2	0	5	1	0	0
22	KIOST-ESM	5	1	4	1	5	2	3	2
23	MRI-ESM2-0	5	6	4	7	5	3	2	6
24	NESM3	5	12	7	4	5	13	5	7
25	ACCESS-CM2	4	7	4	3	5	5	5	3
26	ACCESS-ESM1-5	4	5	8	5	5	0	4	5

classified as an "LPS day" if any low-pressure system was present over the Indian region according to the synoptic track data. For each year, the total number of LPS days was computed based on unique daily occurrences. Years with LPS day counts exceeding one standard deviation above the climatological mean were classified as LPS-active, while those with counts more than one standard deviation below the mean were considered LPS-less-active. This methodology, widely used in monsoon diagnostics, effectively captures both the frequency and persistence of LPS activity and provides a robust framework to examine their linkage with seasonal rainfall. Our analysis shows that LPS-active years are associated with high precipitation over Central India, while LPS-less-active years show markedly reduced rainfall, further underscoring the critical role of LPS in modulating monsoon extremes.

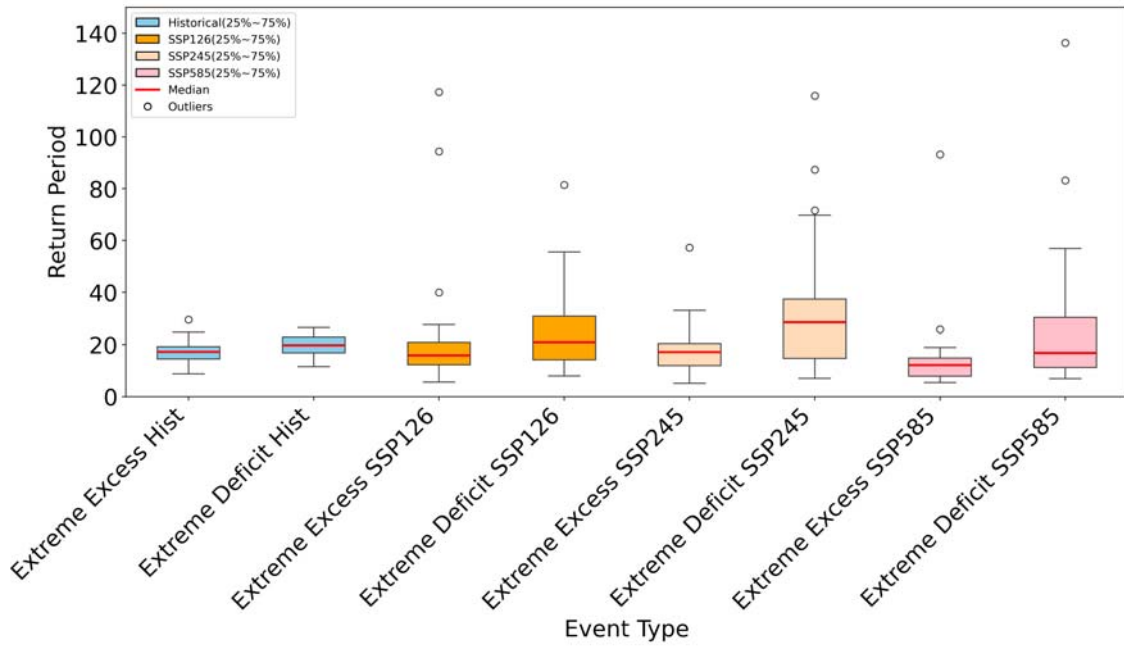


FIGURE 5.8: Box-whisker plot of the return periods (in years) of extreme excess (EE) and extreme deficit (ED) monsoon events across CMIP6 models under historical, SSP126, SSP245, and SSP585 scenarios. The boxes represent the interquartile range (25th–75th percentile), the red line denotes the median, the whiskers extend to 1.5 times the interquartile range, and open circles indicate outliers.

In future projections, the number of LPS tracks per year decreases by 3.27% during EE events and by 7.69% during ED events compared to historical events (Figure 5.12). To compare LPS tracks across the historical and SSP585 scenarios, they are normalized by the respective number of years in each scenario. The difference between the LPS tracks formed during EE and ED during historical and SSP585 is comparatively less and not considerable (Figure 5.9 a and b).

5.3.3 Examination of coincidence of ENSO with EE and ED years

Thirumalai et al. [2024] reported that a shallower mixed layer and a weakened Walker circulation contribute to an increased frequency of extreme El Niño events under

TABLE 5.3: Return period (years) of extreme excess (EE) and extreme deficit (ED) events for IMD and CMIP6 models under historical and future scenarios.

Sr. No.	Model/Observation	Extreme Excess Years Return Period				Extreme Deficit Years Return Period			
		Hist.	SSP585	SSP245	SSP126	Hist.	SSP585	SSP245	SSP126
1	IMD	22.17				24.47			
2	CESM2-WACCM	12.67	6.04	5.13	5.63	26.06	17.41	9.68	11.20
3	MPI-ESM1-2-LR	23.44	5.44	11.04	13.16	16.04	6.91	17.14	17.49
4	NorESM2-LM	15.63	14.75	19.13	39.97	22.98	36.47	31.63	24.32
5	MIROC6	21.59	8.84	11.38	8.72	16.87	11.22	14.73	12.56
6	AWI-CM-1-1-MR	15.43	7.57	27.10	18.96	22.52	14.78	23.02	29.40
7	TaiESM1	18.47	18.93	17.48	20.89	22.18	136.27	71.59	81.44
8	FIO-ESM-2-0	16.23	10.45	11.98	19.42	26.44	16.15	13.89	16.77
9	CAMS-CSM1-0	15.08	7.89	11.19	18.38	12.11	7.74	10.81	13.28
10	CanESM5	20.00	17.86	13.34	13.43	11.54	9.19	7.03	7.94
11	CAS-ESM2-0	13.94	14.26	20.27	14.24	23.06	42.08	87.34	25.87
12	CIESM	20.62	6.76	9.77	10.02	21.26	7.38	12.89	8.92
13	CMCC-CM2-SR5	29.49	14.91	18.33	11.19	18.28	56.93	31.81	20.52
14	CMCC-ESM2	9.05	6.81	14.17	13.62	22.77	23.83	59.07	55.55
15	FGOALS-f3-L	13.67	9.46	24.79	27.59	25.69	16.86	41.98	40.23
16	FGOALS-g3	17.23	16.56	33.03	16.38	16.00	9.79	11.85	9.95
17	GFDL-ESM4	8.80	9.13	20.41	11.62	19.77	15.62	69.77	30.80
18	IITM-ESM	14.50	15.80	13.72	12.25	25.39	22.07	23.89	21.00
19	INM-CM5-0	9.82	7.77	10.50	9.99	24.28	14.09	37.44	21.44
20	IPSL-CM6A-LR	18.52	12.15	23.37	15.94	13.49	14.43	30.00	16.14
21	KACE-1-0-G	18.49	25.73	57.25	117.33	22.38	83.16	115.90	233.72
22	KIOST-ESM	18.30	93.18	17.20	94.35	14.56	30.34	36.06	39.62
23	MRI-ESM2-0	17.10	13.02	18.05	12.97	17.23	26.70	32.61	14.49
24	NESM3	24.68	8.87	14.20	23.19	17.21	9.09	16.46	14.16
25	ACCESS-CM2	17.31	12.84	22.02	21.63	17.21	17.58	21.04	32.12
26	ACCESS-ESM1-5	19.25	14.65	14.93	16.11	17.16	39.62	28.56	23.17

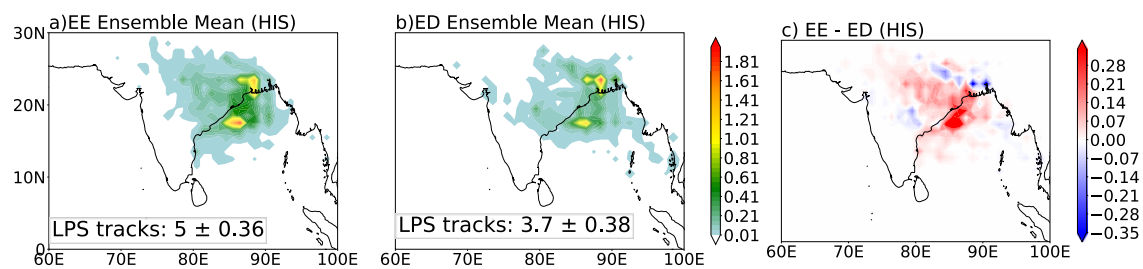


FIGURE 5.9: a-b) Multi model LPS track density composite for extreme excess and extreme deficits for the historical scenario (1930-2014), c) difference between extreme excess and extreme deficit multi model composite of LPS. Unit- Tracks per square degree per year.

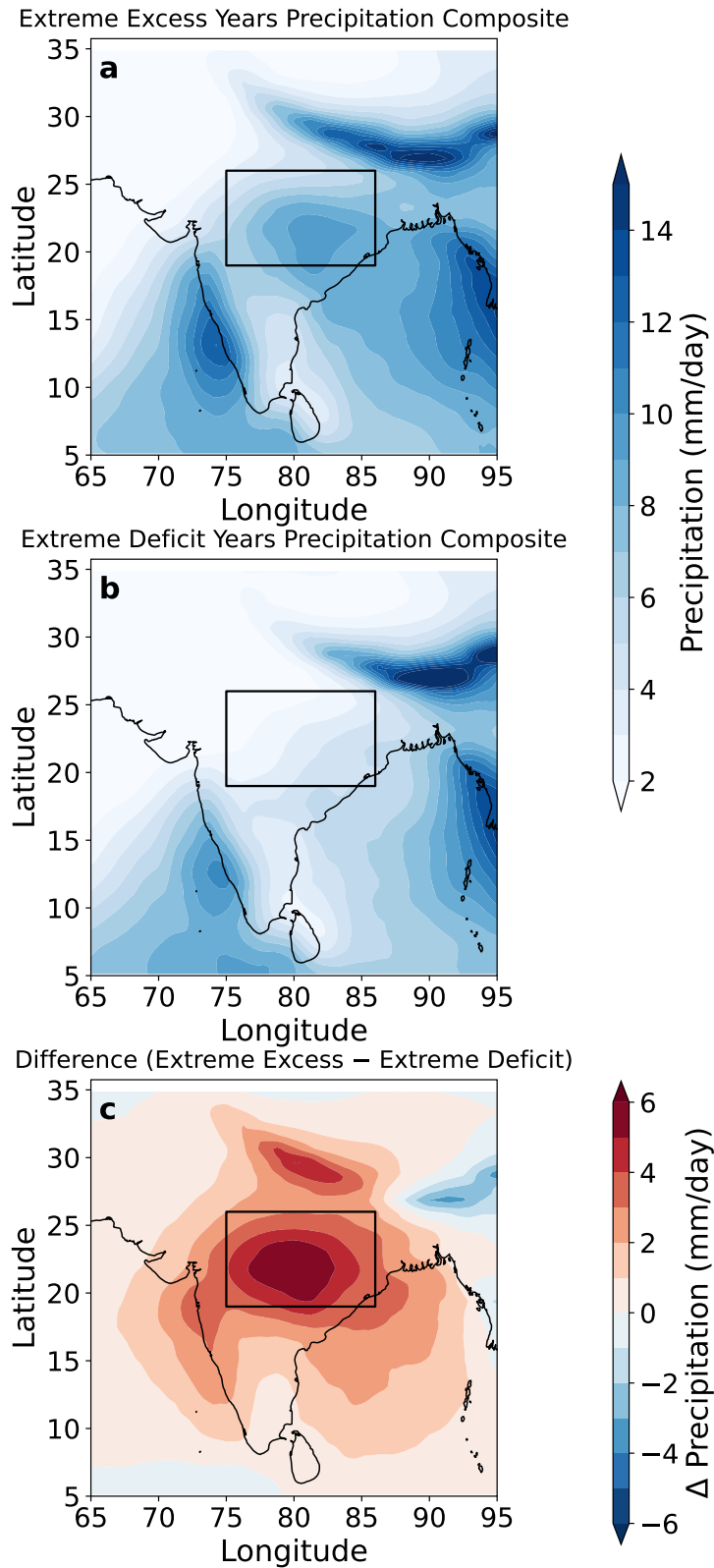


FIGURE 5.10: Multimodel mean composite for a) extreme excess years JJAS precipitation, b) extreme deficit years JJAS precipitation, c) Difference between extreme excess and extreme deficit composite, using CMIP6 historical simulations during the time period of 1930-2014. Hatching in panel (c) indicates regions where the difference is statistically significant at the 95% confidence level based on a bootstrap permutation test. The black box denotes the core monsoon zone (75-86°E, 19-26°N)

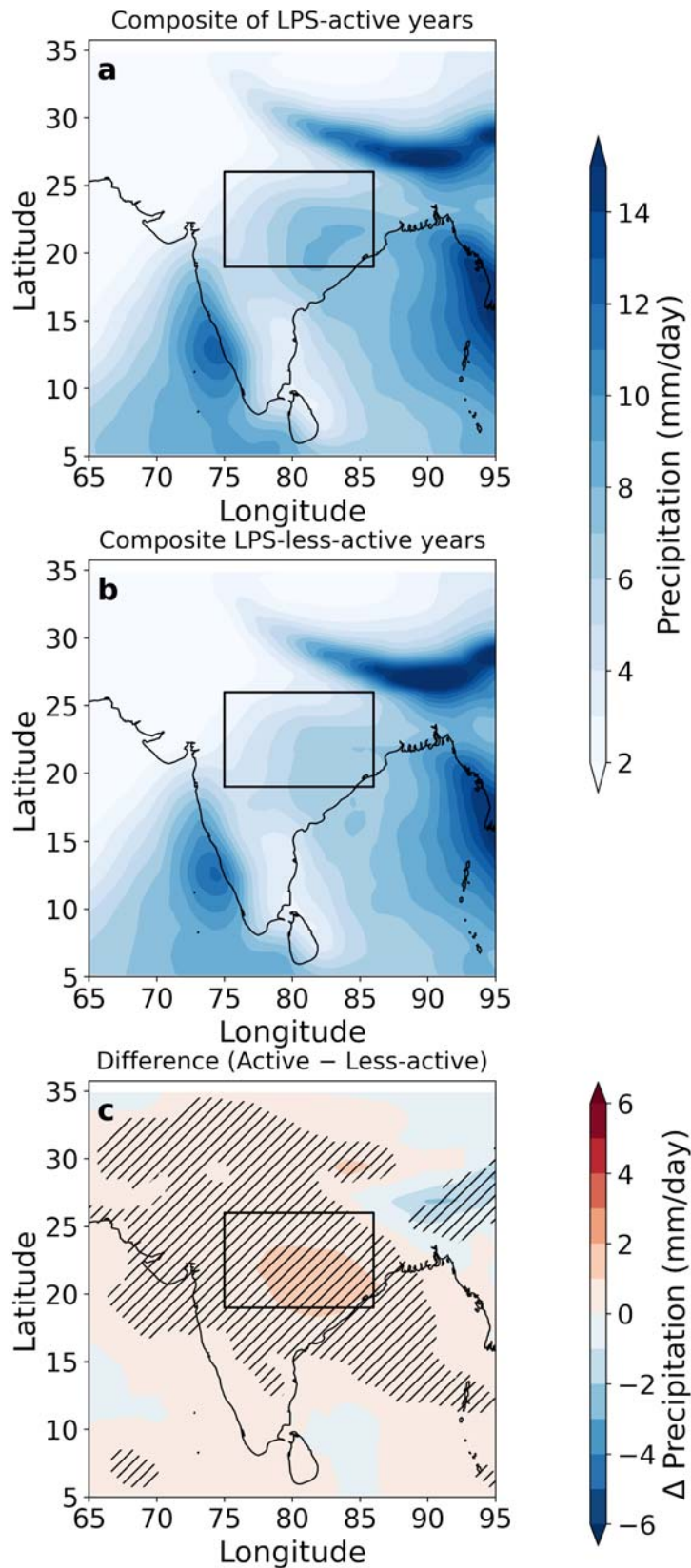


FIGURE 5.11: Multimodel mean composite for a) LPS-active years JJAS precipitation, b) LPS-less-active years JJAS, c) difference between LPS-active years and LPS-less-active years precipitation using CMIP6 historical simulations during the time period of 1930-2014. Hatching in panel (c) indicates regions where the difference is statistically significant at the 95% confidence level based on a bootstrap permutation test. The black box denotes the core monsoon zone (75-86°E, 19-26°N)

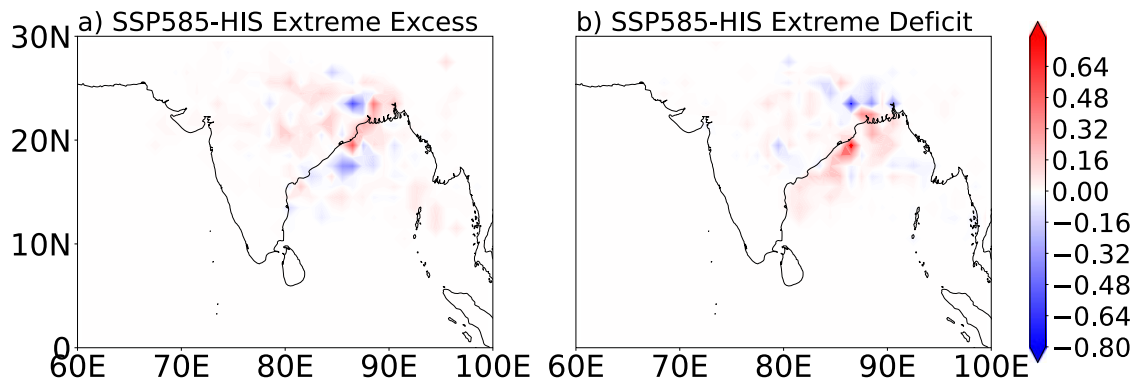


FIGURE 5.12: a) Difference between SSP585 and historical extreme excess multimodel LPS track density composite, b) Same for extreme deficit. Unit- Tracks per square degree per year.

greenhouse warming. To analyze ENSO occurrences in climate models, the Niño3.4 index was calculated for each model, and the total number of years falling within different Niño3.4 bins was determined, as shown in Figure 5.13, for both historical and SSP585 scenarios. The distribution of events reveals a distinct shift in frequency under the SSP585 scenario compared to the historical period. The number of events in moderate to extreme El Niño (positive Niño3.4) and La Niña (negative Niño3.4) categories appears to change, indicating a potential alteration in ENSO variability under future warming. Specifically, extreme El Niño events ($\text{Niño3.4} > 2.5$) are more frequent under SSP585, suggesting an intensification of ENSO extremes in a warmer climate. Conversely, moderate La Niña events ($\text{Niño3.4} < -1.5$) appear to show variations in occurrence, which may imply asymmetric responses of ENSO phases to greenhouse forcing. Moderate ENSO events are projected to decrease under future scenarios of greenhouse warming compared to the historical period, while extreme ENSO events are expected to increase. In the SSP585 scenario, the number of neutral years ($-0.5 \leq \text{Niño3.4} \leq 0.5$) appears to decline, suggesting that ENSO variability is shifting toward more frequent extreme events, with stronger El Niño and La Niña episodes under future warming.

To analyze the relationship between ENSO events and EE/ED occurrences, the probability of EE and ED within each Niño3.4 bins was calculated. Figure 5.14 illustrates the probability or relative frequency of EE and ED in historical Niño3.4 anomaly bins. To quantify the uncertainty in the estimated probabilities of large flood and drought years across Niño 3.4 index bins, 95% confidence intervals (CIs) were computed for each bin. These intervals provide a statistical range within which the true probability is likely to lie with 95% confidence and this confidence interval depicted as error bars in the plot. These findings are further supported by the highly significant chi-square test results ($p < 0.0001$), indicating that the distribution of flood and drought probabilities across ENSO phases deviates significantly from a uniform distribution. EE occurrence is more frequent in moderate La Niña bins (e.g., -2 to -1.5 and -1.5 to -1), reaching approximately 10–15%, consistent with the enhanced rainfall typically associated with La Niña. In contrast, ED shows a higher probability in moderate to extreme El Niño bins. However, in extreme El Niño bins, the presence of large error bars indicates uncertainty in these estimates. Overall, La Niña conditions tend to favor EE, while El Niño favors ED.

Interestingly, in the SSP585 scenario (Figure 5.15), EE occurrences increase in El Niño bins compared to La Niña bins. While historical data clearly show more EE events during La Niña and more ED events during El Niño, this relationship appears to shift in the future, introducing greater uncertainty. The increased presence of EE under El Niño conditions in SSP585 aligns with findings from previous studies [Cai *et al.*, 2014b]. The increase in the number of EE events and the decrease in their return period under the SSP585 scenario (Figure 5.8) can be attributed to the rise in EE occurrences during El Niño years. The reported increase in El Niño events may have contributed to the higher frequency of EE events, likely driven by greenhouse warming. The increase in ED events during La Niña, compared to EE, highlights

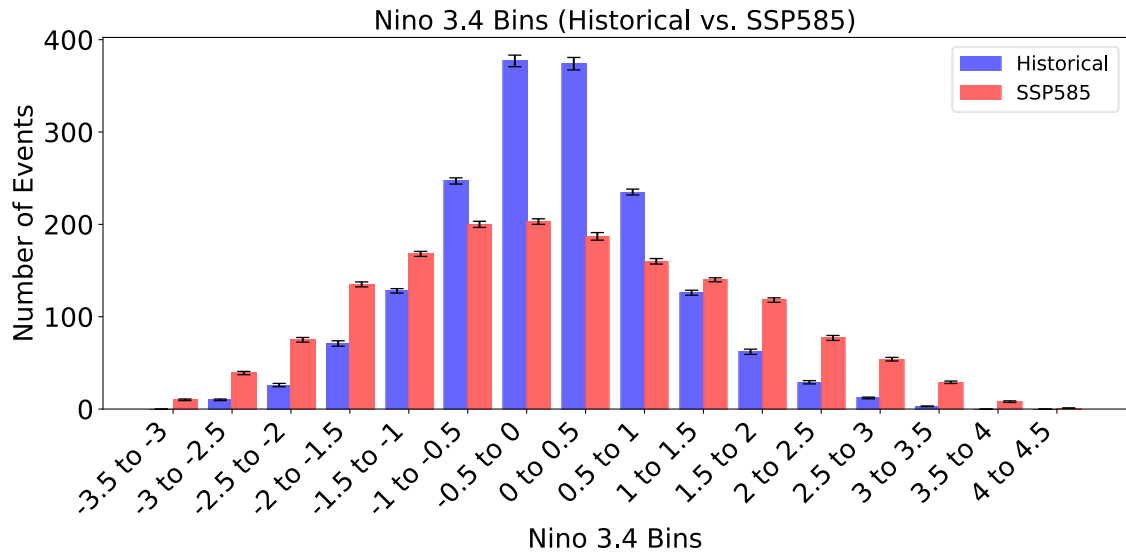


FIGURE 5.13: Frequency of Niño3.4 index in different intensity intervals in historical and SSP585 simulations across all models

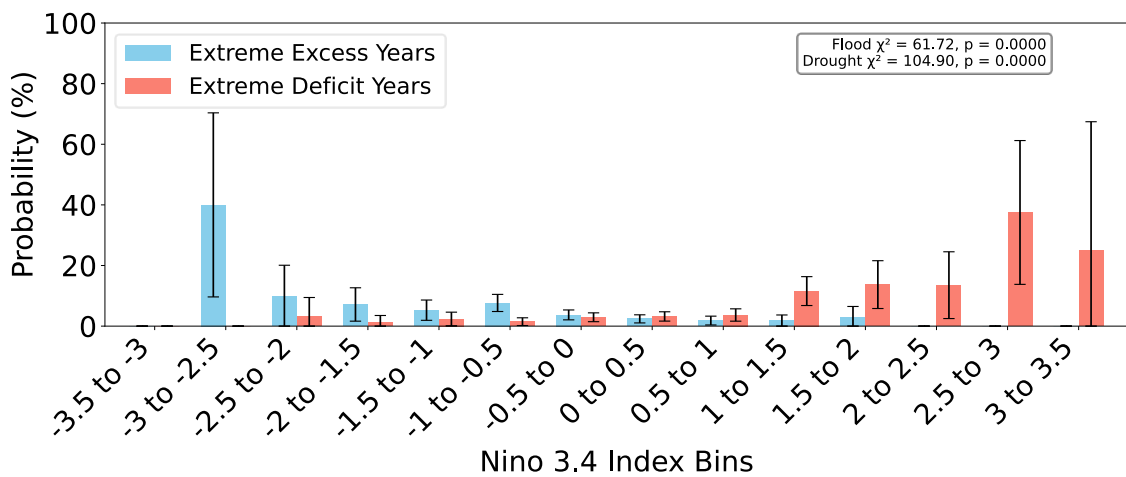


FIGURE 5.14: Probability of occurrences of extreme excess and extreme deficit as a function of Niño3.4 strength in historical simulations.

the uncertainty surrounding the factors driving extreme events in future warming scenarios.

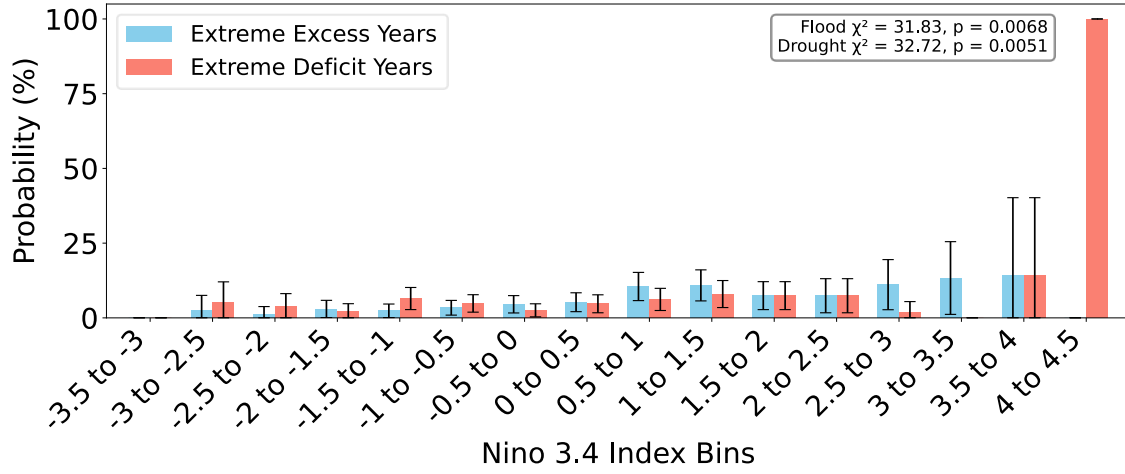


FIGURE 5.15: Probability of occurrences extreme excess and extreme deficit as a function of Niño3.4 strength in SSP585 simulations.

5.4 Discussion

In this study, we use CMIP6 models to analyze the number and return period of the EE and ED and their relationship with the LPS and ENSO. The CMIP6 multimodel ensemble captures the frequency of large floods and droughts during the historical period reasonably well, corroborating IMD observations. This alignment suggests that the models are sufficiently skillful for future projection analysis. The biases in the model simulations are not quantified in this study, which is a constraint. We found that the increase in EE count and decrease in its return period over central India in future scenarios, compared to ED occurrences, suggests that future climates are likely to experience more frequent wetter seasons. Several previous studies have reported intensifying trends of wet seasons under future warming scenarios [*Kamizawa and Takahashi, 2018; Sharmila et al., 2015*]. It is widely recognized that the warming Indian Ocean contributes to the observed trend by increasing atmospheric moisture content, leading to enhanced moisture convergence over the region [*Singh et al., 2019; Cherchi et al., 2011; Mei et al., 2015; Seth et al., 2013; Sooraj et al., 2015*]. The decline in return periods for EE events under SSP245 and

SSP585 supports earlier findings that increased atmospheric moisture and intensifying monsoon variability under warming conditions may drive more frequent extreme rainfall [[Menon et al., 2013](#); [Katzenberger et al., 2022](#)]. The increased frequency of EE events in future scenarios is consistent with Clausius-Clapeyron scaling, which predicts enhanced moisture-holding capacity of a warmer atmosphere and more intense convective precipitation. This result is particularly evident in SSP585, where EE return periods fall sharply, reflecting a more flood-prone future.

However, despite this general trend, a critical issue that emerges is the increasing inter-model spread and ensemble variability, particularly in the SSP245 and SSP585 scenarios. The widening of the interquartile range and the extended whiskers in box-whisker plots [Figure 5.7](#) and [Figure 5.8](#) point to heightened uncertainty in projecting future hydroclimatic extremes. This variability implies that while models agree on an overall increase in EEs and complex changes in EDs, the magnitude and spatial manifestation of these changes are highly model-dependent. Such divergence suggests that internal climate variability and differing model sensitivities to warming play a substantial role in modulating extreme precipitation and dry spells, making regional projections less robust.

The uncertainty is even more evident in the simulation of ED events. While SSP126 and SSP245 scenarios suggest either similar or longer return periods for droughts, indicating less frequent but possibly more persistent droughts, the SSP585 scenario reverses this trend, projecting more frequent EDs with a return period of 12.15 years. This nonlinear response points to the intricate nature of drought formation, which depends not only on precipitation deficits but also on warming-induced evapotranspiration, changes in land-atmosphere coupling, and soil moisture dynamics [[Dai, 2013](#)]. The inconsistencies in ED trends across scenarios and models reflect the difficulty in capturing these feedbacks in global models, contributing to uncertainty.

An additional caveat relates to the relatively coarse spatial resolution of CMIP6 models (~ 100 km), which may limit their ability to capture sub-grid scale processes critical for simulating extremes. Recent advances in high-resolution Earth system modeling demonstrate substantial improvements in representing such events. For example, the high-spatial resolution Community Earth System Model (CESM-HR) reproduces observed temperature skewness and more realistically simulates the persistence and intensity of heatwaves across Asia, including India, compared to lower-resolution models [[Gao et al., 2023](#)]. Similarly, high-resolution CESM-HR simulations capture atmospheric river-induced extreme precipitation events with greater fidelity, projecting that areas affected by such extremes may more than double under strong warming, whereas coarse CMIP models substantially underestimate these intensities [[Guo et al., 2024](#)]. More broadly, high-resolution modeling frameworks have been shown to better capture multi-sphere interactions (atmosphere–land–ocean–chemistry), which are often misrepresented in coarse CMIP-class models [[Gao et al., 2025](#)]. These advances underscore that our CMIP6-based results likely provide conservative estimates of extremes, and future work using high-resolution models or downscaling approaches will be important to refine projections of Indian monsoon floods and droughts.

A key dynamic factor influencing both EEs and EDs is the behavior of monsoon LPS, which are major synoptic-scale rain-bearing systems during the Indian summer monsoon. The composite analysis for historical EE years shows increased LPS occurrence and deeper penetration into central India, reinforcing their role in generating heavy rainfall. These findings are consistent with the composite structure of LPS as described by [Krishnamurthy and Ajayamohan \[2010\]](#), who found that well-organized LPS intensify convection and moisture convergence, significantly enhancing regional rainfall during their passage.

Moreover, the broader climatological trend of increased LPS frequency and activity during the late 20th century, as observed by [Ajayamohan et al. \[2010\]](#), directly supports the current study's results. Their analysis demonstrated a robust link between the rising frequency of LPS and the increased incidence of extreme rain events over central India, consistent with the observed increase in flood years and LPS tracks in this study. They also emphasized that the intensification of synoptic-scale activity could be attributed to warming-induced changes in the background monsoon circulation, which enhances the formation and inland propagation of LPS, a dynamic that is also evident in our historical composites.

However, future projections under SSP585 complicate this picture. Despite an increase in flood frequency, a decline in LPS frequency is noted for both EEs and EDs by 3.27% and 7.69%, respectively. This apparent paradox can be explained by the changing nature of LPS dynamics under high warming scenarios, which may include weakening of the monsoon trough, enhanced stability in the lower troposphere, or deflection of LPS tracks away from central India [[Sandeep et al., 2018](#)]. [Srujan et al. \[2021\]](#) reported that the LPS trajectory structure in CMIP5 models exhibits westward propagation over land, deviating from the observed north-westward movement. Such deviations in the modeled LPS trajectories could lead to spatial shifts in rainfall anomalies and contribute to uncertainty in flood and drought projections in Central India.

The role of ENSO further underscores the complexity and uncertainty in extreme event projections. In historical simulations, EE events are more likely during La Niña conditions, while EDs are associated with El Niño phases. This association aligns with established ENSO-monsoon teleconnections [[Roxy et al., 2014](#)]. However, under SSP585, the ENSO-EE/ED relationship becomes less consistent, with

increased EE occurrences during El Niño years, a reversal from the historical pattern. This shift reflects emerging evidence of ENSO phase asymmetry and altered teleconnection pathways under climate change [[Thirumalai et al., 2024](#); [Cai et al., 2014a](#)]. Additionally, the greater frequency of extreme ENSO events and fewer neutral years under SSP585 further complicate the interpretation of climate extremes, since ENSO is both a driver and modulator of Indian monsoon variability.

5.5 Summary and Conclusions

In this study, 25 CMIP6 models are used to analyze the historical and future frequency of large ISM extremes over central India. The models show good agreement in simulating the historical EE and ED counts and their return periods. However, in future scenarios, this agreement breaks down, with most models exhibiting significant uncertainty and high variability in both the number of events and their return periods. The increase in EE count and decrease in its return period over central India in future scenarios, compared to ED occurrences, suggests that future climates are likely to experience more frequent wetter seasons. Several previous studies have reported intensifying trends of wet seasons under future warming scenarios [[Kamizawa and Takahashi, 2018](#); [Katzenberger et al., 2022](#); [Sharmila et al., 2015](#)]. However, this study focuses on large extreme events and reveals that, beyond the overall wetting trend, strong wet extremes are projected to intensify significantly in future scenarios driven by global warming.

The higher track density and more pronounced northwestward propagation of LPS over the Indian landmass during EE compared to ED indicate the role of sub-seasonal synoptic activity in extreme wet events. The influence of LPS activity, on EE and ED occurrences remains consistent between historical and future scenarios. Although

LPS tracks exhibit a decreasing trend, the reduction is not significant. [Sørland and Sorteberg \[2016\]](#) suggested that LPS forming in a warmer and more humid atmosphere are more likely to produce heavy precipitation events, potentially leading to severe flooding. However, our analysis shows only a marginal change in the number of LPS tracks under warmer future scenarios. A more detailed investigation is required to understand how the moisture-holding capacity of LPS evolves in a warming climate.

The occurrence of El Niño and La Niña years is associated with weak and strong ISM years [[Kumar et al., 2006](#)]. Our analysis reveals that future warming scenarios are likely to alter ENSO variability, with an increase in extreme El Niño events and a decrease in neutral years and moderate El Niño frequency under the SSP585 scenario and this agrees with [[Wang et al., 2017](#)] results using CMIP5 models. This shift in ENSO characteristics significantly influences the frequency of EE and ED occurrences. While historical data show a clear relationship between La Niña and EE events, and El Niño and ED events, this relationship becomes more uncertain in future projections. Notably, EE events are projected to occur more frequently during El Niño years in the SSP585 scenario, suggesting a fundamental change in the link between ENSO and ISM extremes. The increase in EE occurrences and the corresponding reduction in their return periods are likely driven by the rise in El Niño events under greenhouse warming. Conversely, the higher probability of EE during La Niña years in the future highlights the complex and uncertain nature of the mechanisms driving extreme events in a warming climate.

Chapter 6

Conclusions and Scope of Future Work

6.1 Conclusions

The key points of the thesis are as follows:

1. The contribution of Indian Ocean OHT variability on the interannual variability of ISM is not significant.
2. The difference in seasonal mean precipitation over central India between drought and flood monsoons is approximately 20%, whereas the corresponding difference in OHT is less than 2%.
3. Weaker interannual variability in monsoon low-level winds results in reduced variability in OHT.
4. No evidence to support the self regulation of Interannual variability of ISM rainfall through the ocean-atmosphere coupling over the Indian Ocean.
5. ENSO significantly influences the evolution of sea surface temperature (SST) anomalies over the North Indian Ocean in the subsequent spring and summer.
6. The observed ENSO – SST correlation does not imply direct causality, especially given the weak link between Niño3.4 SST anomalies in year 0 winter and ISM circulation and precipitation in year +1.

7. During drought monsoon years, the average number of LPSs decreases by about two storms per summer season.
8. LPS propagation over continental India is more incoherent during drought monsoon years compared to flood years.
9. Variability in LPS activity contributes substantially to the interannual variability of Indian Summer Monsoon rainfall.
10. The projections indicate that extreme excess rainfall years are likely to occur more frequently and with shorter return periods, suggesting a shift toward wetter and more intense monsoon seasons. In contrast, extreme deficit exhibit a weaker and more uncertain response.
11. The higher track density and more pronounced north-westward propagation of LPS over the Indian landmass during extreme excess compared to extreme deficit indicate the role of sub-seasonal synoptic activity in extreme wet events.
12. The historical association of La Niña with floods and El Niño with droughts becomes less reliable. Under high-emission scenarios, extreme excess rainfall events increasingly occur during El Niño years, suggesting a significant change in the relationship between ENSO and the ISM.

6.2 Scope of Future Work

In this section, the future scope of the research presented in this thesis is outlined. Several potential research areas are identified during this thesis work that intrigue extensive analysis in the future. A few key aspects are listed as follows:

1. Investigate why the ENSO – ISM relationship changes under future climate scenarios.
2. Conduct a detailed analysis of the LPS – ISM relationship in future projections.
3. Explore the relationship between Ocean Heat Transport and the Indian Ocean Dipole.

References

- Ajayamohan, R., W. J. Merryfield, and V. V. Kharin, Increasing trend of synoptic activity and its relationship with extreme rain events over central india, *Journal of Climate*, 23(4), 1004–1013, 2010.
- Almazroui, M., et al., Projected changes in climate extremes using cmip6 simulations over srex regions, *Earth Systems and Environment*, 5(3), 481–497, 2021.
- Annamalai, H., P. Liu, and S.-P. Xie, Southwest indian ocean sst variability: Its local effect and remote influence on asian monsoons, *Journal of Climate*, 18(20), 4150–4167, 2005.
- Ashok, K., Z. Guan, and T. Yamagata, Influence of the indian ocean dipole on the australian winter rainfall, *Geophysical Research Letters*, 30(15), 2003.
- Asoka, A., Y. Wada, R. Fishman, and V. Mishra, Strong linkage between precipitation intensity and monsoon season groundwater recharge in india, *Geophysical Research Letters*, 45(11), 5536–5544, 2018.
- Azad, S., and M. Rajeevan, Possible shift in the enso-indian monsoon rainfall relationship under future global warming, *Scientific reports*, 6(1), 20,145, 2016.
- Bhalme, H. N., and D. A. Mooley, Large-scale droughts/floods and monsoon circulation., *Monthly Weather Review*, 108(8), 1197–1211, 1980.
- Cai, W., A. Santoso, G. Wang, E. Weller, L. Wu, K. Ashok, Y. Masumoto, and T. Yamagata, Increased frequency of extreme indian ocean dipole events due to greenhouse warming, *Nature*, 510(7504), 254–258, 2014a.

- Cai, W., et al., Increasing frequency of extreme el niño events due to greenhouse warming, *Nature climate change*, 4(2), 111–116, 2014b.
- Carton, J. A., G. A. Chepurin, and L. Chen, Soda3: A new ocean climate reanalysis, *Journal of Climate*, 31(17), 6967–6983, 2018.
- Charney, J. G., and J. Shukla, Predictability of monsoons, *Monsoon dynamics*, pp. 99–110, 1981.
- Charney, J. G., J. Shukla, J. Lighthill, and R. P. Pearce, *Predictability of monsoons*, p. 99–110, Cambridge University Press, 1981.
- Cherchi, A., A. Alessandri, S. Masina, and A. Navarra, Effects of increased co₂ levels on monsoons, *Climate Dynamics*, 37, 83–101, 2011.
- Chirokova, G., and P. J. Webster, Interannual variability of indian ocean heat transport, *Journal of climate*, 19(6), 1013–1031, 2006.
- Clark, C. O., J. E. Cole, and P. J. Webster, Indian ocean sst and indian summer rainfall: Predictive relationships and their decadal variability, *Journal of Climate*, 13(14), 2503–2519, 2000.
- Dai, A., Increasing drought under global warming in observations and models, *Nature climate change*, 3(1), 52–58, 2013.
- DeFries, R., P. Mondal, D. Singh, I. Agrawal, J. Fanzo, R. Remans, and S. Wood, Synergies and trade-offs for sustainable agriculture: Nutritional yields and climate-resilience for cereal crops in central india, *Global Food Security*, 11, 44–53, 2016.
- Eyring, V., S. Bony, G. A. Meehl, C. A. Senior, B. Stevens, R. J. Stouffer, and K. E. Taylor, Overview of the coupled model intercomparison project phase 6

- (cmip6) experimental design and organization, *Geoscientific Model Development*, 9(5), 1937–1958, 2016.
- Gadgil, S., and S. Gadgil, The indian monsoon, gdp and agriculture, *Economic and political weekly*, pp. 4887–4895, 2006.
- Gao, Y., X. Guo, W. Kou, X. Guo, S. Zhang, H. Gao, and D. Chen, Advancing high-resolution modeling to unravel the interplay between extreme weather events and air pollution under global warming, *Frontiers of Environmental Science & Engineering*, 19(7), 100, 2025.
- Gao, Y., et al., More frequent and persistent heatwaves due to increased temperature skewness projected by a high-resolution earth system model, *Geophysical Research Letters*, 50(18), e2023GL105,840, 2023.
- George, C., H. Varikoden, J. Kuttippurath, R. Chaluvadi, and C. A. Babu, Assessment of droughts and floods during the indian summer monsoon using the coupled model intercomparison project phase 6 historical and future simulations, *International Journal of Climatology*, 45(3), e8729, 2025.
- Godbole, R. V., The composite structure of the monsoon depression, *Tellus*, 29(1), 25–40, 1977.
- Gordon, A. L., Oceanography of the indonesian seas and their throughflow, *Oceanography*, 18(4), 14–27, 2005.
- Goswami, B., Interannual variations of indian summer monsoon in a gcm: External conditions versus internal feedbacks, *Journal of Climate*, 11(4), 501–522, 1998.

- Goswami, B. B., R. Krishna, P. Mukhopadhyay, M. Khairoutdinov, and B. Goswami, Simulation of the indian summer monsoon in the superparameterized climate forecast system version 2: Preliminary results, *Journal of Climate*, 28(22), 8988–9012, 2015.
- Goswami, B. N., and R. A. Mohan, Intraseasonal oscillations and interannual variability of the indian summer monsoon, *Journal of Climate*, 14(6), 1180–1198, 2001.
- Goswami, B. N., and P. K. Xavier, Dynamics of “internal” interannual variability of the indian summer monsoon in a gcm, *Journal of Geophysical Research: Atmospheres*, 110(D24), 2005.
- Goswami, B. N., V. Krishnamurthy, and H. Annmalai, A broad-scale circulation index for the interannual variability of the indian summer monsoon, *Quarterly Journal of the Royal Meteorological Society*, 125(554), 611–633, 1999.
- Goswami, B. N., V. Venugopal, D. Sengupta, M. Madhusoodanan, and P. K. Xavier, Increasing trend of extreme rain events over india in a warming environment, *Science*, 314(5804), 1442–1445, 2006.
- Guo, X., et al., More high-impact atmospheric river-induced extreme precipitation events under warming in a high-resolution model, *One Earth*, 7(12), 2223–2234, 2024.
- Gupta, M., T. Chauhan, R. Murtugudde, and S. Ghosh, Pollutants control the process networks of urban environmental-meteorology, *Environmental Research Letters*, 16(1), 014,021, 2020a.

- Gupta, V., V. Singh, and M. K. Jain, Assessment of precipitation extremes in india during the 21st century under ssp1-1.9 mitigation scenarios of cmip6 gcms, *Journal of Hydrology*, 590, 125,422, 2020b.
- Harzallah, A., and R. Sadourny, Internal versus sst-forced atmospheric variability as simulated by an atmospheric general circulation model, *Journal of Climate*, 8(3), 474–495, 1995.
- Harzallah, A., and R. Sadourny, Observed lead-lag relationships between indian summer monsoon and some meteorological variables, *Climate dynamics*, 13, 635–648, 1997.
- Hastenrath, S., On the prediction of india monsoon rainfall anomalies, *Journal of Applied Meteorology and Climatology*, 26(7), 847–857, 1987.
- Hastenrath, S., and L. Greischar, The monsoonal heat budget of the hydrosphere-atmosphere system in the indian ocean sector, *Journal of Geophysical Research: Oceans*, 98(C4), 6869–6881, 1993.
- Hastenrath, S., and P. J. Lamb, On the heat budget of hydrosphere and atmosphere in the indian ocean, *Journal of Physical Oceanography*, 10(5), 694–708, 1980.
- Hersbach, H., et al., The era5 global reanalysis, *Quarterly Journal of the Royal Meteorological Society*, 146(730), 1999–2049, 2020.
- Hu, P., W. Chen, L. Wang, S. Chen, Y. Liu, and L. Chen, Revisiting the enso–monsoonal rainfall relationship: new insights based on an objective determination of the asian summer monsoon duration, *Environmental Research Letters*, 17(10), 104,050, 2022.
- Huffman, G., D. Bolvin, E. Nelkin, R. Adler, et al., Trmm (tmpa) precipitation l3 1 day 0.25 degree x 0.25 degree v7, *Savtchenko, A., Ed*, 2016.

- Hunt, K. M., and D. J. Parker, The movement of indian monsoon depressions by interaction with image vortices near the himalayan wall, *Quarterly Journal of the Royal Meteorological Society*, 142(698), 2224–2229, 2016.
- Hurley, J. V., and W. R. Boos, A global climatology of monsoon low-pressure systems, *Quarterly Journal of the Royal Meteorological Society*, 141(689), 1049–1064, 2015.
- Izumo, T., C. B. Montégut, J.-J. Luo, S. K. Behera, S. Masson, and T. Yamagata, The role of the western arabian sea upwelling in indian monsoon rainfall variability, *Journal of Climate*, 21(21), 5603–5623, 2008.
- Jena, P., and S. Azad, A novel method to detect drought and flood years in indian rainfall associated with weak and strong monsoon, *Theoretical and Applied Climatology*, 145, 747–761, 2021.
- Kaiser, A., and T. Schreiber, Information transfer in continuous processes, *Physica D: Nonlinear Phenomena*, 166(1-2), 43–62, 2002.
- Kalnay, E., et al., The ncep/ncar 40-year reanalysis project, in *Renewable energy*, pp. Vol1_146–Vol1_194, Routledge, 2018.
- Kamizawa, N., and H. G. Takahashi, Projected trends in interannual variation in summer seasonal precipitation and its extremes over the tropical asian monsoon regions in cmip5, *Journal of Climate*, 31(20), 8421–8439, 2018.
- Katzenberger, A., J. Schewe, J. Pongratz, and A. Levermann, Robust increase of indian monsoon rainfall and its variability under future warming in cmip6 models, *Earth System Dynamics*, 12(2), 367–386, 2021.

- Katzenberger, A., A. Levermann, J. Schewe, and J. Pongratz, Intensification of very wet monsoon seasons in india under global warming, *Geophysical Research Letters*, *49*(15), e2022GL098,856, 2022.
- Kawamura, R., A possible mechanism of the asian summer monsoon-enso coupling, *Journal of the Meteorological Society of Japan. Ser. II*, *76*(6), 1009–1027, 1998.
- Kiladis, G. N., and H. van Loon, The southern oscillation. part vii: Meteorological anomalies over the indian and pacific sectors associated with the extremes of the oscillation, *Monthly weather review*, *116*(1), 120–136, 1988.
- Kirtman, B. P., and J. Shukla, Influence of the indian summer monsoon on enso, *Quarterly Journal of the Royal Meteorological Society*, *126*(562), 213–239, doi: <https://doi.org/10.1002/qj.49712656211>, 2000.
- Koteswara Rao, K., T. Lakshmi Kumar, A. Kulkarni, J. S. Chowdary, and S. Desamsetti, Characteristic changes in climate projections over indus basin using the bias corrected cmip6 simulations, *Climate Dynamics*, *58*(11), 3471–3495, 2022.
- Krishnamurthy, V., and R. Ajayamohan, Composite structure of monsoon low pressure systems and its relation to indian rainfall, *Journal of Climate*, *23*(16), 4285–4305, 2010.
- Krishnamurthy, V., and J. L. Kinter III, The indian monsoon and its relation to global climate variability, in *Global climate: Current research and uncertainties in the climate system*, pp. 186–236, Springer, 2003.
- Krishnamurthy, V., and J. Shukla, Intraseasonal and interannual variability of rainfall over india, *Journal of climate*, *13*(24), 4366–4377, 2000.

- Krishnamurti, T. N., J. Molinari, H. lu Pan, and V. Wong, Downstream amplification and formation of monsoon disturbances, *Monthly Weather Review*, 105(10), 1281 – 1297, doi:10.1175/1520-0493(1977)105<1281:DAAFOM>2.0.CO;2, 1977.
- Krishnan, R., K. Ramesh, B. Samala, G. Meyers, J. Slingo, and M. Fennessy, Indian ocean-monsoon coupled interactions and impending monsoon droughts, *Geophysical research letters*, 33(8), 2006.
- Krishnan, R., D. Ayantika, V. Kumar, and S. Pokhrel, The long-lived monsoon depressions of 2006 and their linkage with the indian ocean dipole, *International Journal of Climatology*, 31(9), 1334–1352, 2011.
- Krishnaswamy, J., S. Vaidyanathan, B. Rajagopalan, M. Bonell, M. Sankaran, R. Bhalla, and S. Badiger, Non-stationary and non-linear influence of enso and indian ocean dipole on the variability of indian monsoon rainfall and extreme rain events, *Climate Dynamics*, 45, 175–184, 2015.
- Kumar, K. K., B. Rajagopalan, and M. A. Cane, On the weakening relationship between the indian monsoon and enso, *Science*, 284(5423), 2156–2159, doi:10.1126/science.284.5423.2156, 1999.
- Kumar, K. K., B. Rajagopalan, M. Hoerling, G. Bates, and M. Cane, Unraveling the mystery of indian monsoon failure during el niño, *Science*, 314(5796), 115–119, 2006.
- Kumar, R., J. Kuttippurath, G. Gopikrishnan, P. Kumar, and H. Varikoden, Enhanced surface temperature over india during 1980–2020 and future projections: causal links of the drivers and trends, *npj Climate and Atmospheric Science*, 6(1), 164, 2023.

- Kutzbach, J. E., Empirical eigenvectors of sea-level pressure, surface temperature and precipitation complexes over north america, *Journal of Applied Meteorology and Climatology*, 6(5), 791–802, 1967.
- Lee, T., and J. Marotzke, Seasonal cycles of meridional overturning and heat transport of the indian ocean, *Journal of Physical Oceanography*, 28(5), 923–943, 1998.
- Levitus, S., Meridional ekman heat fluxes for the world ocean and individual ocean basins, *Journal of Physical Oceanography*, 17(9), 1484–1492, 1987.
- Loschnigg, J., and P. J. Webster, A coupled ocean–atmosphere system of sst modulation for the indian ocean, *Journal of Climate*, 13(19), 3342–3360, 2000.
- Lumpkin, R., and K. Speer, Global ocean meridional overturning, *Journal of Physical Oceanography*, 37(10), 2550–2562, 2007.
- Luo, J.-J., W. Sasaki, and Y. Masumoto, Indian ocean warming modulates pacific climate change, *Proceedings of the National Academy of Sciences*, 109(46), 18,701–18,706, 2012.
- Lutsko, N. J., J. Marshall, and B. Green, Modulation of monsoon circulations by cross-equatorial ocean heat transport, *Journal of Climate*, 32(12), 3471–3485, 2019.
- McMonigal, K., and S. M. Larson, Enso explains the link between indian ocean dipole and meridional ocean heat transport, *Geophysical Research Letters*, 49(2), e2021GL095,796, 2022.
- Meehl, G. A., The annual cycle and interannual variability in the tropical pacific and indian ocean regions, *Monthly Weather Review*, 115(1), 27–50, 1987.
- Meehl, G. A., A coupled air-sea biennial mechanism in the tropical indian and pacific regions: Role of the ocean, *Journal of Climate*, 6(1), 31–41, 1993.

- Meehl, G. A., Influence of the land surface in the asian summer monsoon: External conditions versus internal feedbacks, *Journal of climate*, 7(7), 1033–1049, 1994.
- Meehl, G. A., The south asian monsoon and the tropospheric biennial oscillation, *Journal of Climate*, 10(8), 1921–1943, 1997.
- Mei, R., M. Ashfaq, D. Rastogi, L. R. Leung, and F. Dominguez, Dominating controls for wetter south asian summer monsoon in the twenty-first century, *Journal of Climate*, 28(8), 3400–3419, 2015.
- Menon, A., A. Levermann, J. Schewe, J. Lehmann, and K. Frieler, Consistent increase in indian monsoon rainfall and its variability across cmip-5 models, *Earth System Dynamics*, 4(2), 287–300, 2013.
- Mishra, V., K. Thirumalai, D. Singh, and S. Aadhar, Future exacerbation of hot and dry summer monsoon extremes in india, *Npj Climate and Atmospheric Science*, 3(1), 10, 2020.
- Mooley, D. A., Some aspects of indian monsoon depressions and the associated rainfall, *Monthly Weather Review*, 101(3), 271–280, 1973.
- Moon, S., and K.-J. Ha, Future changes in monsoon duration and precipitation using cmip6, *npj Climate and Atmospheric Science*, 3(1), 45, 2020.
- O'Neill, B. C., et al., The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century, *Global environmental change*, 42, 169–180, 2017.
- Pai, D., M. Rajeevan, O. Sreejith, B. Mukhopadhyay, and N. Satbha, Development of a new high spatial resolution (0.25×0.25) long period (1901–2010) daily gridded rainfall data set over india and its comparison with existing data sets over the region, *Mausam*, 65(1), 1–18, 2014.

- Pant, G. B., and B. Parthasarathy, Some aspects of an association between the southern oscillation and Indian summer monsoon, *Arch. Met. Geoph. Biocl., Ser. B*, 29, 245–252, doi:10.1007/BF02263246, 1981.
- Parthasarathy, B., and D. A. Mooley, Some features of a long homogeneous series of Indian summer monsoon rainfall, *Monthly Weather Review*, 106, 771–781, doi: 10.1175/1520-0493(1978)106<0771:SFOALH>2.0.CO;2, 1978.
- Patel, V. K., and J. Kuttippurath, Increase in tropospheric water vapor amplifies global warming and climate change, *Ocean-Land-Atmosphere Research*, 2, 0015, 2023.
- Pillai, P. A., V. Kiran, and K. Suneeth, The strengthened role of new predictors of indian ocean dipole (iod) during the recent decades of weakened enso-iod relationship, *Dynamics of Atmospheres and Oceans*, 106, 101,432, 2024.
- Praveen, V., S. Sandeep, and R. Ajayamohan, On the relationship between mean monsoon precipitation and low pressure systems in climate model simulations, *Journal of Climate*, 28(13), 5305–5324, 2015.
- Preethi, B., M. Mujumdar, R. Kripalani, A. Prabhu, and R. Krishnan, Recent trends and tele-connections among south and east asian summer monsoons in a warming environment, *Climate Dynamics*, 48, 2489–2505, 2017.
- Preethi, B., R. Ramya, S. Patwardhan, M. Mujumdar, and R. Kripalani, Variability of indian summer monsoon droughts in cmip5 climate models, *Climate Dynamics*, 53, 1937–1962, 2019.
- Rajbanshi, J., and S. Das, The variability and teleconnections of meteorological drought in the indian summer monsoon season: Implications for staple crop production, *Journal of Hydrology*, 603, 126,845, 2021.

- Reynolds, R. W., T. M. Smith, C. Liu, D. B. Chelton, K. S. Casey, and M. G. Schlax, Daily high-resolution-blended analyses for sea surface temperature, *Journal of Climate*, 20(22), 5473–5496, 2007.
- Ropelewski, C. F., M. S. Halpert, and X. Wang, Observed tropospheric biennial variability and its relationship to the southern oscillation, *Journal of Climate*, 5(6), 594 – 614, doi:10.1175/1520-0442(1992)005<0594:OTBVAI>2.0.CO;2, 1992.
- Roxy, M. K., K. Ritika, P. Terray, and S. Masson, The curious case of indian ocean warming, *Journal of Climate*, 27(22), 8501–8509, 2014.
- Sadhuram, Y., Predicting monsoon rainfall and pressure indices from sea surface temperature, *Current Science*, 72(3), 166–168, 1997.
- Saha, K., F. Sanders, and J. Shukla, Westward propagating predecessors of monsoon depressions, *Monthly Weather Review*, 109(2), 330–343, 1981.
- Saji, N., B. N. Goswami, P. Vinayachandran, and T. Yamagata, A dipole mode in the tropical indian ocean, *Nature*, 401(6751), 360–363, 1999.
- Sandeep, S., R. Ajayamohan, W. R. Boos, T. Sabin, and V. Praveen, Decline and poleward shift in indian summer monsoon synoptic activity in a warming climate, *Proceedings of the National Academy of Sciences*, 115(11), 2681–2686, 2018.
- Schreiber, T., Measuring information transfer, *Physical review letters*, 85(2), 461, 2000.
- Seneviratne, S. I., et al., Weather and climate extreme events in a changing climate, in *Climate Change 2021: The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by V. P. Masson-Delmotte, A. Zhai, S. L. Pirani, and C. Connors, pp. 1513–1766, Cambridge University Press, Cambridge, UK, 2021.

- Seth, A., S. A. Rauscher, M. Biasutti, A. Giannini, S. J. Camargo, and M. Rojas, C mip5 projected changes in the annual cycle of precipitation in monsoon regions, *Journal of climate*, 26(19), 7328–7351, 2013.
- Sharmila, S., S. Joseph, A. Sahai, S. Abhilash, and R. Chattopadhyay, Future projection of indian summer monsoon variability under climate change scenario: An assessment from cmip5 climate models, *Global and Planetary Change*, 124, 62–78, 2015.
- Shen, X., M. Kimoto, and A. Sumi, Role of land surface processes associated with interannual variability of broad-scale asian summer monsoon as simulated by the ccsr/nies agcm, *Journal of the Meteorological Society of Japan. Ser. II*, 76(2), 217–236, 1998.
- Shi, H., and B. Wang, How does the asian summer precipitation-enso relationship change over the past 544 years?, *Climate Dynamics*, 52, 4583–4598, 2019.
- Shukla, J., and D. Mooley, Empirical prediction of the summer monsoon rainfall over india, *Monthly Weather Review*, 115(3), 695–704, 1987.
- Shukla, J., and D. A. Paolino, The southern oscillation and long-range forecasting of the summer monsoon rainfall over india, *Monthly Weather Review*, 111(9), 1830 – 1837, doi:10.1175/1520-0493(1983)111<1830:TSOALR>2.0.CO;2, 1983.
- Sikka, D., *A study on the monsoon low pressure systems over the Indian region and their relationship with drought and excess monsoon seasonal rainfall*, 217, Center for Ocean-Land-Atmosphere Studies, Center for the Application of Research on the Environment., 2006.

- Singh, D., S. Ghosh, M. K. Roxy, and S. McDermid, Indian summer monsoon: Extreme events, historical changes, and role of anthropogenic forcings, *Wiley Interdisciplinary Reviews: Climate Change*, 10(2), e571, 2019.
- Singh, R., and S. Sandeep, Dynamics of dry air intrusion over india during summer monsoon breaks, *Climate Dynamics*, 59(5), 1649–1664, 2022.
- Singh, R., and S. Sandeep, A mechanism for the summer monsoon precipitation variability over northwest india driven by moisture deficit transport, *Journal of Geophysical Research: Atmospheres*, 129(5), e2023JD040180, doi:<https://doi.org/10.1029/2023JD040180>, 2024.
- Soman, M., and J. Slingo, Sensitivity of the asian summer monsoon to aspects of sea-surface-temperature anomalies in the tropical pacific ocean, *Quarterly Journal of the Royal Meteorological Society*, 123(538), 309–336, 1997.
- Sooraj, K., P. Terray, and M. Mujumdar, Global warming and the weakening of the asian summer monsoon circulation: assessments from the cmip5 models, *Climate Dynamics*, 45, 233–252, 2015.
- Sørland, S. L., and A. Sorteberg, Low-pressure systems and extreme precipitation in central india: sensitivity to temperature changes, *Climate Dynamics*, 47, 465–480, 2016.
- Sprintall, J., A. L. Gordon, A. Koch-Larrouy, T. Lee, J. T. Potemra, K. Pujiana, and S. E. Wijffels, The indonesian seas and their role in the coupled ocean–climate system, *Nature Geoscience*, 7(7), 487–492, 2014.
- Srivastava, A., D. Nagarjuna, G. George, M. Pradhan, et al., Structure, characteristics, and simulation of monsoon low-pressure systems in cfsv2 coupled model, *Journal of Geophysical Research*, 2017.

- Srujan, K. S., S. Sandeep, and E. Suhas, Downstream and in situ genesis of monsoon low-pressure systems in climate models, *Earth and Space Science*, 8(9), e2021EA001,741, 2021.
- Srujan, K. S. S. S., and S. Sandeep, Clustering of low-pressure systems during the active phase of Indian summer monsoon in climate models, *Clim Dyn*, doi:0.1007/s00382-024-07146-w, 2024.
- Srujan, K. S. S. S., S. Sandeep, E. Suhas, and H. Kodamana, A dynamical linkage between western north pacific tropical cyclones and indian monsoon low-pressure systems, *Geophysical Research Letters*, 49(11), e2022GL098,597, doi:https://doi.org/10.1029/2022GL098597, 2022.
- Stern, W., and K. Miyakoda, Feasibility of seasonal forecasts inferred from multiple gcm simulations, *Journal of Climate*, 8(5), 1071–1085, 1995.
- Suhas, E., J. M. Neena, and B. N. Goswami, Interannual variability of Indian summer monsoon arising from interactions between seasonal mean and intraseasonal oscillations, *Journal of the Atmospheric Sciences*, 69(6), 1761 – 1774, doi:10.1175/JAS-D-11-0211.1, 2012.
- Thirumalai, K., P. N. DiNezio, J. W. Partin, D. Liu, K. Costa, and A. Jacobel, Future increase in extreme el niño supported by past glacial changes, *Nature*, 634(8033), 374–380, 2024.
- Trenberth, K. E., and Y. Zhang, Observed interhemispheric meridional heat transports and the role of the indonesian throughflow in the pacific ocean, *Journal of Climate*, 32(24), 8523–8536, 2019.
- Turner, A. G., and H. Annamalai, Climate change and the south asian summer monsoon, *Nature Climate Change*, 2(8), 587–595, 2012.

- Van Vuuren, D. P., et al., A new scenario framework for climate change research: scenario matrix architecture, *Climatic change*, 122, 373–386, 2014.
- Vishnu, S., W. Boos, P. Ullrich, and T. O'brien, Assessing historical variability of south asian monsoon lows and depressions with an optimized tracking algorithm, *Journal of Geophysical Research: Atmospheres*, 125(15), e2020JD032,977, 2020.
- Vishnu, S., A. Chakraborty, and J. Srinivasan, Why the droughts of the indian summer monsoon are more severe than the floods, *Climate Dynamics*, 58(11), 3497–3512, 2022.
- Vishnupriya, S., E. Suhas, and S. Sandeep, Extratropical stratospheric air intrusions over the western north pacific and the genesis of downstream monsoon low-pressure systems, *Geophysical Research Letters*, 49(23), e2022GL100,976, doi: <https://doi.org/10.1029/2022GL100976>, 2022.
- Von Storch, H., and F. W. Zwiers, *Statistical analysis in climate research*, Cambridge university press, 2002.
- Wacongne, S., and R. Pacanowski, Seasonal heat transport in a primitive equations model of the tropical indian ocean, *Journal of physical oceanography*, 26(12), 2666–2699, 1996.
- Wang, G., W. Cai, B. Gan, L. Wu, A. Santoso, X. Lin, Z. Chen, and M. J. McPhaden, Continued increase of extreme el niño frequency long after 1.5 c warming stabilization, *Nature Climate Change*, 7(8), 568–572, 2017.
- Watterson, I. G., R. J. Keane, M. Dix, T. Ziehn, T. Andrews, and Y. Tang, Analysis of cmip6 atmospheric moisture fluxes and the implications for projections of future change in mean and heavy rainfall, *International Journal of Climatology*, 41(S1), E1417–E1434, 2021.

- Webster, P., V. Magana, T. Palmer, et al., Dynamical theory, *Encyclopedia of atmospheric sciences*, pp. 1370–1385, 2003.
- Webster, P. J., V. O. Magaña, T. N. Palmer, J. Shukla, R. A. Tomas, M. Yanai, and T. Yasunari, Monsoons: Processes, predictability, and the prospects for prediction, *Journal of Geophysical Research: Oceans*, 103(C7), 14,451–14,510, doi:<https://doi.org/10.1029/97JC02719>, 1998.
- Webster, P. J., C. Clark, G. Cherikova, J. Fasullo, W. Han, J. Loschnigg, and K. Sahami, The monsoon as a self-regulating coupled ocean—atmosphere system, in *Meteorology at the Millennium, International Geophysics*, vol. 83, edited by R. Pearce, pp. 198–219, Academic Press, doi:10.1016/S0074-6142(02)80168-1, 2002.
- Xie, S.-P., Y. Kosaka, Y. Du, K. Hu, J. S. Chowdary, and G. Huang, Indo-western pacific ocean capacitor and coherent climate anomalies in post-enso summer: A review, *Advances in Atmospheric Sciences*, 33(4), 411–432, 2016.
- Yoon, J.-H., and T.-C. Chen, Water vapor budget of the indian monsoon depression, *Tellus A: Dynamic Meteorology and Oceanography*, 57(5), 770–782, 2005.
- Zaveri, E., D. S. Grogan, K. Fisher-Vanden, S. Frolking, R. B. Lammers, D. H. Wrenn, A. Prusevich, and R. E. Nicholas, Invisible water, visible impact: ground-water use and indian agriculture under climate change, *Environmental Research Letters*, 11(8), 084,005, 2016.
- Zhang, L., W. Han, Y. Li, and N. S. Lovenduski, Variability of sea level and upper-ocean heat content in the indian ocean: Effects of subtropical indian ocean dipole and enso, *Journal of Climate*, 32(21), 7227–7245, 2019.

- Zuo, H., M. Balmaseda, and K. Mogensen, The ecmwf-myocan2 eddy-permitting ocean and sea-ice reanalysis orap5. part 1: Implementation, *ECMWF Tech. Memo.*, 736, 1–42, 2015.

List of Publications

Journals

1. **Rajendran, Saran.** and S. Sandeep (2025) The Lack of Influence of the Cross-Equatorial Ocean Heat Transport on the Interannual Variability of Indian Summer Monsoon, ***Scientific Reports***, DOI:10.1038/s41598-025-14120-x, Article ID:41598_2025_14120_Article.
2. **Rajendran, Saran.** and S. Sandeep (2025) Increasing Uncertainty in Large Flood and Drought Projections over Central India, ***Environmental Research Communications***, 7 125018, DOI 10.1088/2515-7620/ae1dde.

Conferences & Workshops

1. **Rajendran, Saran.,** Sukumaran Sandeep. Projected shifts of large floods and large droughts over the central India, AGU 25 Annual Meeting, New Orleans, LA (Online).
2. **Rajendran, Saran.,** Sukumaran Sandeep. Relationship between low pressure systems and interannual variability of Indian summer monsoon in CMIP6 models”, International Symposium on Tropical Meteorology (INTROMET 2025), IITM Pune, November 2025.
3. **Rajendran, Saran.,** Sukumaran Sandeep. Increasing Uncertainty in Large Drought and Flood Projections over Central India, WMO-IWM8, IITM Pune, 2025. (Poster)
4. **Rajendran, Saran.,** Sukumaran Sandeep. The Role of Ocean Memory in the Interannual Variability of Indian Summer Monsoon, ***TROPMET -2024***, National Institute of Technology Rourkela, Odisha. (Poster)

-
5. **Rajendran, Saran.** and Sukumaran Sandeep. Indian Ocean heat transport and its role in developing SST pattern in the post-monsoon season in CMIP6 models, ***EGU General Assembly 2023***, Vienna, Austria. (Poster)
 6. **Saran Rajendran** and Sandeep Sukumaran. Indian Ocean Heat Transport and its Role in the Persistence of Marine Heatwaves, ***AGU FALL MEETING 2022***, Chicago & Online. (Oral)

SARAN RAJENDRAN

Centre for Atmospheric Sciences, IIT Delhi, India

Email: Saran.Rajendran@cas.iitd.ac.in, happysaran.raj@gmail.com | +91 95624 43007

RESEARCH PROFILE

Doctoral researcher (thesis submitted) specializing in climate dynamics and climate extremes, with expertise in ocean-atmosphere coupling, hydroclimate variability, and uncertainty in climate projections. My research integrates observations, reanalysis datasets, and CMIP6 climate model simulations to investigate extreme events and large-scale circulation processes influencing monsoon and global climate variability.

RESEARCH INTERESTS

- Climate dynamics and large-scale circulation
- Climate extremes: floods, droughts, compound events
- Ocean-atmosphere coupling and ocean heat transport
- Climate model evaluation and uncertainty (CMIP6)
- Teleconnections and monsoon–midlatitude interactions

EDUCATION

Ph.D., Centre for Atmospheric Sciences, IIT Delhi (Thesis submitted: May 2026)

Thesis Title: Interannual variability of Indian summer monsoon: Roles of ocean atmosphere coupling, teleconnections and synoptic variability.

M.Sc. Oceanography, Cochin University of Science and Technology, Kerala (CGPA: 7.54/10)

Masters thesis Title: Seasonality and trends of western Arabian sea acidification and its controlling factors (IITM PUNE)

B.Sc. Physics, University of Calicut (CGPA : 2.93/4)

PUBLICATIONS

Rajendran, S. & Sandeep, S. (2025). Increasing uncertainty in large flood and drought projections over Central India. *Environmental Research Communications*.

Rajendran, S. & Sandeep, S. (2025). Lack of influence of cross-equatorial ocean heat transport on the interannual variability of the Indian Summer Monsoon. *Scientific Reports* , 15(1), 1-13.

Sreeush, M.G., **Rajendran, S.**, et al. (2019). Variability and controlling factors of ocean acidification over the western Arabian Sea upwelling region. *Marine Chemistry* , 209, 14-24.

RESEARCH EXPERIENCE

Project Assistant, IIT Delhi (February 2026 – March 2026)

Project title: A Deep Learning Framework for Subseasonal Climate Prediction of Rainfall Extremes over India during the Summer Monsoon.

Project Assistant, IIT Delhi (October 2023 – November 2025)

Project title: Understanding the Genesis Mechanisms of Monsoon Low Pressure Systems.

UGC Senior Research Fellow, IIT Delhi (July 2020 – July 2023)

UGC Junior Research Fellow, IIT Delhi (July 2018 – July 2020)

TECHNICAL SKILLS

Programming & Analysis: Python, MATLAB, NCL, Ferret, CDO, ORIGIN, HPC

Data: Oceanic & atmospheric observations, reanalysis datasets, CMIP6 simulations.

Modeling: Ocean Tracer Transport Model (OTTM)

CONFERENCE PRESENTATIONS

1. Rajendran Saran, Sukumaran Sandeep., “Projected shifts of large floods and large droughts over the central India”, AGU 25 Annual Meeting, New Orleans, LA (Online).
2. Rajendran Saran, Sukumaran Sandeep., “Relationship between low pressure systems and interannual variability of Indian summer monsoon in CMIP6 models”, International Symposium on Tropical Meteorology (INTROMET 2025), IITM Pune, November 2025
3. Rajendran Saran, Sukumaran Sandeep., “Increasing uncertainty in large drought and flood projections over central India”, WMO–IWM8, IITM Pune, March 2025.
4. Saran Rajendran, Sukumaran Sandeep., “Indian Ocean heat transport and its role in developing SST pattern in the post-monsoon season in CMIP6 models”, EGU General Assembly 2023, Vienna, Austria.
5. Saran Rajendran, Sukumaran Sandeep., “Indian Ocean Heat Transport and its Role in the Persistence of Marine Heatwaves”, AGU Fall Meeting 2022, Chicago & Online.
6. Saran Rajendran, Sreeush M. G and Vinu K. Valsala. Seasonality and Trends in Western Arabian Sea Acidification and its Controlling Factors, OSICON-17, ESSO-NCESS, Thiruvanthapuram, Kerala, September 2017.

FELLOWSHIPS & AWARDS

CSIR–UGC Junior Research Fellowship (JRF) & National Eligibility Test (NET) in Earth, Atmospheric, Ocean & Planetary Science, November 2017

AGU 25 Travel grant Award.

REFERENCES

Dr. Sandeep Sukumaran

Associate Professor, Centre for Atmospheric Sciences, IIT Delhi, India

Email: sandeep.sukumaran@cas.iitd.ac.in | Phone: +91 11 2659 1387

Dr. Vinu K. Valsala

Scientist G, Indian Institute of Tropical Meteorology (IITM), Pune, India

Email: valsala@tropmet.res.in | Phone: +91 20 2590 4514

Dr. P. K Saji

Assistant Professor & Head of Department, Department of Physical Oceanography, CUSAT, Kerala, India Email: sajipk1975@gmail.com | Phone: 0484 2863218