Remote Sensing and Ground Based Analysis of Drought in Karnali River Basin (KRB), Nepal

A Dissertation work submitted to:

Central Department of Hydrology and Meteorology

Tribhuvan University, Kirtipur, Kathmandu, Nepal

In partial fulfillment for the requirement of Master's Degree

of Science in Hydrology and Meteorology

Submitted by:

Prabin Acharya

T.U. Registration No.: 5-2-37-738-2013

August, 2023

Declaration

The thesis entitled “Remote Sensing and Ground Based Analysis of Drought in Karnali River Basin (KRB), Nepal” is being submitted to the Central Department of Hydrology and Meteorology, Institute of Science and Technology (IOST), Tribhuvan University, Nepal, for the achievement of the degree of Master of Science (M. Sc). This is a research work carried out by me under the supervision of Associate Prof. Dr. Madan Sigdel, Central Department of Hydrology and Meteorology, Tribhuvan University. This research having this title has not been submitted earlier in this or the any other University of Institute, here or elsewhere, for the achievement of any degree.

……………………..

Mr. Prabin Acharya

Central Department of Hydrology and Meteorology

Tribhuvan University, Kritipur, Kathmandu, Nepal

Acharyaprabin07@gmail.com

Letter of Recommendation

This is to recommend that the dissertation entitled, “Remote Sensing and Ground Based Analysis of Drought in Karnali River Basin (KRB), Nepal” has been carried out by Mr. Prabin Acharya for the partial fulfillment of Master’s Degree of Science in Hydrology and Meteorology. This is the original work and has been carried out under my supervision. This thesis work has not been submitted for any other degree in any institution to the best of my knowledge.

Therefore, I recommend this dissertation for approval and acceptance.

……………………..

Supervisor

Dr. Madan Sigdel

Associate Professor

Central Department of Hydrology and Meteorology,

Tribhuvan University, Kirtipur, Kathmandu, Nepal

Date: ………….......

Letter of Approval

The dissertation entitled, "Remote Sensing and Ground Based Analysis of Drought in Karnali River Basin (KRB), Nepal" by Mr. Prabin Acharya has been accepted as a work for partial fulfillment of the requirements for the Master's Degree of Science in Hydrology and Meteorology.

Evaluation Committee

…..……………………..

Prof. Dr. Deepak Aryal
Head of Department
Central Department of Hydrology and Meteorology, Tribhuvan University, Kirtipur, Kathmandu, Nepal

…..……………………..

Assoc. Prof. Dr. Madan Sigdel
Supervisor
Central Department of Hydrology and Meteorology, Tribhuvan University, Kirtipur, Kathmandu, Nepal

…..……………………..

Assoc. Prof. Dr. Binod Dawadi
Internal Examiner
Central Department of Hydrology and Meteorology, Tribhuvan University, Kirtipur, Kathmandu, Nepal

…..……………………..

Dr. Hemu Kharel (Kafle)
External Examiner
Scientist/ Kathmandu Institute of Applied Science (KIAS), Nepal

Acknowledgement

I am deeply indebted to a multitude of individuals who have significantly contributed to the completion of this research. Their unwavering support, guidance, and encouragement have been instrumental in shaping the outcomes of this study. I extend my heartfelt gratitude to my esteemed supervisor, Dr. Madan Sigdel, whose expertise, mentorship, and insightful feedback have been invaluable throughout this research journey. His dedication to scholarly excellence and commitment to my academic growth have been truly inspiring. I would like to express my sincere appreciation to Dr. Deepak Aryal, Head of the Department, CDHM for his encouragement, and valuable suggestions that have enriched the direction of this study. I would like to acknowledge my internal examiner Dr. Binod Dawadi and external examiner Dr. Hemu Kharel (Kafle) for their valuable comments to enhance quality of my work. I would appreciate the help of Assit. Prof. Damodar Bagal for his guidance in trend mapping using MK-test and Mr. Bhumi Raj Budathoki for his remarkable encouragement.

I am grateful to Mr. Arnab Singh and Mr. Kaman Ghimire for invaluable assistance which played a pivotal role and also Assit. Prof. Ramhari Acharya and Meteorologist Sanjib Adhakari for guiding me to collect data to accomplish this work. I would also like to acknowledge the support of Monarch Hydro Climate and Environment Consultant Pvt. Ltd. (MHCE), Nepal for providing the necessary financial resources. Any errors or omissions remain solely my responsibility.

Finally, I am indebted to my family for their kindness towards me and deepest respect to my Grandmother, who have stood me with unwavering encouragement and understanding during every phase of my life. Your belief in me has been a constant source of motivation.

Prabin Acharya
CDHM, TU
Khajura-3, Banke
August, 2023

Abstract

Drought, a frequent and impactful climatic extreme, has significant impact on the context of topographically varied Karnali River Basin (KRB) in Nepal. This study executed a comprehensive assessment of drought dynamics by employing two key indices based on Vegetation Condition Index (VCI) derived from Moderate Resolution Imaging Spectroradiometer (MODIS) data, and single parameter based Standard Precipitation Index (SPI) from ground based station data, with a focus on spatial and temporal variations. Remote sensing and Ground based indices were utilized across all seasons within a year, while also establishing correlations between vegetation dynamics and climatic parameter (precipitation). MK-Trend test have been performed to analysis SPI trend inside the basin. Drought indices derived by climatic data were correlated with Southern Oscillation Index (SOI) to evaluate relationship with indices and seasons. This analysis revealed that drought has occurred more than half of the study period, underscoring its recurrent nature inside the KRB spatially. In particular, the winter and monsoon SPI drought patterns exhibited an alarming increasing rate, which can be surmounted by concerning decrease in precipitation by 4 mm per year. Concurrently, the VCI time series demonstrated an upward trajectory of drought occurrences during the pre-monsoon and winter seasons inside the basin emphasizing increasing winter drought in the lower altitude and summer monsoon drought in the whole basin accessing 50% area experienced vegetation failure temporally. Further investigation revealed that the manifestation of drought is intricately linked not only to local conditions but also to larger climatic oscillations, notably the SOI. Negative value examined between drought events and SOI index in the monsoon season, with enhancing El-Nino phase. The correlation between VCI and precipitation, particularly when precipitation leads VCI by one month, proved to be a robust and noteworthy observation, emphasizing the predictive utility of this relationship. Notably, during the pre-monsoon season, the correlation nearly doubled when a one-month lag in VCI-precipitation is considered. Lower elevations face heightened pre-monsoon and winter drought, while higher altitudes encountered intensified monsoon-related droughts. This results from shifting atmospheric circulation patterns, uneven convection, and increased temperatures, leading to excessive evaporation and soil moisture loss within the year. These findings hold crucial implications for water resource management, agriculture, and overall resilience strategies in the face of changing climatic conditions inside the KRB.

Keywords: Drought, SPI, VCI, SOI, Nepal, KRB.

Table of Contents

List of Acronyms

ACF	Auto correlation Function
AVHRR	Advanced Very High Resolution Radiometer
CCF	Cross Correlation Function
CDHM	Central Department of Hydrology and Meteorology
DHM	Department of Hydrology and Meteorology
DMI	Dipole Mode Index
ENSO	El Nino Southern Oscillation
EVI	Enhanced Vegetation Index
GEE	Google Earth Engine
GIS	Geographical Information System
IPCC	Intergovernmental Panel on Climate Change
KRB	Karnali River Basin
masl	meter above sea level
Max	Maximum
Min	Minimum
MK	Mann-Kendall
mm	millimeter
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
NOAA	National Oceanic and Atmospheric Administration
PET	Potential Evapotranspiration

SOI	Southern Oscillation Index
SPEI	Standardized Precipitation Evapotranspiration Index
SPI	Standard Precipitation Index
SST	Sea Surface Temperature
VCI	Vegetation Condition Index
VHI	Vegetation Health Index
WMO	World Meteorological organization

List of Tables

List of Figures

Chapter I: Introduction

1.1 Introduction and Background

Climate change has been identified as the main factor for exacerbating the rate and intensity of extreme weather events with losses of billions of economy worldwide (Kogan et al., 2013; Van Loon, 2015; Zhang et al., 2011). Extreme weather events, including droughts, heat waves, cyclones, and erratic changes in precipitation have been increasing due to the global rise in carbon concentration, affecting 90 to 95% of regions of the world (IPCC, 2021). Droughts, a complex phenomenon influenced by multiple factors such as temperature, precipitation, soil moisture, and vegetation cover, have been aggravated by warming temperatures, leading to increased drought severity in various regions around the world with less precipitation and high evaporation (Dai, 2013). These climate extreme creates adverse environment for the living beings without food and shelter in impacted area. Globally, different types of extreme weather condition prevails that shows more than normal condition in the weather parameter prevails from day to years in temporal scale (Zhang et al., 2011). Long term impact of those events may on the food shortage and socioeconomic condition of the community driving waterborne diseases. Among them drought is the most devastating weather extreme driven by the lack of soil moisture for agriculture and hydrological imbalance of the ecosystem (Mishra and Singh, 2010).

Drought is the most devastating climatic extreme driven by long term water deficiency in and out of the ground surface. The definition of drought as provided by the Intergovernmental Panel on Climate Change (IPCC) in its Sixth Assessment Report (AR6) states that drought is characterized by a prolonged absence or significant deficiency of precipitation, resulting in a shortage of water for specific activities or groups, or a prolonged period of abnormally dry weather that leads to a significant hydrological imbalance (Baniya et al., 2018; Karki et al., 2017). The impact of droughts are widespread and devastating, with significant economic losses and loss of lives. The widespread nature of droughts makes monitoring and addressing them challenging, especially with conventional system (Sigdel and Ikeda, 2010; Trenberth et al., 2014).

Globally, extreme weather events like droughts, tornados, tsunamis, hurricanes, and hot and cold waves damaged about 90% of economic including major earthquakes (Eckstein, Künzel, et al., 2021). Weather-related disaster were impacted $215 billion by extreme weather events (including earthquake) where drought only contributed about 85% economic damage among extremities, having a total climatic loss of $225 billion in the same year (WMO, 2019). Drought is the most devastating phenomenon affecting parts of Africa, Asia, South America, Europe, etc. Drought changes stem from Palmer Drought Severity Index issues, precipitation data accuracy, and the influence of natural variability like El Niño, while global warming intensifies its severity and frequency (Trenberth et al., 2014).

Drought has had significant impacts on agriculture and water resources in Nepal despite of being identified as “fresh water tower” of South Asia and densely populated floodplains downstream of Asia's mountains rely on mountain water for irrigation, vital for crop production (Biemans et al., 2019). Drought hits not only in the single sector of ecosystem but spreads with huge damaged done in many fields like Agriculture, water resources, livelihoods and economics (Dahal et al., 2021; Yao et al., 2018). Droughts have led to significant crop losses in Nepal, particularly in the mid-hills and terai regions, found that the most affected crops were maize, rice, wheat, and vegetables, with losses ranging from 10% to 80% depending on the severity of the drought (Panthi et al., 2016). Droughts can also have significant impacts on water resources in Nepal, particularly in areas that rely on surface water for drinking and irrigation and also derived significant reductions in stream flow and groundwater recharge in the different river basin of Nepal (Dahal et al., 2021; Khatiwada et al., 2016). Droughts have led to food shortages, increased food prices, and loss of income for farmers in Nepal, particularly in the mid-hills and southern plane regions.

Drought is categorized into four main types: meteorological drought, agricultural drought, hydrological drought, and socio-economic drought and it propagates from moderate meteorological to extreme hydrological affecting the hydrological cycle of the environment and meteorological drought influenced in agriculture practices (Mishra and Singh, 2010). The extent and spread of drought depends on various factors such as precipitation, temperature, solar insolation, altitude, wind patterns, and soil moisture (Van Loon, 2015). Mountain barriers can also play a significant role in drought conditions by enhancing orographic effect on distribution and amount of precipitation in surrounding areas (Sigdel and Ikeda, 2012).

Drought is also linked with large scale atmospheric circulation that originated from sea surface are Nino, Indian oceanic dipole mode index (DMI). Those are the large scale synoptic feature influencing large area of land mass nearby coastal region including Nepal (Bagale et al., 2021; Khatiwada et al., 2016; Sigdel and Ikeda, 2012). Drought in Nepal is caused by the poor linkage of the monsoon circulation during summer and westerly circulation in the winter season. During El-Nino phase, Nepal experienced drought condition in the monsoon where winter does not impacted by El-Nino condition rather than other atmospheric circulation like western disturbances (Sigdel and Devkota, 2013; Sigdel and Ikeda, 2012). When moist air masses encounter a mountain range, they are forced to rise and cool, resulting in condensation and precipitation. Typically, the windward side of the mountain range receives more precipitation, while the leeward side, known as the rain shadow, may experience less (Sharma et al., 2020). Karnali River basin in western Nepal found that the region is highly vulnerable to drought conditions, partly due to the influence of the Himalayan mountain range (Karki et al., 2017).

Extreme events and it’s monitoring is a kind of hectic job for the research due to inhomogeneity of data and topography in Nepal (Lamichhane et al., 2020). On the other hand, remote sensing can provide more accurate results with proper handling of satellite data for computing vegetation indices over vast areas of the topography (Rousta et al., 2020). Remote sensing techniques offer several advantages for drought monitoring, including the ability to capture large-scale spatial and temporal information, which is critical for understanding drought dynamics over extensive areas (Aghakouchak et al., 2015; Lui and Kogan, 1996; Thenkabail et al., 2004). Vegetation indices derived from remote sensing data, such as the Normalized Difference Vegetation Index (NDVI) and VCI, VHI can provide valuable insights into the health and vigor of vegetation, which can serve as an early warning indicator of drought stress (Kogan, 1995; Wang et al., 2011).

KRB is frequently affected by droughts that causes significant socio-economic and environmental problems such as food shortage and water scarcity for drinking and sanitation (Panthi et al., 2019). Drought characterization, monitoring, and forecasting are potentially useful to support water resource management to cope with the extreme condition of the drought, the analysis reflects that 70% of the stations showed winter drought in 2006 while 55% during 2008, and 50% in 2009 (Khatiwada and Pandey, 2019).The irregular pattern of the monsoon and winter disturbance are the major causes of the recurrence of the drought condition inside the KRB (Karki et al., 2017; Khatiwada et al., 2016). Despite of being rich in water resources, has still lack of irrigation networks having high risk of future drought. Frequency and severity of drought varied on temporal scale of SPI as northwestern part impacted by short term SPI and northeastern part of country hits by long-term SPI drought (Sigdel and Ikeda, 2010).

Different drought indices can be used to monitor and assess drought conditions over different timescales, ranging from weeks to months and even years. By tracking changes in drought indices, it is possible to identify the onset, severity, and duration of drought conditions in a particular area (Kogan, 1997; McKee et al., 1993). Some of them are single parameter based and rest are multi parameter based drought indices which quantify drought severity and its propagation. Drought can be identified with the SPI index for different time scales from 1 to 72 months monitoring short term meteorological to long term hydrological drought (Edwards and McKee, 1997). A wide range of globally available drought indices are used to evaluate drought conditions, including the SPI, SPEI , Palmer Drought Severity Index (PDSI), Effective Drought Index (EDI) , Rainfall Anomaly Index (RAI), Deciles, Crop Moisture Index (CMI), Bhalme and Mooly Drought Index (BMDI), Surface Water Supply Index (SWSI), and others. These indices provide valuable insights into the severity and extent of drought events association with different meteorological parameters (Hayes et al., 2011; McKee et al., 1993).

In addition, remotely sensed data is commonly used for drought monitoring through the calculation of vegetation indices. Popular remote sensing-based drought indices include NDVI, EVI, VCI, VHI, Normalized Difference Water Index (NDWI), Absolute Difference Normalized Difference Vegetation Index (ADVI), and Standardized Vegetation Index (SVI) (Baniya et al., 2018; Lui and Kogan, 1996; Viovy et al., 1992). Beside those, Drought can be also monitored using long term paleo-climatic study of tree ring that tells us about the weather condition of the particular time period, and visibly seen in the growth of tree ring. Tree ring growth in association of temperature and precipitation determines drought year indicated by the weak growth of tree ring (Dawadi, 2013).

SPI is popular and flexible single parameter based meteorological drought index acquire only long term monthly precipitation data (Dahal et al., 2021; McKee et al., 1993). It has many advantages than other data based drought indices due to its coherent and flexible nature on temporal scale. SPI can be used for the short-term agriculture drought (SPI-3) to long-term hydrological drought (SPI-12, 24) mapping according to the time scale of data fed into the calculation under gamma distribution function (Sigdel and Ikeda, 2010; Guttman, 1998). Similarly, VCI index is calculated to monitor the vegetation condition of the desired land surface using vegetation indices (VI) of the different satellite product which are fitted for monitoring land surface vegetation condition. VCI accumulates the information from long term NDVI data with present condition of the NDVI to evaluate the dynamics of vegetation condition change over the land surface. Indeed, VCI is applicable for agriculture monitoring for different vegetation type and its response to the climatic parameter (Hu et al., 2020; Baniya et al., 2019). The first threshold of the VCI indicates a decline in vegetation vigor, signaling the emergence of drought, while the second threshold indicates the onset of a severe drought (Kogan, 1995). VCI assessment inside the basin have been performed to understand the reliability of drought monitoring over station based data for future forecasting of drought.

In the context of Nepal, station data based drought monitoring is widely carried out for different spatial and temporal scale using SPI, SPEI and few study done using remote sensing data in river basin. Reliability and accuracy of the result is always questionable to the researchers due to lack of adequate weather station in high elevation in northern belt of country (Khatiwada et al., 2016; DHM, 2015). Drought analysis approached by manual data is chaos and difficult to maintain and update record in all range of topography inside the country (Dahal et al., 2021). Agriculture and micro animal farming are the major income sources of people inside the KRB which has impacted by drought frequently. Regular monitoring of the drought events using remote sensing could enhance the understanding and copping capacity against climatic extremities inside the basin eventually contributes to the field of food production and well beings of people (Thenkabail et al., 2004). So, remote sensing based drought mapping could bring huge potential of managing climatic risk of extreme phenomena in KRB using MODIS vegetation indices and adopted as a beginning of the new technique in drought monitoring inside the basin.

1.2 Research Questions

These are the research question raised to accomplish this work in KRB for temporal and spatial pattern of drought.

1. What is the temporal and spatial pattern of drought in the KRB?
2. How does the drought pattern relate with vegetation condition of the KRB?
3. What is the relationship between VCI index with SPI and SOI in specific drought event?
4. What is the possible lag time of vegetation with climatic parameter (precipitation) inside the KRB?

1.3 Objectives

The general objective of the study is to find out spatial and temporal pattern of drought inside the KRB using remote sensing and station data.

To fulfill above mentioned objective, these are the specific objectives which are as follows:

- To analysis SPI in spatial and temporal scale in KRB.
- To analysis VCI in spatial and temporal scale in KRB.
- To compare SPI, VCI and their connection with SOI in KRB.

Chapter II: Literature Review

Excessive atmospheric carbon is the primary driver of global warming, expected to elevate temperatures by 1.5°C in the next decade. This rapid warming is set to intensify extreme climatic events worldwide, leading to significant economic losses and widespread human hardships (IPCC, 2021). Globally, huge amount of fossil fuel supply and consumption is the main challenge for climate change and its restoration for the future sustainability of mankind. Meteorological parameters are based on the daily weather of the localities, with the rise and fall in precipitation, temperature, humidity, sunshine hours, etc. Much climatic research aims to find out the exact change in the long-term period of time for better simulation of future events to sustain but still unable to meet their goal significantly (Taylor et al., 2012).

More than fifty percent of world’s populated areas including all continents are vulnerable to drought which is almost occupied all agricultural lands of the world. The impacts of climate extremities can be severe, including loss of life, damage to infrastructure, and significant economic losses. Huge population was about 1.3 million people died out of 3.5 million deaths caused by natural disasters, with drought being a major contributing factor (Obasi, 1994). Droughts have also affected large areas, with 50% of the 2.8 billion people impacted by natural disasters between 1967 and 1991 being affected by droughts (Kogan, 1995, 1997). The Sahel drought, which occurred from 1968 to 1990, resulted in widespread famine, displacement of people, and loss of life. It is estimated that up to 50 million people were affected by this drought (Williams et al., 2012). The consequences of the Sahel drought were severe, with reduced access to water, food, and other resources, leading to increased vulnerability and suffering among affected populations. Similarly, the Millennium drought, which lasted from 1997 to 2009, had significant impacts on water availability, agricultural productivity, and the environment in Australia, especially in the south-eastern regions. This drought caused water shortages, reduced agricultural yields, and resulted in environmental damage such as drying up of rivers and loss of wildlife habitats. The economic losses associated with the Millennium drought are estimated to be in the billions of dollars (Hughes et al., 2021), with significant impacts on the agricultural and tourism sectors. Drought has had significant impacts on East Asia, particularly in northern and south-western China, where high frequency and long duration droughts have been observed.

Historical data shows that major drought periods occurred during 1959-61, 1978-82, 1987-94, and 1997-2002 (Yao et al., 2018; Zhang and Zhou, 2015). Drought in East Asia is influenced by monsoonal circulation, affecting the onset, duration, and ending of monsoons. However, studies on the predictability of drought in East Asia are limited, with most research focused on precipitation and circulation prediction (Zhang et al., 2011). Similarly, research on drought-related prediction in South Asia is also limited, with the Standardized Precipitation Index (SPI) being commonly used in South Asian countries , highlighted the gap in research on drought prediction in East Asia and South Asia, indicating the need for further investigation in this area (Zhang and Zhou, 2015). Drought effects on Yellow River Basin (YRB) vegetation found that about 50% to 60% area prone to drought, 77.4% of vegetated areas depended on water resources, with cumulative effects lasting longest in semi-humid zones. Lagged drought affected 91.8% of the area, with varying sensitivities. Increasing water availability reduced vegetation sensitivity to drought. Cumulative effects were generally more pronounced than lagged effect impacting short term (one to three months) to long term (six to eight months) drought. It has not found similar propagation of VCI condition rather than respond differently according to types of vegetation.

Droughts in South Asia, exacerbated by increasing population and demand for water, have caused significant water shortages, economic losses, and social consequences. The latest drought (2000-2003) impacted over 100 million people, particularly in Gujarat and Rajasthan in India, Sind and Baluchistan in Pakistan, Iran, and Afghanistan (Mirza et al., 2008).Climatic condition of the basin is highly variable with precipitation and temperature changes with different seasons and the year. Climate extremities are unusual or extreme weather events that deviate from the typical weather patterns spatially and temporally all around the world. It is meant that more extreme event more likely to impact society and environment. Different level of warming triggered by climate change bringing use of various drought indices in the real world (Trenberth et al., 2014).

Between 1980 and 2016, the Himalayan region saw an uptick in drought events, particularly after 2000. Short-term droughts (SPI-3), characterized by an average duration of 2.8 months and a severity index of -4.3, occurred approximately 17.1% of the time. In contrast, long-term droughts (SPI-12) persisted for an average of 8.6 months with a severity index of -13.9, impacting around 23.5% of the period (Sharma et al., 2021). It is emphasized that duration of short term drought is significant on damaging agriculture product where long term drought certainly impacts on the dry season water budget. Recently research carried out on drought for 107 stations across Nepal from 1977 to 2018 using the Standard Precipitation Index (SPI) to characterize summer and annual drought events. The worst drought years were identified as 1982 and 2015, after nearly three decades, with about 44% of Nepal's areas affected by extreme drought events. Droughts were observed during both El-Niño and Non El-Niño years, and became more frequent after 2005. The study found that extreme, severe, and moderate droughts affected different proportions of areas during summer and annual events, ranging from 7% to 18% of Nepal's areas (Bagale et al., 2021). The research conducted in the far and mid-western regions of Nepal from 1982-2012, using the Standardized Reconnaissance Drought Index (RDI), identified all types of drought from moderate to extreme. Far western region experienced higher number of drought events, while mid-western region faced more extreme drought events. Most droughts occurred during the 1990s and 2000s, with an increasing trend in drought frequency towards the latter part of the study period (Kafle, 2015). Central Nepal experienced large inter annual variation in precipitation with no significant overall trends in mean annual, monsoon, and winter rainfall. Some areas showed increasing precipitation, while dry areas had decreasing trends. Standardized Precipitation Index (SPI) revealed increasing drought frequency and intensity in recent years, particularly during the summer seasons of 2004, 2005, 2006, and 2009, and the winters of 2006, 2008, and 2009 (Dahal et al., 2021). This drought condition has severely affected agricultural production in central Nepal which impacted on the gross production of major crops like rice, maize (Dahal et al., 2016; Panthi et al., 2016).

Precipitation pattern of the whole Nepal is changing including KRB that brings significant changes in the extreme weather intensity and frequency. It has been examined that precipitation pattern of the western hill is in decreasing trend after year 2000 (Karki et al., 2017; Khatiwada et al., 2016). Dry days are increasing and intensity of precipitation is increasing creating flooding condition in the low land area of western Terai and Siwalik region. Minimum and maximum temperature were increasing trend mainly in the pre-monsoon and winter season inside the KRB enhancing drought condition in the coming future (Khatiwada et al., 2016; Wang et al., 2013). Based on historical data from ten station in the complex topography of the Himalayan as KRB, this study analyzed 34 years (1981-2014) of data to characterize drought events using various indices. Major drought events were observed in recent years (1984-85, 1987-88, 1992-93, 1994-95, 2004-09, and 2012), winter drought of 1999, 2006, 2008-09 were widespread and the 22 monsoon drought is in increasing its frequency and crop yield was affected by drought inside the basin (Khatiwada and Pandey, 2019). Among all the drought monitoring based on ground data, SPI was found flexible and responsive in the KRB.

Characteristics of drought events in Nepal using satellite-derived VCI data from 1982 to 2015 identified severe drought events in 1982, 1984, 1985, and 2000, with higher occurrences during monsoon and pre-monsoon seasons. The study also predicted increasing severe drought in western and far-western regions during pre-monsoon seasons, with climate parameters such as temperature and precipitation correlated with VCI changes where temperature correlated better than precipitation in the VCI dynamic of the Nepal (Baniya et al., 2019). Correlation between VCI and precipitation factor was affected by lag time of vegetation response over precipitation inside the Nepal. So, this study seeking the lag time of VCI with precipitation parameter inside the KRB due to crucial role of lag time in vegetation vigor as studied all over the world (Lui and Kogan, 1996; Wan et al., 2004). Vegetation sustainability differ with the vegetation type to the intensity and duration of the drought in the topographic area. Such as short grass and shrubs land could not sustain for long term drought where as tall and dense forest can bear dry condition from months to even year (Naumann et al., 2018; Wan et al., 2004). Vegetation based drought indices linked with meteorological indices also considering vegetation lag time with the climatic parameter of precipitation (Ji et al., 2021). Estimating the precise lag time for vegetation found to be a complex task due to the resilience and distinct reactions exhibited by various types of vegetation, coupled with the varying durations of crop cycles at different stages of growth because of the complexities with no distinct pattern of land cover inside the KRB.

Station based drought monitoring is challenging with inadequate station data due to difficult topography inside the country including study area. KRB having difficult terrain more than 50% of its area lies above 2500 masl so remote sensing could be the best option in monitoring agricultural and meteorological drought (Khatiwada et al., 2016; Thenkabail et al., 2004). The fitted Random Forest (RF) model indicated that the linear trend in NDVI was primarily influenced by CO2 levels or another quasi-linear environmental parameter, rather than temperature or precipitation trends. Linear trend primarily due to CO2 level, not temperature or precipitation showed increasing trend of NDVI in Nepal mostly during Post-monsoon season. Inter annual fluctuation correlated with temperature, and precipitation (Krakauer et al., 2017). Many part of the country spotted as a drought region due to less rainfall associated to delayed monsoon, abnormally high summer temperature and insufficient precipitation in the Nepal as the years 1991, 1992, 2005, 2006 and 2009 has been observed to be rainfall deficit years (Bagale et al., 2021; Hamal et al., 2021). In 2019, The South Asian region is also facing a high risk of extreme events $ 1 billion loss due to extreme events and Nepal lies 11th most affected country by extreme weather events according to German Climate Risk Index (Eckstein et al., 2021). Global warming affects the Hindu-Kush Himalayas, causing snow melt and erratic rainfall. In Nepal, drought posed severe challenges due to the rugged mountainous terrain specially in KRB (Panthi et al., 2019).

Over all, studying drought in mountain areas is crucial for water resource management, ecosystem conservation, energy production, agriculture, disaster risk reduction, and the overall well-being of communities living in and depending on these regions. It helps in developing strategies and policies to adapt to changing climate conditions and ensure the sustainable use of mountain resources. So, this study attempted to seek relationship of drought indices with climatic parameter inside KRB to further ensuring the impact of drought in the near future to cope with devastating climate extremity.

Chapter III: Study Area

3.1 General Features and Topography of KRB

Nepal, located in South Asia in the Northern Hemisphere, lies between 80º 40’ and 88º 12’ east longitudes, and 26º 12’ and 30º 27’ north latitude. It is a landlocked country divided into five physiographic regions, namely Terai, Siwalik, Middle Mountains, High Mountains, and High Himalayas, ranging from low to high altitudes (Kansakar et al., 2004). Karnlai basin covers all twelve districts of the western Nepal from high Himalayan to the Terai region.

The KRB, is trans-boundary river basin extending from the lowlands to the high Himalayas, spans an area of approximately 45,000 square kilometers in Nepal. It lies between 80º 90’ and 83º 80’ east longitudes, and 28º 30’ and 30º 50’ north latitude. Karnali river originates from Mansarovar and Rakas lakh in Tibet, China, and eventually drains into the Ganga River in India. The Karnali watershed consists of seven tributaries, namely Humla Karnali, Mugu Karnali, Thuli Bheri, Sani Bheri, Tila Karnali, Seti, and Babai. With a length of about 507 km, the Karnali River is the longest river system within Nepal.

The KRB exhibits a wide altitudinal range, with elevations ranging from 186 m to 7707 m. It spans diverse geographical features, including Terai (186-200m), Siwalik (201-700m), Middle Mountains (701-2000m), High Mountains (2001-4000m) and High Himalayas (4001-7707m). The basin is characterized by its unique topography and rich biodiversity, with various ecosystems supporting a wide range of flora and fauna. KRB is important source of water for irrigation, hydropower generation, and domestic use, supporting the livelihoods of millions of people in the region.

Understanding the hydro-meteorological characteristics of the KRB, including precipitation, temperature, and hydrological flows, is crucial for assessing the impacts of climate change and developing sustainable water management strategies. Research and monitoring of the KRB are essential for informing policies and practices related to water resources, agriculture, and livelihoods in the region.

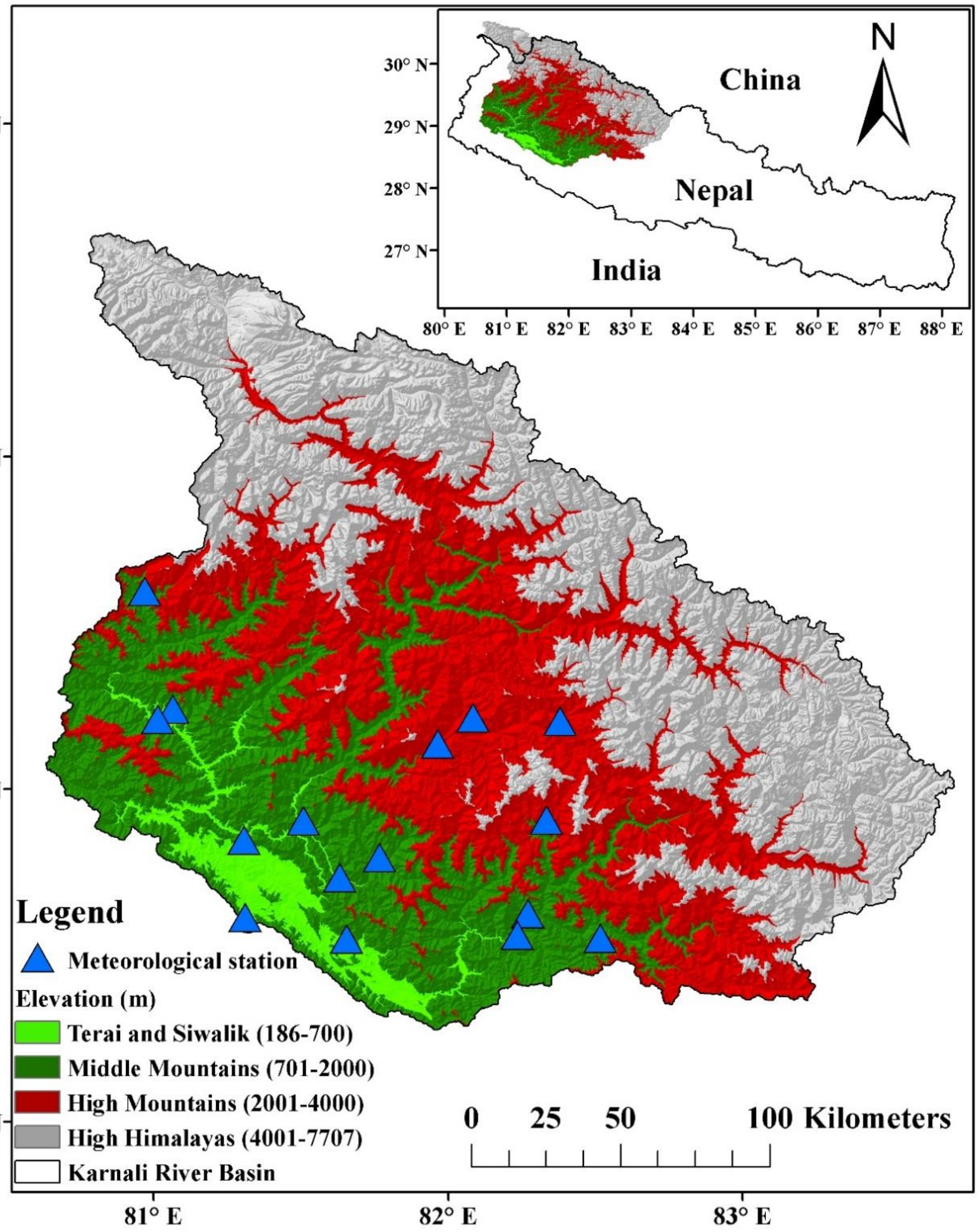

Fig. 1: Elevation map of Karnali River Basin (KRB)

3.2 Climate and Land Cover of KRB

Climate of Nepal mainly controlled by the seasonal reversal of wind patterns in different time scale of the year and is characterized by four distinct seasons throughout the year (DHM, 2015). Similarly, the Karnali River Basin experiences four main seasons: winter (Dec-Feb), pre-monsoon (Mar-May), monsoon (Jun-Sep), and post-monsoon (Oct-Nov).

Over the years, the Karnali Basin has been observed to have a decreasing trend in precipitation, with an average annual decrease of 4.99 mm/year, which accounts for approximately 10% of the average precipitation. On the other hand, temperature trends in the basin showed an increasing trend, with maximum temperature during the pre-monsoon season increasing at a rate of 0.08 01 ^{o}C/year and minimum temperature increasing at a rate of 0.01 ^{o}C/year (Khatiwada et al., 2016). Climate of basin reveals from hot in Terai to the cold in the Himalayan region and found dense forest in the lower portion of the basin to the barren land in the high altitude.

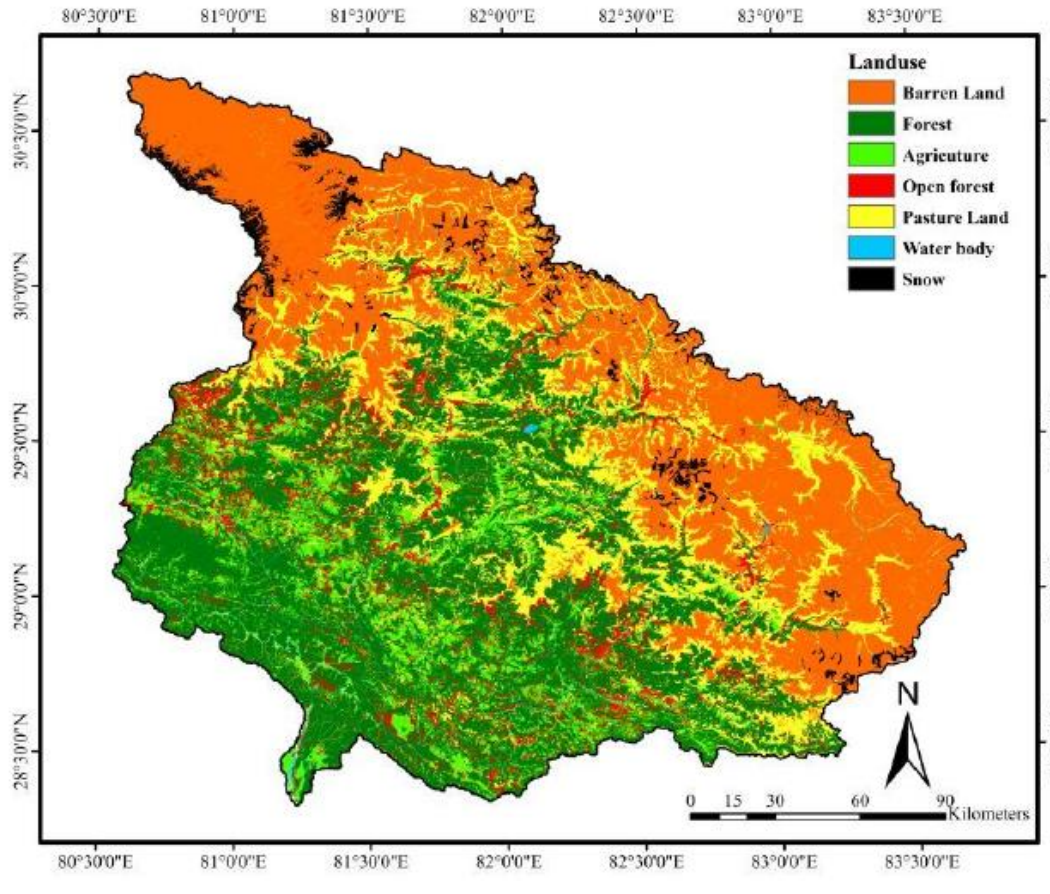

Fig. 2: Land Cover map of KRB (Pandey et al., 2015)

The largest expanse was forests, encompassing 33.45%, followed closely by bare areas accounting for 30.3% of the region. Shrub and grassland areas constituted 18.49% of the total, while agricultural land occupied 13.12%. Snow and ice-covered regions made up 4.32% of the landscape, while water bodies were relatively scarce, comprising just 0.3%. The smallest portion was allocated to built-up areas, representing a mere 0.04% of the overall land cover within the KRB (Shrestha et al., 2019). Middle of the basin seemed to have water body named Rara lake and north east part has Shey Phoksundo lake. Lower most part of basin highly dominated by forest cover and above it dominated by agriculture land.

Chapter IV: Data and Methodology

4.1 Data

Table 1: Types of Research Data in KRB

Product Name	**Data Sources**	**Spatial Resolution**	**Temporal Resolution**	**Data Range**
Meteorological Data (Precipitation)	DHM	Point Data	Monthly	1986-2019
MOD13Q1.0061(Terra Vegetation Indices)	https://appeears.earthdatacloud.nasa.gov/	250m×250m	16-Day Global	2002-2020
Southern Oscillation Index (SOI)	bom.gov.au	Point Data	Monthly	2006_Winter and 2015_Monsoon

4.1.1 Precipitation Data

Precipitation data were obtained from the Department of Hydrology and Meteorology (DHM) in Nepal, specifically from 16 meteorological stations located inside the KRB. Data has been taken from stations where data availability was more than 95% of total time of data period. Data were ranged from 1986-2019 which lies from 225 to 3000 m above mean sea level altitude spatially inside the KRB.

Table 2: List of Meteorological station of KRB

Station Name	Station No.	Type of station	District	Latitude	Longitude	Elevation(m)
Pipalkot	0201	Precipitation	Bajhang	29.62	80.87	1456
Pilgadhi Doti	0203	Climatology	Doti	29.26	80.98	1360
Asara Ghat	0206	Precipitation	Achham	28.95	81.45	650
Dipayal (Doti)	0218	Synoptic	Doti	29.23	80.93	720
Jumla	0303	Synoptic	Jumla	29.28	82.02	2300
Guthi Chaur	0304	Precipitation	Jumla	29.28	82.32	3080
Nagma	0308	Precipitation	Kalikot	29.20	81.90	1905
Pusma Camp	0401	Climatology	Surkhet	28.88	81.25	950
Dailekh	0402	Climatology	Dailekh	28.85	81.72	1402
Jajarkot	0404	Precipitation	Jajarkot	28.70	82.23	1231
Chisapani (Karnali)	0405	Climatology	Bardiya	28.65	81.27	225
Surkhet (Birendra Nagar)	0406	Synoptic	Surkhet	28.60	81.62	720
Bale Budha	0410	Precipitation	Dailekh	28.78	81.58	610
Maina Gaun	0418	Precipitation	Jajarkot	28.98	82.28	2000
Chaur Jhari Tar	0513	Climatology	Rukum	28.63	82.20	910
Musikot (Rukumkot)	0514	Climatology	Rukum	28.63	82.48	2100

4.1.2 MOD13Q1.0061 Terra Vegetation Indices 16-Day Global (250) m

Satellite data from MODIS (Moderate Resolution Imaging Spectro Radiometer) of land cover product was used for Spatio-temporal mapping of vegetation. MODIS data, spanning from 2002 to 2020, was used for vegetation study inside the KRB. These data were employed to assess changes in vegetation patterns in the KRB, which can provide valuable insights into drought conditions inside the basin. It is available for the vegetation phenology study using vegetation index (VI) per pixel as MODIS13Q1

V6 level three product. This product offers two layers of the data as NDVI and EVI. The first is the Normalized Difference Vegetation Index (NDVI) which is referred to as the continuity index to the existing National Oceanic and Atmospheric Administration-Advanced Very High Resolution Radiometer (NOAA-AVHRR) derived NDVI. The second vegetation layer is the Enhanced Vegetation Index (EVI) that minimizes canopy background variations and maintains sensitivity over dense vegetation conditions. These data are available from 18th February 2000 to present so there is temporal limit for this study. MOD13Q1.0061 Terra Vegetation Indices 16-Day Global 250m (NDVI) downloaded from MODIS for VCI index calculation from 2002-2020 (https://lpdaacsvc.cr.usgs.gov/appeears/).

4.1.3 Southern Oscillation Index (SOI)

Southern Oscillation Index data utilized to link precipitation phenomena with large scale atmospheric circulation for the winter of 2006 and 2015 summer drought in the basin. SOI data was downloaded from Southern Oscillation Index (SOI) history (bom.gov.au) of Australian government site.

4.2 Methodology

4.2.1 Precipitation Data

After collecting Precipitation data, further quantifying for the data quality control have been done to minimize the error in the result. Initially more than 25 station data were collected and ultimately 16 station have been selected for the analysis focusing with data gap less than 5% of the time. Data gap of less than one year continuously were selected under the World meteorological organization (WMO) guide to fill gap. Normal ratio method have been applied to the station to make data set more homogeneous. 10 station have been selected with no data gap and 3 station have less than 2% and 3 station have less than 5% data gap were used for the final calculation of the result.

4.2.2 MOD13Q1.0061 Terra Vegetation Indices 16-Day Global 250 m

After collection of data, there were certain steps done for the preparation of data in order to make easy access for the processing which are as follows:

I. Folders were created to store data, one for MODIS NDVI files (MOD13Q1) data and other for pixel reliability files.
II. Data was arranged in correct order of date as "DOY_", e.g. DOY_001.
III. Loaded all data into R-program with suitable file format then stack long term data using function to calculate long term NDVI to visualize VCI.
IV. Calculate seasonal spatial and time series of VCI using vegetation indices data of 18 years.

4.2.3 SPI Index

Time series of precipitation data of 34 years from 1986-2019 is used for calculation SPI -3, 4 and 12. The Standardized Precipitation Index (SPI) is a widely used meteorological drought index that quantifies the deviation of precipitation from the long-term climatological average of precipitation (McKee et al., 1993). Standardized Precipitation Index (SPI) involves fitting a chosen probability distribution (e.g., gamma, incomplete beta, or Pearson III) to the long-term precipitation data, typically spanning over 30 years, through maximum likelihood estimation of the distribution parameters (Guttman, 1998; McKee et al., 1993). The SPI is calculated using the following formula:

Table 3: SPI Index Quantification (Mckee et al., 1993)

Drought Classification	**SPI**
Extreme	< -2.0
Severe	-1.99 to -1.50
Moderate	-1.49 to -1.0
Mild	-0.99 to -0.01

$$SPI = (P - \mu) / \sigma \quad (1)$$

Where,

SPI is the Standardized Precipitation Index

‘P’ is the precipitation value in mm for a given time period (e.g., monthly, seasonal, annual)
‘μ’ is the long-term mean precipitation for the same time period
‘σ’ is the long-term standard deviation of precipitation for the same time period

Negative SPI values indicate below-average precipitation (indicating drought), while positive SPI values indicate above-average precipitation (indicating wetter than normal conditions). SPI values close to zero represent near-normal precipitation conditions. Drought are classified as extreme (<-2), severe (-1.99 to -1.50), moderate (-1.49 to -1) and mild (-0.99 to -0.01).

The SPI can be calculated for different time scales (e.g., 1-month, 3-month, 4-month, 12-month) to capture different drought characteristics to analysis winter, pre-monsoon, summer monsoon and annual scale of SPI index. SPI is flexible for space and time and applicable for the short term agriculture monitoring to long term hydrological balance of the water bodies (Hayes et al., 2011). Additionally, different threshold values for SPI can be used to define different drought categories based on the specific research objectives and characteristics of the study area. R- Program with SPEI package has been used to calculate SPI index under Gamma distribution and graphical visualize of the spatio-temporal time series of the index have been performed using same platform. SPI-3 for February is calculated for winter drought, SPI-4 for September is calculated for summer monsoon drought also known as monsoon, SPI-3 for May calculated for pre-monsoon drought and SPI-12 for December calculated for annual pattern of drought inside the basin. GIS tool has been used for the spatial and trend mapping of the SPI index for different seasons and specific event wise visualization of the station wise drought.

4.2.4 Mann-Kendall Trend Test (MK-Test)

MK-test have been performed for the trend test of SPI of winter, monsoon and annual scale. Time series data using the Mann-Kendall (MK) trend test in R, utilizing the 'Kendall' package. The time series data, representing the variable of interest, was loaded into R and stored as a vector. The 'trend.test ()' function from the 'Kendall' package was applied to the data, and the tau statistic and p-value were extracted from the output. A significance level of 0.05 was used to interpret the results, with a p-value less than 0.05 indicating a significant trend. MK-test is a non-parametric test used to find trend of the long term data collected over time for consistently increasing or decreasing trend (monotonic). It is categorized as significant increasing, increasing, no trend, significant decreasing, decreasing shows the strength of trend and slope of data (Mann, 1945).

4.2.5 Correlation between VCI, Precipitation and SPI

Pearson correlation coefficient (r) have been calculated for SPI and precipitation with VCI index of the basin for different time scale of the year for winter, monsoon and annual. Cross correlation factor is also calculated for the long time daily data of VCI and precipitation. It is performed in the R using auto correlation function under ($p<0.05$). Positive correlation between two variable with p-value less than 0.05, considered statistically significant trend. Cross correlation between VCI and precipitation indicated the relation between precipitation and vegetation response with lag time between them. Lag time between vegetation growth and precipitation indicates the gap time between precipitation and vegetation occurs and the change in vegetation greenness up to its maximum level (Zhan et al., 2022). Mathematically, the cross correlation function is defined as the correlation coefficient between two time series that is considered with the lag time between two variable with one response later than other. The ccf function in R will return an object of class "acf" (auto correlation function) that contains the cross-correlation function values, time lags, and other information that can be used for further analysis or visualization. Cross correlation function in R-program calculated in accumulated correlation function (acf) as below.

h (lag) is the time factor of lag extended to positive and negative value of month. In case of cross correlation between VCI and precipitation.

h (lag) < 0 where, precipitation leads VCI
h (lag) > 0 where, precipitation lags VCI

When precipitation leads VCI, it indicates that changes in precipitation conditions are followed by changes in vegetation condition with a time lag. In contrast, when precipitation is lagged in relation to VCI, it suggests that vegetation condition does not depend on precipitation. However, in general, VCI is considered to be more responsive to changes in precipitation rather than a driver of precipitation.

4.2.6 MODIS (MOD13Q1) Data Processing

The Normalized Difference Vegetation Index (NDVI) is a widely used measure for quantifying vegetation health, calculated by comparing the reflectance of near-infrared and red light. NDVI relies on the phenomenon where healthy green leaves reflect Near-Infrared (NIR) light due to their internal structure, while they absorb much of the visible red light. Unhealthy or water-stressed vegetation exhibits the opposite behavior.

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{2}$$

Where, Red and NIR represent the reflectance values in the red and near-infrared bands, respectively. NDVI values range from -1 to +1, with negative values indicating water bodies and values close to +1 denoting dense vegetation. Red band reflects high amount of radiation when vegetation is dry and weak and NIR bands reflects more radiation during healthy and green vegetation condition (Krakauer et al., 2017; Viovy et al., 1992).

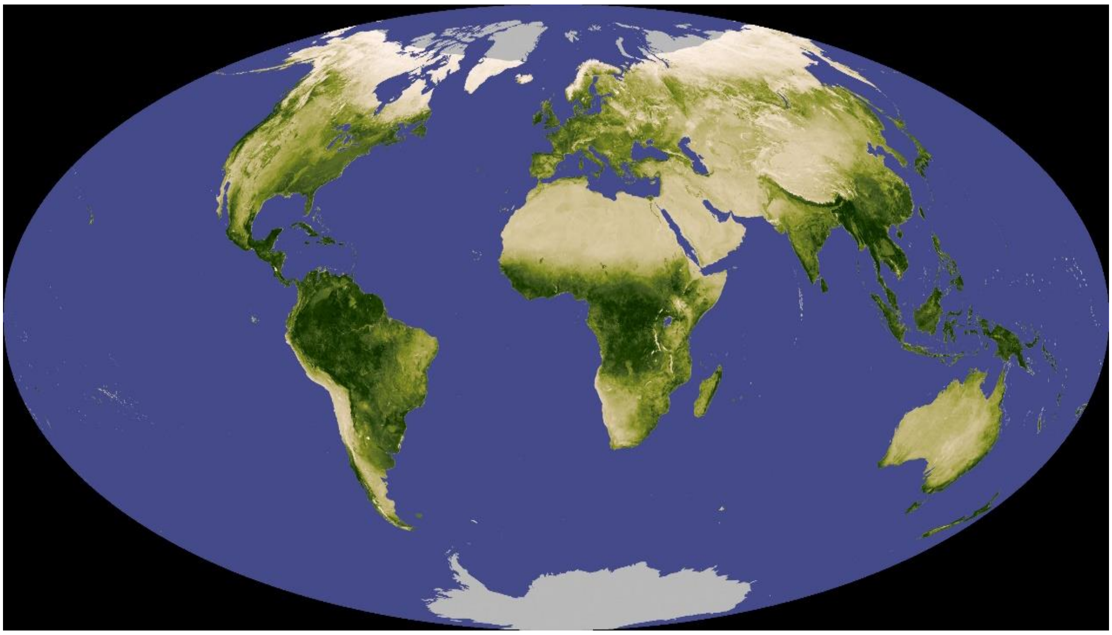

Fig. 3: Modis Global NDVI mapping

It is relative changes in vegetation indices as Normalized Difference Vegetation Index (NDVI) change with respect to long term minimum and maximum of historical NDVI (EVI) value (Dutta et al., 2015; LIU and KOGAN, 1996).

$$VCI_{ijk} = \frac{(VI_{ijk} - VI_{i,min})}{(VI_{i,max} - VI_{i,min})} * 100 \qquad (3)$$

where, VCI_{ijk} is the VCI value for the pixel i during week/month/DOY j for year k, VCI_{ijk} is the weekly/monthly/DOYs VI value for pixel i in week/month/DOY j for year k whereby both the NDVI or EVI can utilized as VI, $VI_{i,min}$ and $VI_{i,max}$ are the multiyear minimum and maximum VI, respectively, for pixel i. In this paper, NDVI is taken as a vegetation indices for calculating VCI which is given as:

$$VCI = \frac{(NDVI_i - NDVI_{min})}{(NDVI_{max} - NDVI_{min})} * 100 \qquad (4)$$

Where, $NDVI_i$ is vegetation pixel value of calculation time, $NDVI_{max}$ is long-term maximum value and $NDVI_{min}$ is long-term minimum value of VI as NDVI.

The VCI is expressed as a percentage and provides an indication of where the current vegetation condition falls within the historical range of values. Lower VCI values indicate poor vegetation health, potentially indicating drought conditions, while higher VCI values indicate good vegetation health. The VCI is commonly used to identify drought conditions and assess the severity of drought by comparing current vegetation conditions with historical values. VCI is categorized in three different condition according to the vegetation cover percentage inside the geographical boundary (Kogan, 1997; Baniya et al., 2019).

Table 4: VCI Index Classification (Kogan, 1996)

Drought Classification	**VCI (%)**
Severe Drought	<35
Drought	35-50

Normal	>50

The Vegetation Condition Index (VCI) is typically classified into three categories: normal, drought, and severe drought. When VCI exceeds 50%, it signifies normal vegetation conditions. VCI ranging from 35% to 50% indicates a moderate level of vegetation stress, often signaling early signs of drought impact. If VCI drops below 35%, it indicates a severe drought condition. Additionally, areas like water bodies and barren lands tend to have near-zero vegetation values on the VCI drought scale.

4.2.7 Research Design

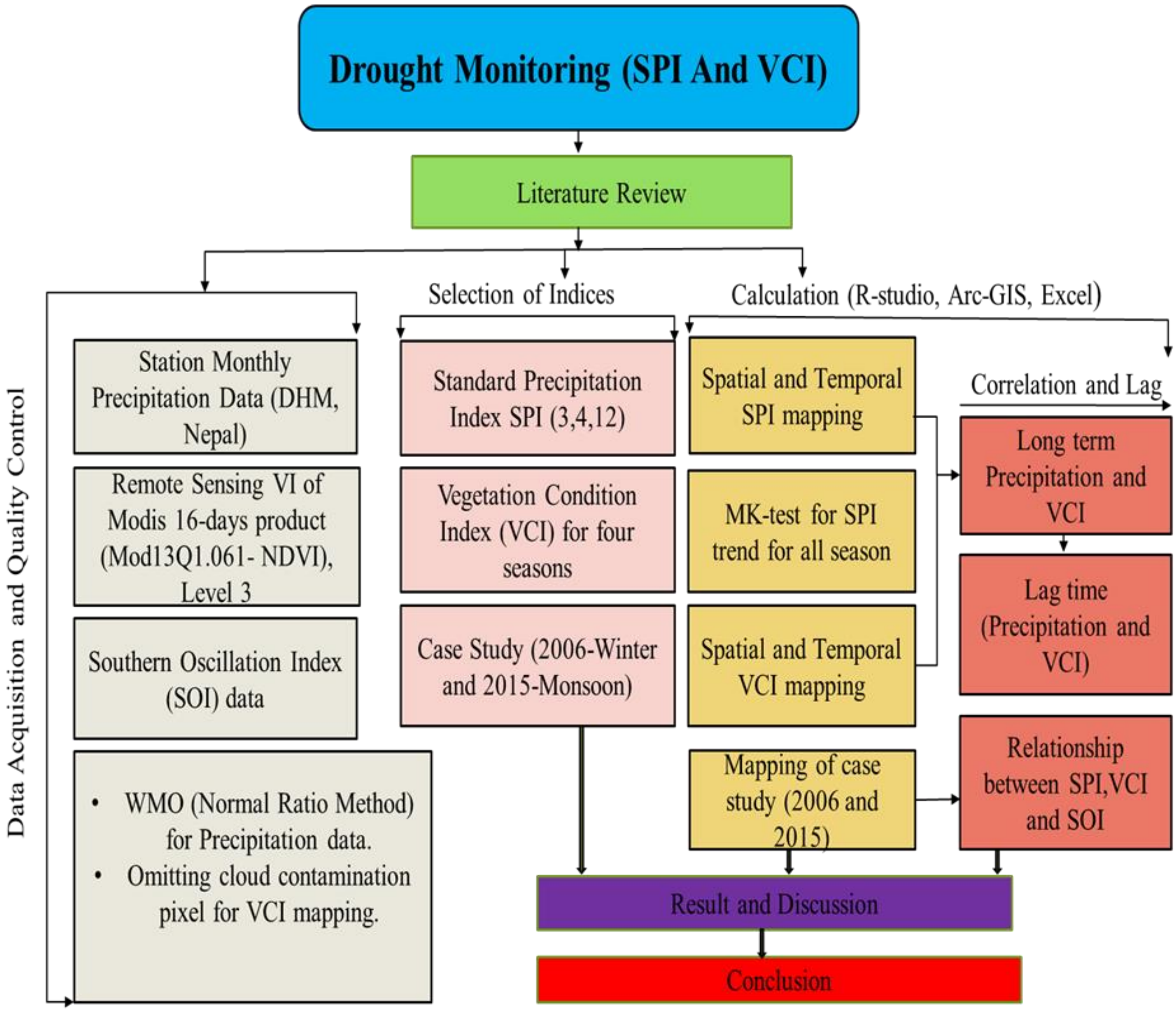

Fig. 4: Flow chart for the methodology incorporated in the study

Both indices have been calculated in the R-studio environment using suitable packages for SPI and VCI calculation. It is smooth and dynamic platform to study time series data of climatic parameter and visualization of temporal and spatial scale of data. After collecting data and quality control process, it is loaded in the R-console, SPI is computed in SPEI package for different time scale of SPI as SPI-3, SPI-4 and SPI-12. Similarly, VCI is computed with long term NDVI max and min value with current NDVI of the grid

Chapter V: Result

5.1 Time series Analysis of Precipitation

Precipitation data collected from meteorological stations located inside the KRB were meticulously analyzed for a period of 34 years, spanning from 1986 to 2019. The analysis revealed a decreasing pattern in the average intensity of precipitation after the year 2000.

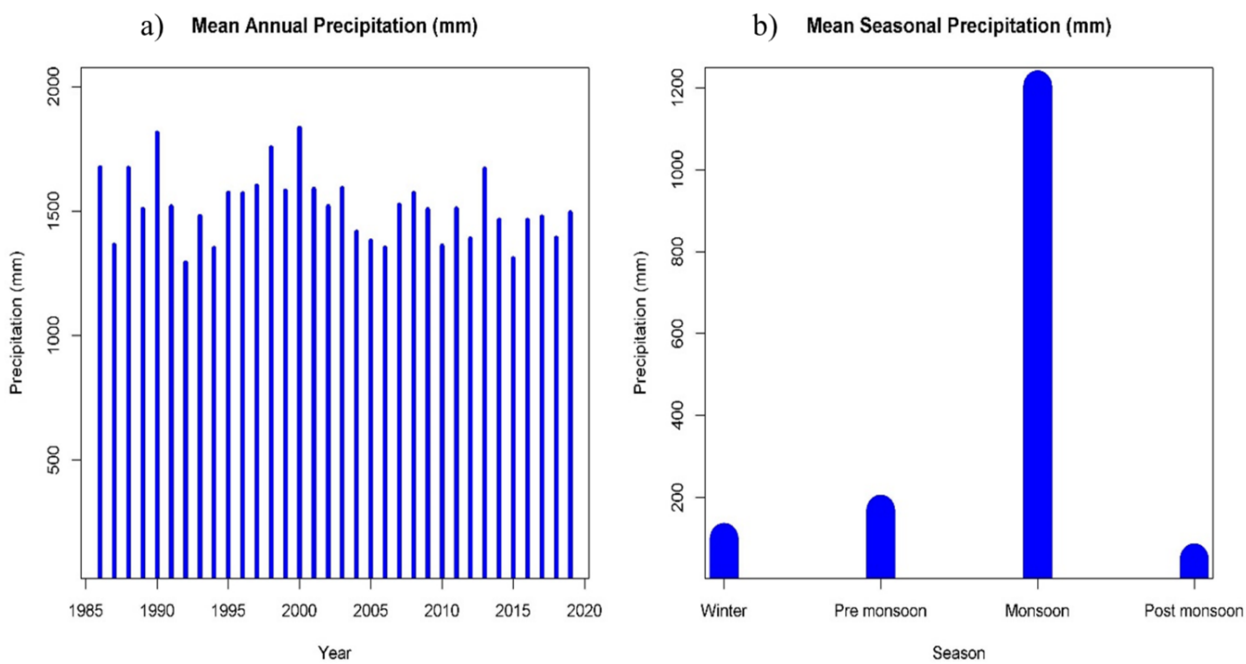

Fig. 5: a) Time-series of mean precipitation (1986-2019), b) Seasonal mean Precipitation in KRB

The highest recorded precipitation amount was observed in the year 2000, reaching an approximate value of 1833 mm, while the lowest recorded amount was noted in 1992, with a value of 1292 mm. Notably, out of the 34 years analyzed, 13 years were identified as rainfall deficit years within the basin, with 7 of those years occurring since 2000. Furthermore, the analysis revealed consecutive dry years in 1991, 1992, 1993, and 1994, indicating a persistent water deficit during that period. Similarly, the years 2004, 2005, and 2006 also experienced water deficit conditions, as depicted in the graph. The mean annual precipitation recorded within the basin, as per the station records, was approximately 1600 mm.

The total amount of precipitation recorded at all stations was aggregated and averaged to derive seasonal totals of precipitation for different time scales within the same time period of all years. The analysis of seasonal variation in precipitation revealed a general pattern consistent with other regions in the country, with summer monsoon rainfall being the dominant contributor, accounting for approximately 1200 mm (75%) of the annual precipitation in the Karnali river basin. Winter precipitation, contributing approximately150 mm (10%) to the annual precipitation. On the other hand, post-monsoon precipitation was observed to be the lowest contributor to the seasonal pattern, accounting for approximately 50 mm (3%) where pre-monsoon contributed 205 mm (12%) as second highest precipitation season inside the KRB.

5.2 Spatio-Temporal Analysis of SPI

Time series analysis of all stations inside the basin is plotted with spatio-temporal graph to represent the spatial extent of SPI inside the basin for study period. SPI-12 for December showed negative (red) SPI and positive (blue) has occurred most of the time in between 1986- 2019 inside the KRB at different altitude of station and identified the combination of different negative and positive SPI years. Pipalkot station (201) showed extreme SPI condition in 1992 and five year with moderate SPI where Silgudhi Doti (203) indicated severe SPI for 1992, 2008 and more negative SPI year after 2000. Doti Dipayal (218) experienced negative SPI in 1992, 1999 followed by moderate SPI in 2016 and 2018. Higher elevation station lies in the northern portion Jumla (303) and Guthichaur (304) showed different pattern negative SPI year , station (303) have severe negative SPI year in 1999,2005 and five moderate SPI year where as station (304) had extreme negative SPI year in 2009, severe in 2001 and moderate in 2006. Station (401) of Surkhet experienced extreme SPI year in 1987 and 2012, severe in 1992 and moderate in 2001. Chisapani (405) experienced severe negative

SPI in 1992, 1994 and moderate in 2010. Station (410) experienced severe negative SPI in 1991, 1992 and moderate in 1987 and 2018. Similarly station (514) experienced extreme drought in 2006 and 2015. Most of the station experienced negative SPI after 2015 and percentage of extreme negative SPI is around 20%, severe of 30% and moderate is 50%. It is assumed that 1992, 2006, 2008, 2010, 2015 and 2017 were severe impact year inside the basin.

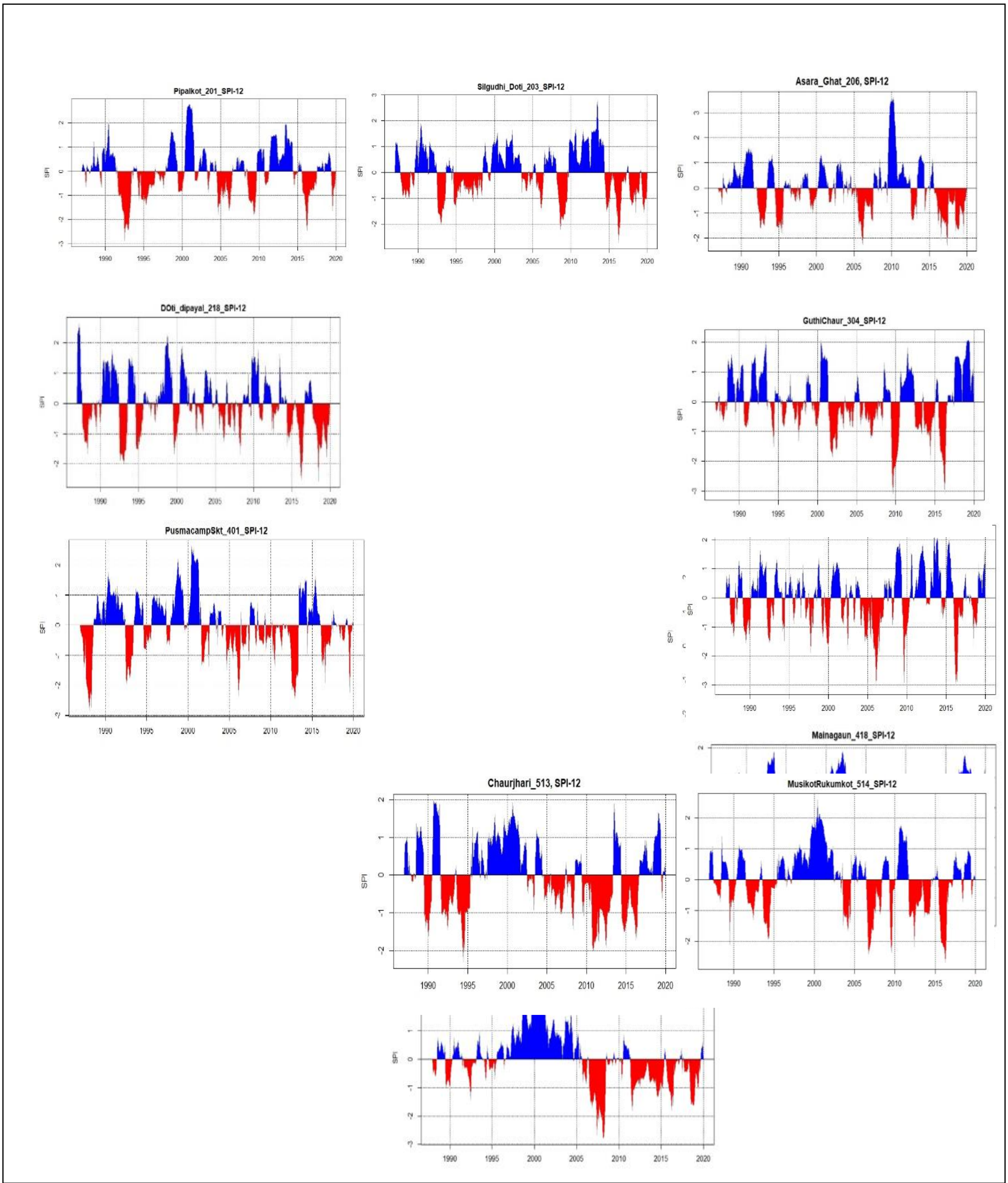

Fig. 6: Station Wise Spatio-temporal variation of Drought in KRB (1986-2019)

5.3 Temporal and Spatial Analysis of (SPI)

The temporal and spatial variation of drought within the KRB analyzed using long-term time series meteorological data spanning 34 years from 1986-2019. The Standardized Precipitation Index (SPI) was employed as a drought index, with different time scales, including SPI-3, SPI-4, and SPI-12, used to quantify the temporal variation of drought.

SPI-3 calculated for the winter season, was used to assess the trend of winter drought in the basin. SPI-4, calculated for the monsoon season, was used to analyze the trend of monsoonal drought. SPI-12, calculated for the annual scale, was used to assess the trend of drought over the entire year in the KRB.

5.3.1 Temporal Analysis of SPI

Seasonal precipitation data were used for the winter drought analysis for December to February has been taken of study period for winter SPI as SPI-3.

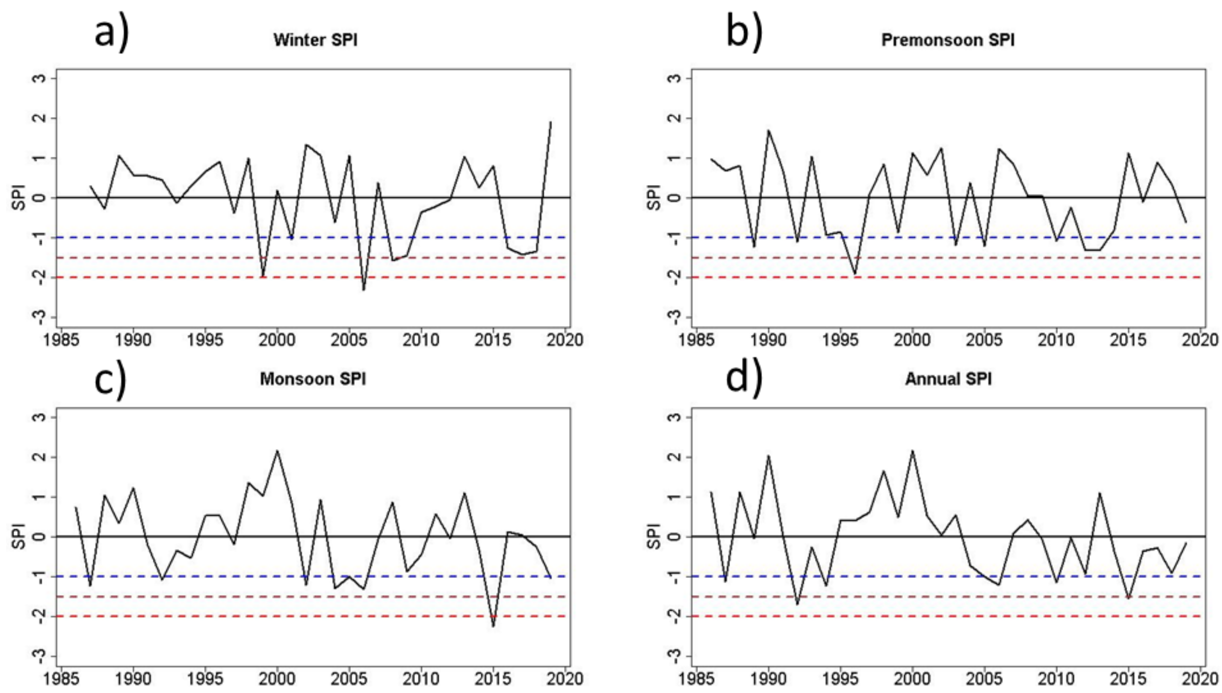

Fig. 7: Time series of SPI index for a) Winter, b) Pre-monsoon, c) Monsoon, d) Annual inside KRB (1986-2019)

Most of the stations experience winter negative extreme SPI value in 1999, 2006 and 2008. Consecutive winter negative SPI has been identified in 2008, 2009,2010,2011,2012 and 2016, 2017 and 2018. Negative SPI occurred 17 out of 34 years according to time series analysis of winter SPI index.

Pre-monsoon SPI-3 for May showed more than half of time experienced negative value of SPI during dry months (MAM) inside KRB. It has indicated consecutive year 1994, 1995 and 1996 was negative SPI where 1996 was the extreme negative SPI on the record followed by 2010 and 2014 were also negative SPI value.

Summer monsoon SPI-4 for September computed for monsoon season (JJAS) over 34 years inside KRB. About 50% of years exhibited negative SPI values, signifying below-average precipitation. Most negative SPI years were moderately negative, except 2015, an extreme negative SPI case. Post-2000, a rising negative SPI trend emerged. Consecutive negative SPI years occurred in 1991-1994 and 2004-2007. Overall, 19 of 34 years experienced negative SPI years inside the KRB.

The annual SPI-12 plot for December in the basin (January to December) revealed a notable increase in negative SPI values post-2000, predominantly indicating moderate to severe negative conditions. Severe negative SPI-12 instances were observed in 1992, 2015, and 1987. Consecutive negative SPI-12 years occurred in 1991-1994, followed by 2009-2019 (except 2014). Overall, 18 out of 34 years on the annual time series exhibited negative SPI values, underscoring a significant prevalence of such occurrences.

5.3.2 Spatial Analysis of SPI

All stations inside the basin were quantified to assess the significance of the SPI using MK-trend test for seasonal and annual pattern of SPI index for 34 years.

The Mann-Kendall trend test evaluated winter SPI trends across all stations. Results indicated a decreasing trend in winter SPI within the basin. Specifically, Chisapani Karnali and Silgudhi Doti displayed significant decreasing SPI trends. The south-western part of basin was identified as highly vulnerable during winter, with the remaining area also exhibiting negative SPI trends. Winter trend evaluated with moderate to severe condition of negative SPI trend inside the KRB.

Historical data exposed pre-monsoon vulnerability to precipitation scarcity in most basin stations, except three in the central-west to east. Pre-monsoon SPI exhibited a consistent decreasing trend across the basin, except in select areas like Dadeldhura, Jumla, and Rukum. The southern basin experienced a more prominent SPI decline than the middle portion, highlighting substantial moisture deficiency.

Furthermore, an investigation into the summer monsoon season revealed dry conditions in nearly ten out of sixteen stations, indicative of a declining SPI trend. The monsoon SPI trend remained unaffected in the middle part of the basin, whereas the lower portion experienced a negative SPI trend. Particularly, the monsoon SPI exhibited a decreasing trend in the southern portion and far west region of the KRB, encompassing areas like Doti, Dadeldhura, Achham, Bajhang, Bajura, and Darchula.

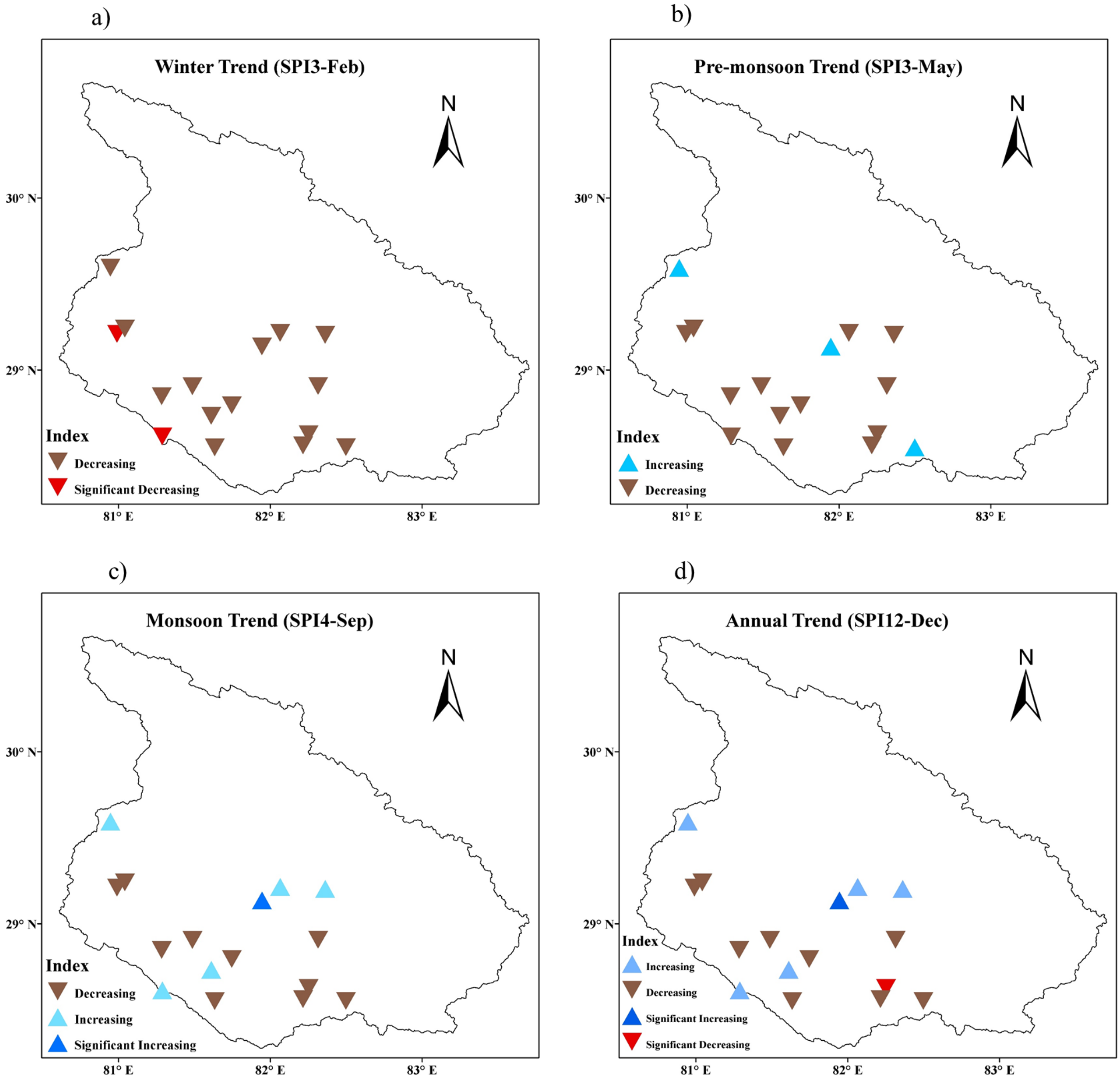

Fig. 8: Spatial Trend mapping of SPI index for, a) Winter, b) Pre-monsoon, c) Monsoon, d) Annual time scale

Annual SPI-12 pattern indicated approximately 50% of stations with a decreasing trend. Station-418 in Mainagaun, Jajarkot, displayed a significant decreasing trend, while station-308 in Nagma, Kalikot, exhibited a noteworthy increasing trend, along-side five other stations. Nine stations within the basin showed a decreasing trend of SPI. Notably, the south eastern part and the lower stretch from west to east exhibited decreasing annual SPI trends. Districts like Doti, Dadeldhura, Achham, Dailekh, Surkhet, Jajarkot, Dang, Salyan, and Rukum experienced a decreasing SPI trend, whereas Jumla, Kalikot, and Mugu did not follow this pattern.

5.4 Temporal and Spatial Analysis of VCI

5.4.1 Temporal Analysis of VCI

The comprehensive analysis of Vegetation Condition Index (VCI) time series data across the entire basin reveals distinct seasonal patterns. Notably, the pre-monsoon and winter seasons exhibited poorer VCI vigor compared to the summer monsoon and post-monsoon periods. The highest VCI, reaching 58%, was recorded during the monsoon of 2015, while the lowest, at 35%, occurred in the pre-monsoon of 2008. The monsoon and post-monsoon seasons displayed an upward VCI trend, in contrast to the decreasing trend observed during winter. Significantly, over 50% of the year sustained VCI levels exceeding 50% during the monsoon and post-monsoon phases. Monsoon VCI fell below 50% in 2002, 2008, and 2010, while post-monsoon VCI remained above 50% consistently from 2002 to 2020. Pre-monsoon exhibited VCI above 40% in 2002, 2007, 2015, and 2020, with the rest of the year below 40%. Winter VCI ranged from 40% to 45%, with the lowest at 40% in 2019 inside KBR. Winter VCI showed a slightly decreasing trend, while pre-monsoon VCI displayed a significant increasing trend despite its lowest values among seasons.

Over a span of 2002-2020, a comprehensive analysis extracted station wise VCI time series for monsoon, winter, post-monsoon and pre-monsoon periods. Notably, the summer monsoon season consistently exhibited the highest vegetation condition, boasting an average VCI of 68% in 2019, indicative of robust vegetation health. Between 2002 and 2020, monsoon VCI displayed an ascending percentage, consistently surpassing 50% and reaching a low of 58% in 2010. Post-2010, a notably ascending monsoon VCI trend emerged, characterized by a positive slope value, signifying improved conditions compared to the preceding decade. Post monsoon time series showed slightly increasing trend of VCI having highest VCI of 63% in 2013 where lowest VCI with 56% in 2011. It is shown than post monsoon VCI concentrated of around 60% for most of the year. VCI was decreasing trend in 2002 to 2010 decade, contrarily VCI has found increasing trend after 2010 to 2020.

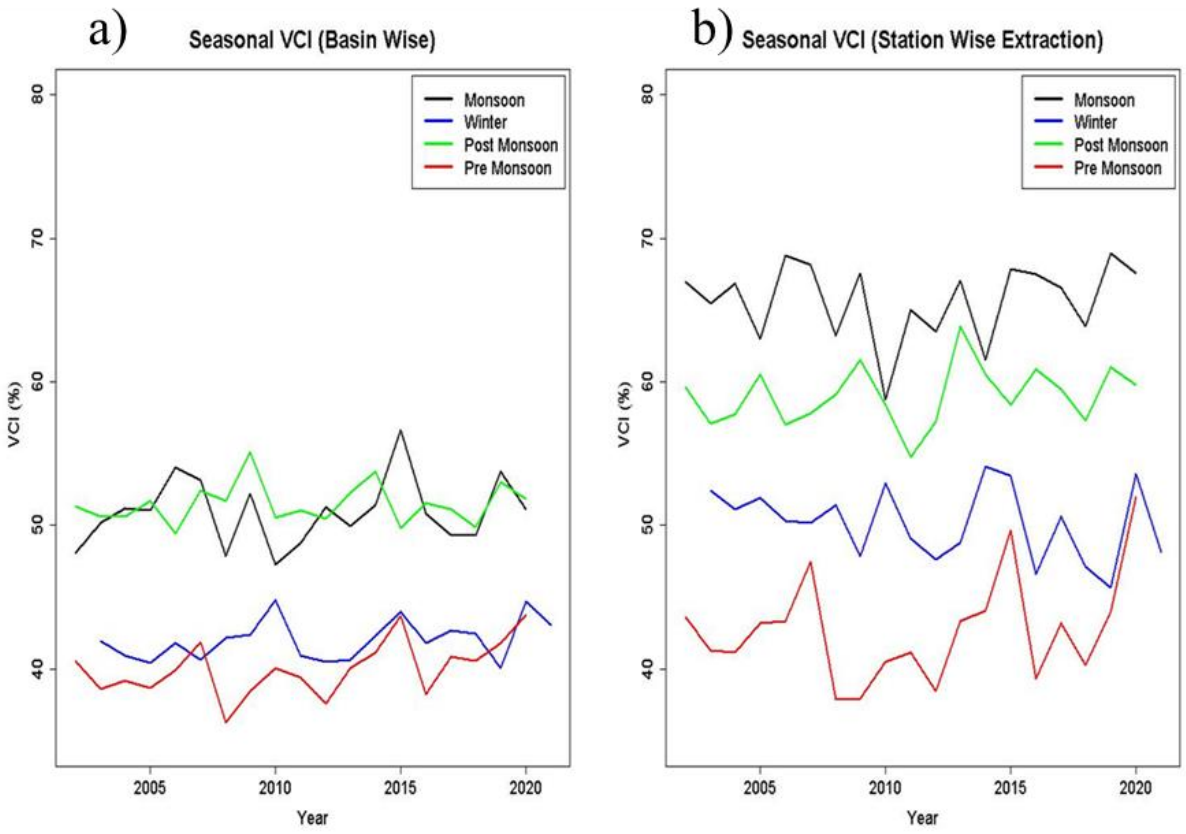

Fig. 9: VCI Time-series of a) Basin Wise, b) Station Wise for Monsoon, Winter, Post-Monsoon and Pre-Monsoon (2003-2020)

From 2003 to 2020, winter VCI exhibited a decreasing trend. Notably, the lowest VCI percentage was recorded in 2018 at 42%, while the highest occurred in 2020 at 52%. Instances of winter VCI below 50% were noted in 2009, 2011, 2012, 2013, 2016, 2018, 2019, and 2021, indicating a moderate drought pattern during this season in VCI mapping. Pre-monsoon VCI displayed an increasing trend, particularly after 2010, except in 2015 and 2020. Except for those years, pre-monsoon VCI remained below 50%, with the lowest values of 37% in 2008 and 2009. On average, pre monsoon VCI within KBR displayed less vigor than other seasons, with a mean VCI of 42% across the study period.

5.4.2 Spatial analysis of VCI

5.4.2.1 PRE-MONSOON VCI

The pre-monsoon spatial analysis of VCI throughout the year revealed consistent weak vegetation conditions across the basin's vegetated land. Approximately 80% of the time exhibited this weakness, predominantly in the southern region rather than the middle.

Particularly severe impact was observed in 2008, 2009, 2011, 2012, 2016, and 2018, where VCI remained around 30%, affecting almost 70% of the basin. The lowland southern and mid-region, encompassing areas such as Dadeldhura, Surkhet, Dailkeh, Dang, Rukum, and Kalikot, were severely impacted in 2008. The northeast suffered more than the northwest. Notably, only the middle of the basin remained relatively less affected. However, in 2015 and 2020, the VCI condition was healthy, with 2020 exhibiting the highest VCI coverage, except for certain parts of Dadeldhura and the central region in the west.

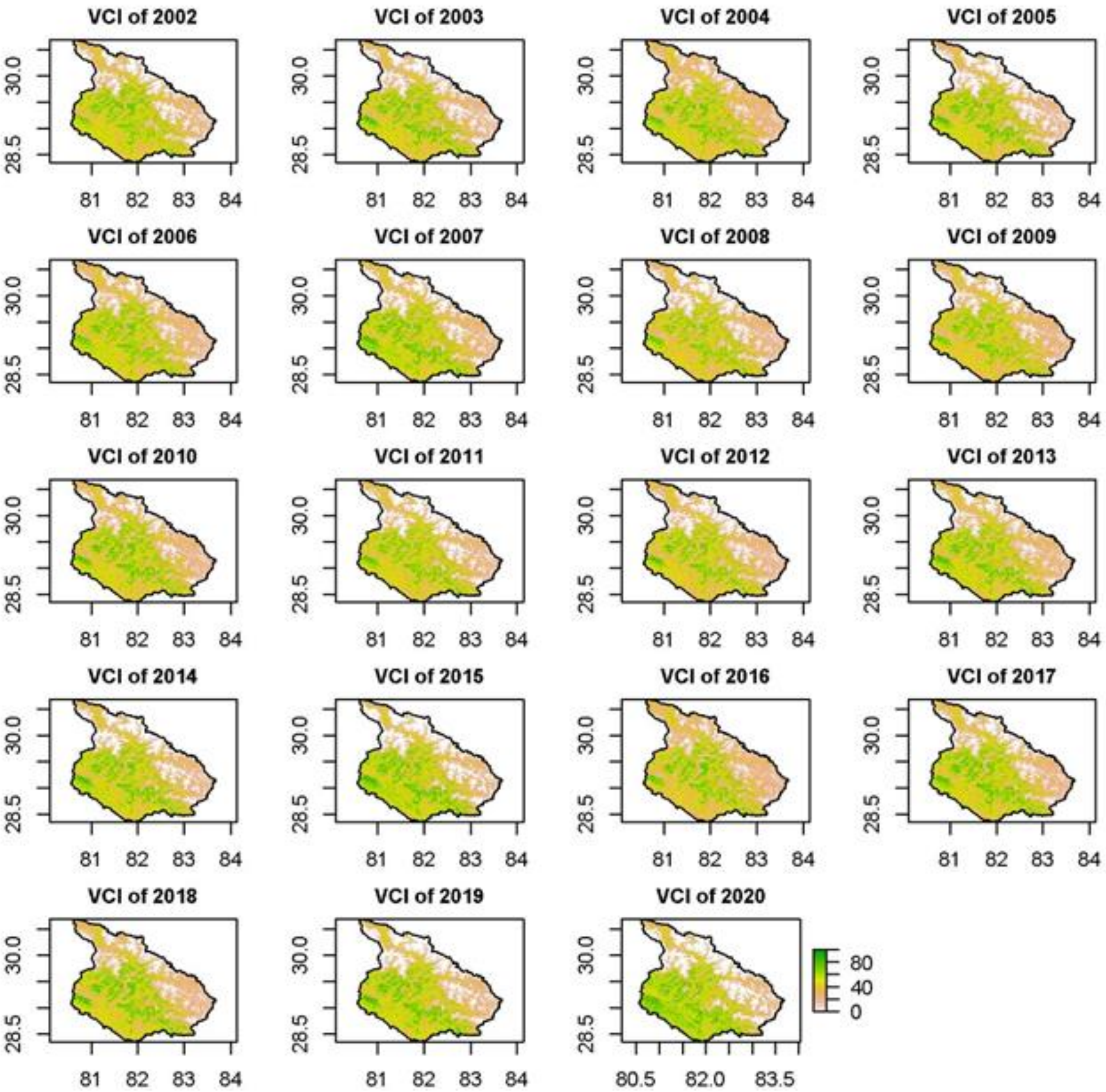

Fig. 10: Spatial mapping of Pre-monsoon VCI (2002-2020)

5.4.2.2 MONSOON VCI

Spatial analysis of VCI mapping during the summer monsoon seasons from 2002 to 2020 reveals distinct variations within the basin.

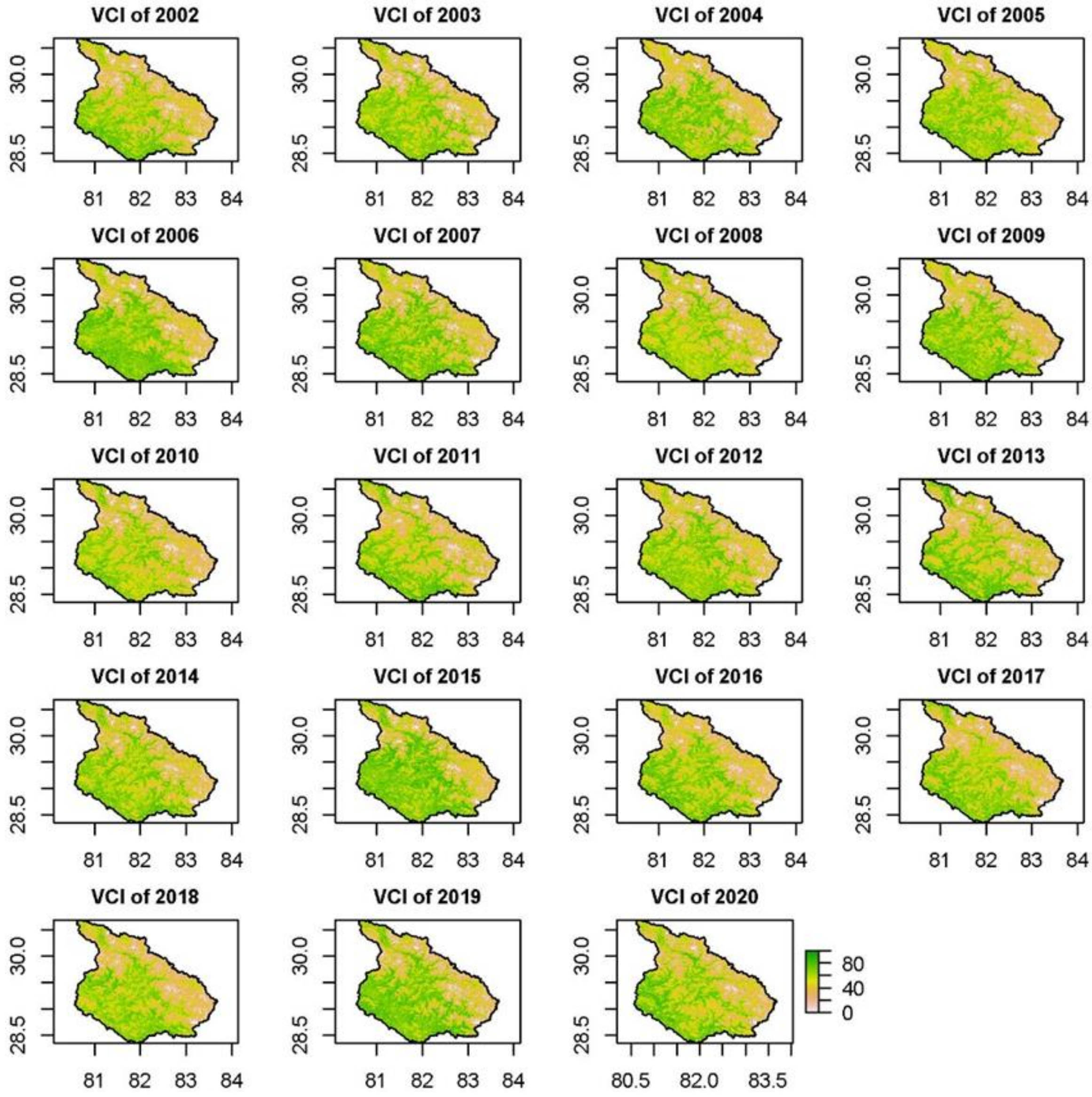

Fig. 11: Spatial mapping of Monsoon VCI (2002-2020)

The southern region consistently exhibits higher VCI levels compared to the northern counterpart. Particularly weak VCI coverage is observed in 2002, 2008, 2010, 2011, 2013, 2014, 2016, 2017, 2018, and 2020. The northeast and west sectors consistently demonstrate the lowest VCI percentages, hovering around 30%, while the southern part consistently maintains over 50% VCI. The years 2010 and 2008 had the lowest

VCI, below 45% basin-wide. In 2010, the southeast and northeast regions saw significant declines, while 2008 had the weakest VCI in the southwest and middle basin.

5.4.2.3 POST-MONSOON VCI

VCI cover during post-monsoon is shown higher than other seasons inside the KRB. Post-monsoon season comes after monsoon so it is directly impacted by the monsoon rainfall.

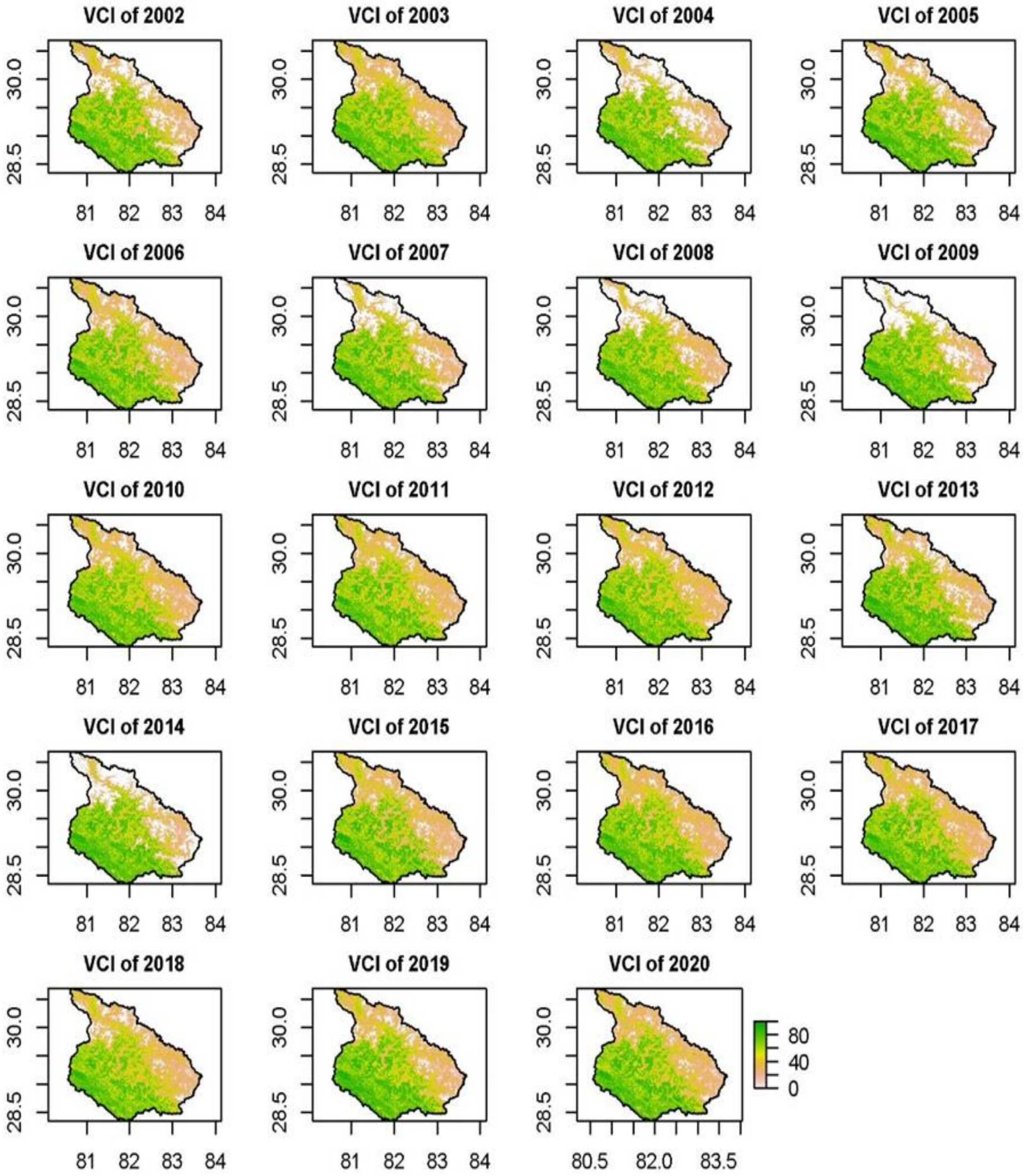

Fig. 12: Spatial mapping of Post-monsoon VCI (2002-2020)

More than 70% of the study period from 2002 to 2020 observed that VCI is moderate and remaining year experienced less than 50% of VCI. VCI condition during post-monsoon is weak in 2006, 2010, 2015, 2018 and 2002; among them 2006 and 2015 have weakest VCI inside the

KRB. VCI condition during post-monsoon indicated that high altitude region of northeast, northwest and middle part of the basin characterized weakest condition of vegetation. During 2006, Southwest part along with middle east-west part of the basin highly impacted VCI of Dadeldhura, Bajhang, Surkhet and Rukum. Another VCI weak year 2015 of post-monsoon showed weakening vegetation in the Bajura, Surkhet, Dailekh, Jajarkot, Humla, Rukum and part of the Kalikot.

5.4.2.4 WINTER VCI

Winter VCI inside the basin from 2003-2020 is given below which showed winter is vulnerable than any other season inside the KRB.

Spatio-temporal variation of the winter vegetation dominated VCI less than 40% for whole basin. All year except 2010, 2015 and 2020 showed weak vegetation condition during winter season in KRB. VCI is less than 40% in the year 2005, 2006, 2008, 2012, 2016, 2019 and rest of the winter year experienced moderate condition of the VCI around 40 to 43%. VCI condition in 2008 has found less than 35% except the south west part of the basin.

Winter is seemed more extreme around 80% area including southeast and mid portion of the basin. Southern west to east part having comparatively good vegetation than the middle and northern part. East-west of the middle portion including Dolpa, Mugu, Humla, Jumla, Kalikot, Bajhang and Bajura seen severely effected in 2011, 2012, 2013 and 2019.

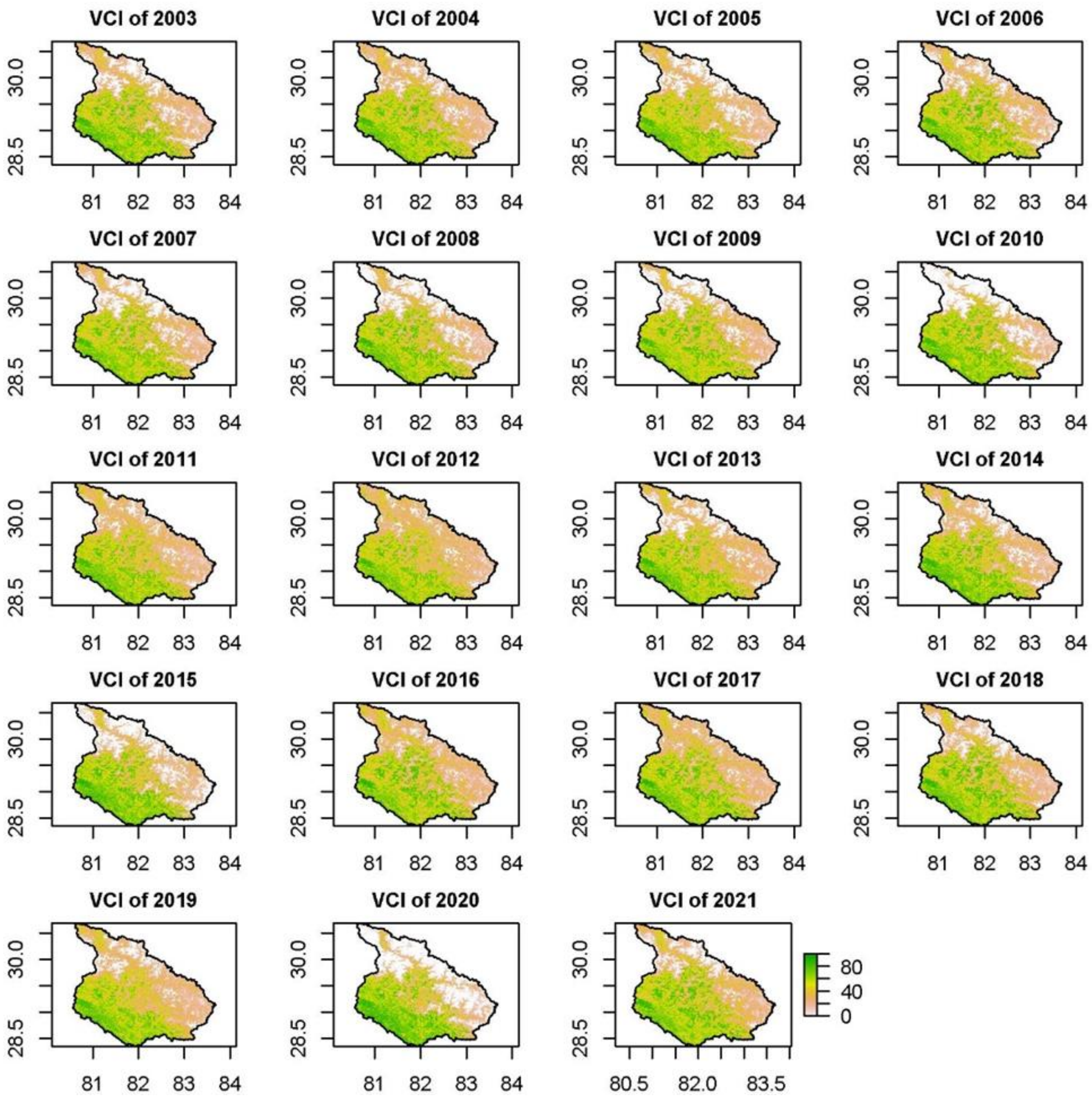

Fig. 13: Spatial mapping of Winter VCI (2003-2021)

5.5 Spatio-Temporal mapping of seasonal VCI

The research examined the VCI across four seasons in KRB for study period. Pre-monsoon displayed weaker vegetation compared to post-monsoon. Spatially, north-west and east had VCI <30%, while southwest and east had VCI>50%, except pre-monsoon. Higher elevations showed weaker vegetation than lower areas, revealing season-topography interactions in KRB's vegetation dynamics. The pre-monsoon period demonstrated widespread weakened VCI across the basin, except Doti, Dadeldhura, Dailekh, Surkhet, Rukum had VCI approximately 30%, while middle regions (Jajarkot, part of Doti, Jumla) exhibited moderate VCI. Overall, around 90% of the basin displayed fluctuation in the VCI within 20 years study. Notably, Chisapani Karnali, Dang, Salyan experienced extreme weakness (VCI ≈ 25%) in the southern basin. The monsoon VCI mapping of the basin revealed that the impact on vegetation condition during the monsoon season was comparatively less than during the rest of the seasons. Less than 20% of the vegetated land in the basin was affected by the monsoon. However, the impact of drought on vegetation condition within the basin was heterogeneously distributed from west to east and south to north. The middle part of the basin, in the west to east coverage, was particularly affected by monsoon drought, with VCI percentages falling below 50%. Spatially, weak VCI values were observed in areas such as Bajura, Rukum, Jajarkot, and parts of Dailekh. The lowest VCI percentages were recorded in most parts of Dolpa and some upper Rukum areas during the monsoon season. These findings highlight the non-uniform distribution of drought impact on vegetation condition within the basin, some part of Doti, Dang, Mugu, Surkhet having VCI less than 40%.

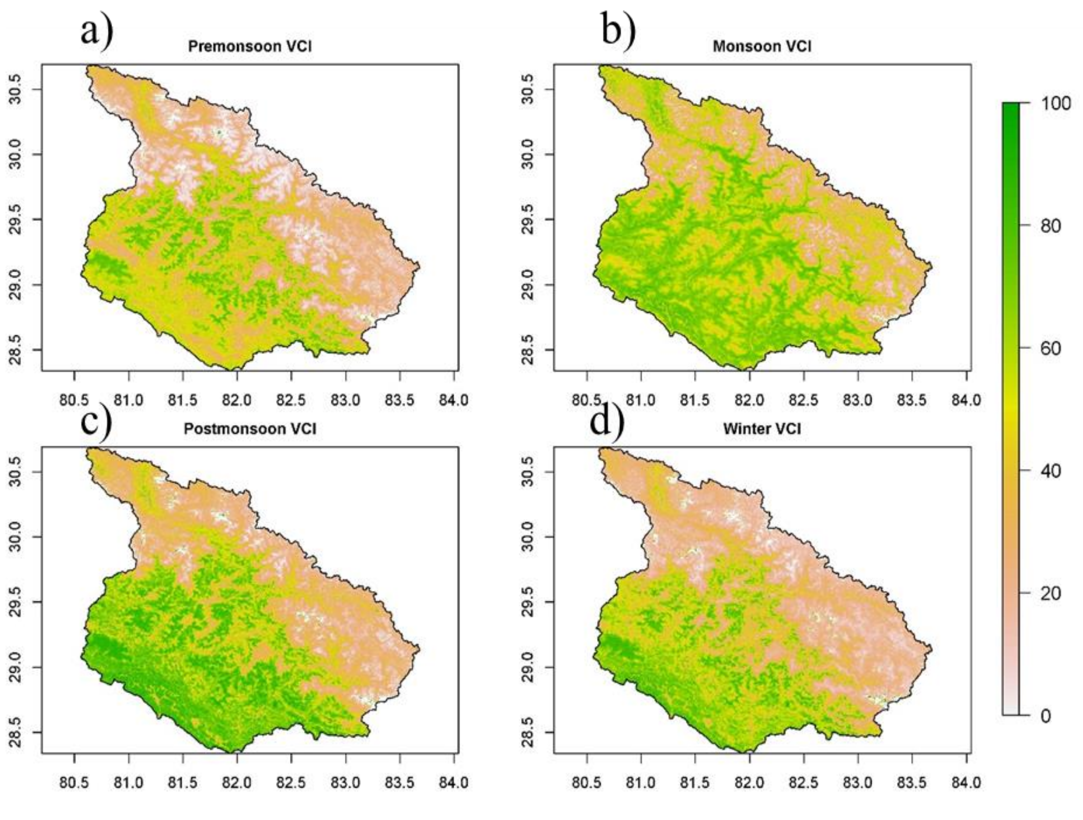

Fig. 14: Seasonal mean VCI for a) Pre Monsoon, b) Monsoon, c) Post Monsoon, d) Winter (2002-2021)

Post-monsoon spatial mapping indicated the healthy condition of VCI inside the basin in comparison to three other seasons. Almost 70% area of the basin having VCI more than 50% where north part of the basin did not show good condition of VCI. Middle part of basin indicated VCI of 45% including Jumla, Jajarkot, Mugu. Similary, VCI condition in the southernmost part of basin showed more than 70%. Northern part of basin showed extreme weak to no VCI in part of Darchula, Humla, Dolpa and Mugu.

The long-term winter VCI map revealed that over two third part of the Karnali River basin experienced VCI values of less than 40%, indicating unhealthy vegetation conditions during the winter season. However, the lower part of the basin, excluding Chisapani karnali and southwest area, had VCI values higher than 60%. Winter drought was particularly intensive in areas such as Bajhang, Bajura, western part of Dadeldhura, Jumla, Humla, and parts of Jajarkot. In Jumla, Mugu, Kalikot and Bajura, the winter VCI values were less than 30%, indicating severe impact on vegetation health. The southeastern part of the basin, including Musikot and Chaurjhari of Rukum, as well as Dailekh and Jajarkot, also showed unhealthy vegetation condition during the winter season with certain region experiencing more severe impact, particularly in the north western and southeastern parts of the basin.

5.6 Lag Time in VCI and Precipitation

VCI response with climatic parameter (precipitation) is divided with lag and lead time of VCI which shown in figure for different month up to 10 month on both side of lag and lead time of VCI with cross correlation factor.

Maximum positive value of correlation 0.8 has seen at one month lag (h= -1) when precipitation leads VCI, means vegetation response is late to precipitation. So, precipitation peak leads to significant VCI only after 1 month of precipitation. Similarly, with two month lag (h= -2) of VCI, correlation is around 0.68 which is the second highest positive correlation. Without considering lag time between VCI and precipitation, correlation is found +0.58. But high negative correlation is also seen at (h= 3), when precipitation lags VCI. This is the adverse and rare condition in the geographical location which signifies vegetation control the precipitation trend.

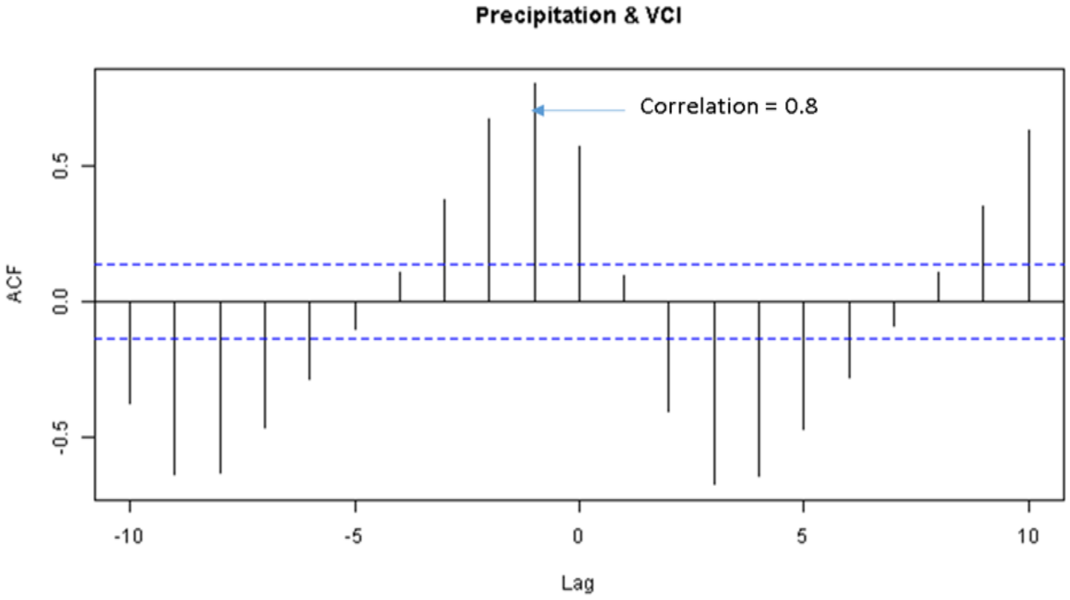

Fig. 15: Correlation coefficient of precipitation and VCI with lag time in months (h) on both sides

5.7 Comparison between SPI, SOI and VCI index of Winter (2006)

SPI and VCI analysis of all year showed 2006 winter was the most severe than any other year of the study. SPI-3 of winter (DJF) showed extreme to severe condition in all used station where VCI also showed moderate to severe vegetation condition inside the basin.

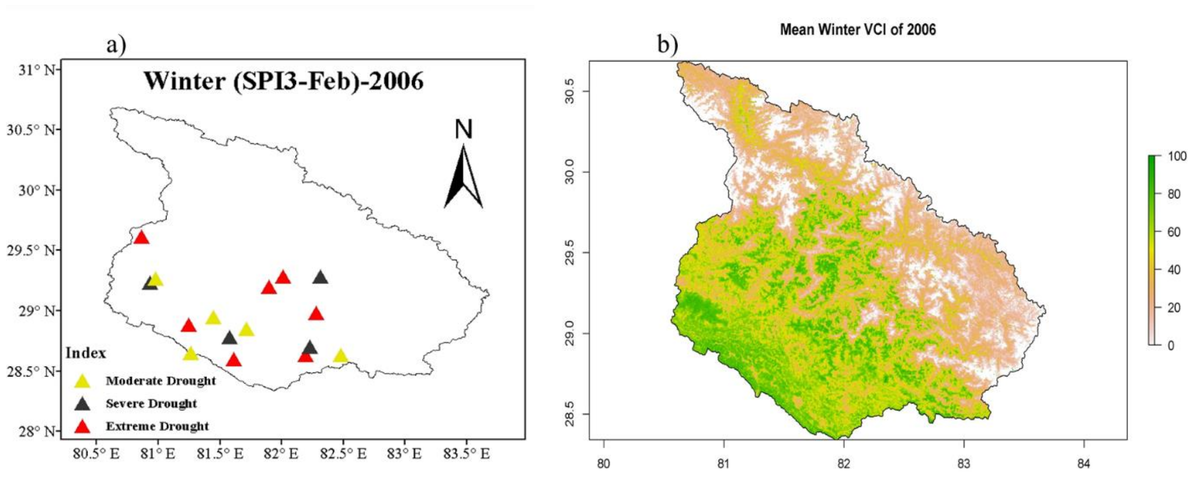

Fig. 16: Winter a) SPI-3 (2006), b) VCI (2006)

SPI plot a) indicated that 7 stations with extreme negative SPI all part of the basin, 4 stations with severe SPI and remaining had moderate SPI condition inside the basin. Mid-eastern part of the basin including Surkhet, Rukum, Jajarkot, Jumla, Kalikot, part of Dolpa and Bajura was highly affected by extreme negative SPI and rest part has severe negative SPI condition. Mid and south part of the basin with extreme condition of SPI according to SPI mapping than the southwest part of the basin. It is noticed that all altitude station shown negative value of SPI in the winter spreading dry condition inside the KRB.

The VCI mapping of winter in 2006 revealed a grim picture of severe to extreme drought conditions across more than 80% of the basin, with particularly severe impacts in certain regions. The forest cover area, with the exception of lower Doti, experienced severe drought conditions. The western part of the basin, including Dadeldhura, Bajhang, Bajura, and the southernmost areas, were particularly affected, experiencing the brunt of the drought. Salyan, Surkhet, and

Jajarkot were hit extremely hard, with VCI values dropping below 30%, indicating severe drought conditions. Even the northernmost parts of the basin, including Dolpa and Mugu, experienced drought impacts, and certain areas of Lipulekh were also affected in the same year. Map revealed that 50% of the basin has suffered from severe drought, with another 30% experienced severe to moderate drought conditions, characterized by intense dryness during the winter.

Table 5: Relation between SOI, SPI, VCI and Precipitation of Winter (2006)

Time Scale	SOI	SPI	VCI (%)
Winter	0.97	-2.3	47
Winter (1 month lag)	0.8	-2.3	43

It is analyzed the condition of the SOI in relation to two drought indices, both with and without considering the lag time of SOI and VCI over precipitation. During the winter of 2006, the positive phase of the SOI index with 0.97 indicated the absence of El-Nino conditions in the basin. However, the SPI and VCI showed drought conditions, with an extreme SPI value of -2.3 and a moderate VCI value of 47% indicating initiation of the moderate dry condition in the basin.

When a one-month lag was considered for both SOI and VCI, slight changes were observed compared to the analysis without lag. The SOI value was found to be 0.8, with the same extreme SPI value of -2.3, but the VCI marginally decreased to 43%, indicating a moderate to severe dry condition in the basin.

5.8 Comparison between SPI, SOI and VCI of Monsoon (2015)

SPI-4 of monsoon (JJAS) in 2015 have been analyzed as drought year in SPI index analysis from moderate to extreme condition.

Figure a) indicated the SPI trend of monsoon where about 90% of the station with moderate, severe to extreme negative SPI value. Two station indicated extreme SPI condition lies in the middle-east part the basin of Guthi Chaur (304) and Musikot Rukum (514). Both stations are above 2000 masl.

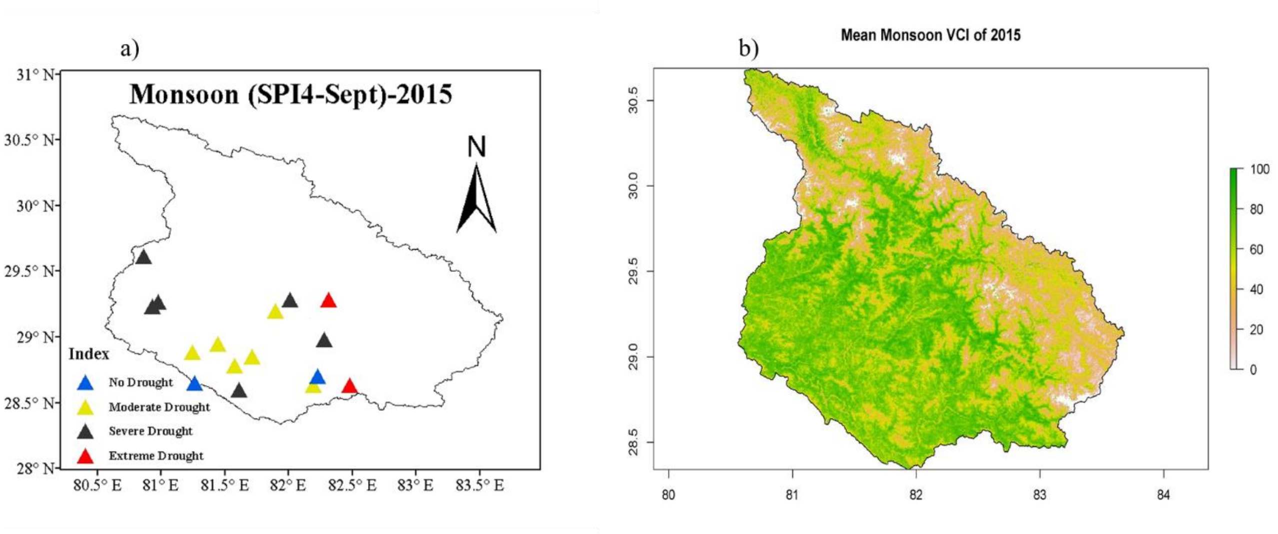

Fig. 17: Monsoon a) SPI-4 (2015), b) VCI (2015)

Six stations experienced severe SPI including middle-eastern and far western part of the basin of basin of Jumla, Jajarkot, Doti, Dadeldhura and Bajhang. Remaining six station having moderate SPI condition in the summer monsoon season. Only two station have not shown negative SPI in Chisapani Karnali station (405) and Jajarkot (404). Middle part of basin has consistent moderate SPI pattern for almost 30% of the basin area including Aacham, Dailekh, Surkhet.

VCI image of 2015 monsoon also seen as a weak vegetation condition support the SPI result. West to east forest cover of the lower portion is also identified as affected by monsoon drought.

Western part of the basin including Dadeldhura, Bajhang, Bajura, Darchula were effected by moderate to severe VCI where Northern most part of the basin have VCI less than 30% indicating severe vegetation condition. Middle east part of the basin was experienced weak vegetation around 50% where Jumla and Mugu area have been calculated VCI around 35% indicating severe condition of vegetation. South east portion of basin also experienced moderate drought in VCI mapping and the Dolpa, Humla, Mugu, Darchula, Bajura , Jumla including all upper portion of the basin were expected worse VCI condition than lower portion of the basin. Those area have seen less VCI percentage less than 40% than the rest of the part having VCI range 50% to 60% inside basin.

Climatic parameter with large scale atmospheric circulation pattern have been analyzed during summer monsoon of 2015 for better understanding of drought event inside the basin for SOI index along with SPI and VCI index of drought.

Table 6: Relation between SOI, SPI, VCI and Precipitation of Monsoon (2015)

Time Scale	SOI	SPI	VCI (%)
Monsoon	-2	-2.2	60
Monsoon (1 month lag)	-1.6	-2.2	55

Monsoon season of 2015 has been linked with the negative value of the SOI having mean -2 for monsoon period without lag time.The northeast suffered more than the northwest. Notably, only the middle of the basin remained relatively less affected. However, in 2015 and 2020, the VCI condition was healthy, with 2020 exhibiting the highest VCI coverage, except for certain parts of Dadeldhura and the central region in the west.

The northeast suffered more than the northwest. Notably, only the middle of the basin remained relatively less affected. However, in 2015 and 2020, the VCI condition was healthy, with 2020 exhibiting the highest VCI coverage, except for certain parts of Dadeldhura and the central region in the west.

Monsoon season of 2015 has been linked with the negative value of SOI and VCI. SPI time series mean showed extreme condition -2.2 along with VCI of 60%. Based on one month lag time of VCI and SOI, found that SOI value of -1.6 which is changed than regular value, and unchanged SPI value with decreasing VCI of 55%. Lag time support to study vegetation condition that weaken from 60% to 55% with one of VCI lags to precipitation.

5.9 Correlation between VCI and Precipitation (2002-2019)

The relationship between different variables can be determined by analyzing the movement and calculating the Pearson correlation coefficient of data from the same time period and time scale. In this study, the Pearson correlation coefficient has calculated for two variable precipitation and VCI data that for all seasonal and annual scale, using time series data from 2002 to 2019.

Table 7: Correlation between VCI and Precipitation without lag time, with 1 month lag time of VCI

Time Scale	VCI and Precipitation (r) without lag time	VCI and Precipitation (r) with one month lag time
Winter	0.20	0.33
Pre-monsoon	0.42	0.82
Monsoon	-0.25	-0.18
Post-monsoon	0.31	0.48

Annual	0.13	0.23

Without considering the lag time of VCI in the analysis, it was found that the highest positive correlation coefficient was found in pre-monsoon (r = 0.42), while the lowest negative was observed during monsoon (r = -0.25). Pre-monsoon and post-monsoon season showed a significant positive correlation compared to other seasons. On the other hand, monsoon season indicated the highest negative correlation coefficient, suggesting that monsoon VCI does not solely depend on precipitation of that season, and a rise in one variable corresponds to a fall in the other with a weak correlation.

With considering one month lag time of VCI, highest positive correlation coefficient between VCI and precipitation was found to be significant during pre-monsoon (r = 0.82), while the lowest negative correlation coefficient was observed during monsoon (r = -0.18). Additionally, it was observed that when considering a lag time of one month on VCI values, the correlation coefficient increased towards more positive values for all seasons. It has identified lag time on Specifically, with a one-month time, the correlation coefficient changed up double for pre-monsoon, 0.17 for post-monsoon and 0.15 for winter, but showed less changes, up to 0.7 for monsoon and 0.10 for annual scale.

Chapter VI: Discussion

A comprehensive spatio-temporal analysis was conducted on drought dynamics in the KRB, utilizing station-based SPI and satellite-derived VCI data across seasonally and annually. The study revealed a clear link between precipitation patterns and drought propagation, with calculated precipitation decreasing at 4.5mm per year inside the KRB which indicated sign of drought in the meteorological based drought indices. Temporal analysis of SPI trends highlighted a consistent increase in drought occurrences, notably after post-2000. This study revealed SPI-12 drought in 1992, 1994, 2004, 2005, 2006, 2010, 2015 and 2016 with increasing pattern of drought. And station wise SPI showed increasing severity of winter drought. Remarkable extreme winter drought years were identified (1992, 2006, 2008, 2015 and 2016), with 2015 and 2016 exhibiting severe drought, particularly in Nepal's western regions, consistent with previous research (Bagale et al., 2021; Khatiwada and Pandey, 2019). Seasonal influence of the drought dominated in the winter season inside the KRB as 2006 was the extreme drought year in SPI trend mapping and it is highly influenced by the weakening western disturbance during the winter season inside the KRB aligned with Terai and Siwalik shown increasing trend of the winter drought means decreasing trend of winter precipitation which was previously studied with decreasing trend of winter precipitation strongly in the western part of Nepal (Karki et al., 2017). Winter drought's detachment from SOI highlighted the influence of alternative climatic factors, as supported by previous research (Wang et al., 2013) shown positive value of SOI prevailed during severe winter drought in the western region of Nepal and warming sea surface temperatures (SST) in the southern Indian Ocean, along rising levels of anthropogenic aerosols, both locally and from neighboring countries brings excessive subsidence of air mass around the western part of the Nepal. The meteorological-based SPI demonstrated increasing summer monsoon drought frequency post 2000 and 2015 was spotted as severe summer monsoon drought year inside the all station record in KRB and previous study strengthen the result of increasing drought event in monsoon season (Khatiwada and Pandey, 2019). Frequent summer monsoon drought indicated the direct impact in the agriculture and water balance in the KRB because it is known as major season of precipitation contributing 75% annually. Intense convective activities during summer monsoon changed the track of moisture coming from

Bay of Bengal (BOB) sometimes even stretching convective level of tropopause during hot summer lift the air mass over the mountain ranges as earlier mentioned eastern part of Africa experienced dry static energy with subsidence of dry air mass coming from southern tropical Indian ocean (Williams et al., 2012). Southern and southwestern basin's susceptibility to monsoon drought is evident from SPI-4 of September and its interaction with large-scale atmospheric circulation, particularly the negative SOI phase, emerged as a major driver of drought in the KRB as seen in the case study of 2015 monsoon drought inside the KRB triggering El-Nino phase of ENSO cycle. Relationship between drought indices (SPI) and large scale atmospheric circulation (SOI) aligned with previously studied negative SOI association in monsoon drought (Sigdel and Devkota, 2013; Sigdel and Ikeda, 2012).

Rising pre-monsoon drought trends after 2000, impacting vegetation sustainability and Consecutive dry years (2010-2014) with mild pre-monsoon drought in the basin, influenced by antecedent dry winter conditions and persistent high temperatures during pre-monsoon. Severe drought (1996) and moderate drought (1994, 1995) aligned with rising pre-monsoon and winter temperatures (Khatiwada et al., 2016), suggesting heightened drought propensity. Monsoon SPI-12 for December has been calculated for all years and found that year 1992, 1994, 2006 and 2008 were the extreme drought years inside the KRB. Time scale of drought varied spatially and found mid-western is more vulnerable than far-western region of the Nepal (Bagale et al., 2021; Kafle, 2015) but it is not same for all seasons inside the KRB. Winter is more vulnerable to the mid-western than the far-western region and reverse situation for monsoon season. It is mainly due to the origin of the large scale circulation during monsoon enters from the eastern Nepal where western disturbance enters from the western part the country (Bagale et al., 2021; Sigdel and Ikeda, 2012) . SPI mapping inside the basin showed year 1992, 1994, 2004, 2005, 2006 and 2015 were cumulative drought years inside the basin. Spatial variation of drought have shown winter drought trend is in increasing trend compared to other season. Long-term winter drought is increasing significantly in Doti and Chisapani Bardiya and all station recorded as winter has severe impact of drought inside the KRB. Recent year experienced mild to no precipitation record during winter inside the KRB indicating failure of existing vegetation with surmounting prolonged dry condition during winter strengthen the result of rising temperature about 1°C after 1990 with high evaporation losses of soil moisture (Wang et al., 2013).

VCI time series analysis for all four seasons indicated that vegetation condition were impacted highly in the dry winter season than rest of seasons in both basin wise and station wise extraction of VCI for all years. Basin wise analysis showed pre-monsoon was severe and station wise indicated winter is severe inside the basin which meant lower elevation has higher rate of vegetation cover than the whole basin inside the KRB because station wise analysis occupied only lower half portion of the basin. So that, lower portion of the basin is highly vulnerable during winter than other seasons where overall basin seemed to be impacted by pre-monsoon drought because per-monsoon has high mean daily temperature creating intensive evaporative losses from the soil as well as infrequent rainfall inside the basin triggering adverse condition in the soil moisture for plant growth (Krakauer et al., 2017; Viovy et al., 1992) but it is not considered the situation of rising VCI coverage in latest decade due to the environmental campaign of afforestation as well as having more than 40% area covered by forest land which tolerate well against drought as previous studied showed Grasslands and cultivated vegetation exhibit stronger drought effects compared to forests, possibly linked to root system characteristics (Zhan et al., 2022). Highest VCI were recorded during monsoon and post-monsoon because monsoon deals with significant amount of precipitation inside the basin (Sharma et al., 2020). Long term spatio-temporal mapping showed pre-monsoon and winter spotted as less vegetation cover seasons. Both seasons have been impacted of drought more in the southern and northern part of basin than middle portion. It is due to the impact of the large scale atmospheric circulation does not cross the high mountains creating wind ward and Lee ward side inside the basin as suggested in the study of precipitation trend of Nepal highly contributed in the middle part of east to west extend including Siwalik and middle mountains (DHM, 2015; Karki et al., 2017). So, Humla and Dolpa showed poor condition of VCI for all seasons due to its barren and rock type land cover and divided by the high hills that surpassed the flow of air mass. Most part of the lower portion of basin including southwestern portion has VCI less than 30% due to the high temperature commencing high evaporative losses of moisture from soil surface and also prevailing dry condition in pre-monsoon period as investigated earlier with coupled observation model drought analysis under global warming, study analyzed climate model simulations under intermediate future greenhouse gas emissions scenarios, indicating decreases in soil moisture content in the top 10 cm for most models with rising trend of sea surface temperature (SST) in north mid to high latitude (Dai, 2013; Naumann et al., 2018). Early vegetation is highly impacted by the intense temperature condition as mentioned by pervious study on thermal infrared remote sensing is highly effective for early-stage agricultural drought monitoring due to its rapid response to vegetation water stress (Hu et al., 2020).

Pearson's correlation have been performed and found pre-monsoon have significant positive correlation between VCI and precipitation than other seasons because of the highly dependency of the precipitation to maintain greenery during dry and hot pre-monsoon period. So, dry pre-monsoon certainly brings huge crop failure inside the basin including maize, vegetables and grass land for wildlife in couple of conservation area inside the basin. It has also negative impact in the water resources depletion during hot seasons. Monsoon has examined negative correlation coefficient which was not found in VCI mapping of Nepal done in previous study (Baniya et al., 2019) . It is inferred that monsoon VCI has not high dependency in the precipitation for just four month because VCI lag time respond later that the assumed (JJAS) of summer monsoon and another major caused by the layering cloud cover spotted most of the time in the monsoon seasons in Nepal. Post-monsoon responded with positive correlation because monsoon effect can be seen clearly in the post-monsoon season by the lag time between precipitation and VCI. Lag time effect has clearly seen in the all seasons and mainly seen in the post-monsoon, previously studied on the different factor of post vegetation response not only linked with the lag effect of VCI as well as cumulative effect of the VCI condition (Ji et al., 2021; Zhan et al., 2022) . Winter has reacted with positive correlation coefficient inside the KRB where whole Nepal presented with negative correlation in winter between VCI and precipitation (Baniya et al., 2019). It has observed that western part of the Nepal including KRB deals with high precipitation trend than the rest of the country due to effect of western disturbance in winter season but it has identified that winter precipitation trend is in decreasing trend due to the weak deal of western disturbance inside KRB (Karki et al., 2017).

Relationship between large scale SOI with monsoon and winter SPI and VCI have found monsoon is highly impacted by negative value of SOI where winter does not show huge impact of SOI rather than the western disturbance (Bagale et al., 2021; Hamal et al., 2021). Monsoon has less precipitation when SOI is negative built up of El-Nino condition around South Asia including KRB. It brings severe dry condition inside the country for rainfall dependent plantation of paddy crop mostly in the altitude below 3000m (Panthi et al., 2016).

Overall, Drought monitoring using both indices suggested that the severity of drought in the KRB has been increasing for all seasons. Drought mapping in remote sensing and ground based indices differ in the seasons and land cover type of the geographical areas inside the KRB. It has identified alarming trends in precipitation patterns, increasing drought occurrences, and the significant impact on vegetation and agriculture. It is represented that severity of drought has highest in the winter and pre-monsoon season than the monsoon season. But frequency and intensity of summer monsoon drought has been increasing in most of the station inside KRB (Khatiwada and Pandey, 2019; Baniya et al., 2019; Zhang et al., 2011) challenging in agriculture and water management of the whole year.

Chapter VII: Conclusion

Study identified diverse drought patterns: Remote sensing and Ground based indices differ due to vegetation's lagged response to precipitation throughout calendar year inside KRB. Ground-based SPI index revealed increasing winter and pre-monsoon drought trends compared to annual pattern of SPI-12 for December, impacting basin agriculture with drought years: 1987, 1992, 1999, 2006-2011, 2015-2017. Monsoon amplified drought frequency most, followed by winter and pre monsoon affecting basin mean precipitation severely after year 2000. Spatially, southern and northern basin sections, including Doti, Chisapani Bardiya, Surkhet, Rukum, Jumla, and Dolpa, showed severe drought in both indices. It has been computed vegetation dynamics during pre-monsoon and winter, intensifying drought severity from February to mid-summer monsoon. Approximately 50% of the year witnessed critical vegetation states, causing crop failure and high-elevation water scarcity inside the KRB. Despite SPI drought severity, winter and pre-monsoon vegetation cover showed an increasing VCI in basin analysis, possibly due to elevated temperatures at higher altitudes due to global warming elevated CO_2 level enhancing photo synthesis process. Sub-3000m pre-monsoon VCI decline suggested weakening winter and pre-monsoon precipitation in the basin's southern part. VCI mapping identified drought years (2002, 2006, 2008, 2009, 2013, 2016, 2017), with winters experiencing severe impact. VCI exhibited better response to dry season due to lagged effect, reflecting post-moisture vegetation growth. Notably, 2006's severe SPI drought lacked VCI correspondence due to prolific monsoon and post-monsoon precipitation impacted by vegetation sustainability. VCI-precipitation link enabled short-term drought monitoring, aiding crop assessment and has been emphasized a stronger correlation between drought and SOI-driven circulation during the monsoon than in winter, attributed to similar circulation pattern with intensive convection during hot summer monsoon. VCI proved reliable for short-term pre-monsoon and winter crop drought monitoring, while SPI comprehended diverse drought scaling without capturing vegetation dynamics. VCI respond vary across land covers; forests, grass lands, barren land due to VCI lag response with precipitation. All vegetation types exhibited a one-month lag in post-precipitation growth to reach optimal greenness where Dry season vegetation responded promptly, maintaining maximum greenery, distinct from wet season counterparts.

Overall, the comprehensive spatio-temporal analysis of drought dynamics in the KRB presented in this study underscores the critical need for ongoing monitoring and adaptive management in this region. The research has revealed a concerning trend of increasing drought occurrences, particularly in the winter, pre-monsoon and summer seasons, with significant implications for agriculture, water resources, and vegetation sustainability. It has also shed light on the complex interplay of climatic factors, including precipitation patterns, the influence of SOI, which contributed to the region's evolving drought landscape. These insights serve as valuable guidance for policymakers, water resource managers, and local communities, emphasizing the urgency of climate resilience strategies and sustainable land-use practices to mitigate the growing impacts of drought in the KRB. It has been also emphasized that linkage of remote sensing and ground based drought indices varied temporally and spatially in the distinct topography and seasons inside the KRB.

References

Aghakouchak, A., Farahmand, A., Melton, F. S., Teixeira, J., Anderson, M. C., Wardlow, B. D., & Hain, C. R. (2015). Remote sensing of drought: Progress, challenges and opportunities. *Reviews of Geophysics*, *53*(2), 452–480. https://doi.org/10.1002/2014RG000456

Bagale, D., Sigdel, M., & Aryal, D. (2021). Drought Monitoring over Nepal for the Last Four Decades and Its Connection with Southern Oscillation Index. *Water*, *13*(23), Article 23. https://doi.org/10.3390/w13233411

Baniya, B., Tang, Q., Huang, Z., Sun, S., & Techato, K. (2018). Spatial and Temporal Variation of NDVI in Response to Climate Change and the Implication for Carbon Dynamics in Nepal. *Forests*, *9*(6), Article 6. https://doi.org/10.3390/f9060329

Baniya, B., Tang, Q., Xu, X., Haile, G. G., & Chhipi-Shrestha, G. (2019). Spatial and Temporal Variation of Drought Based on Satellite Derived Vegetation Condition Index in Nepal from 1982–2015. *Sensors*, *19*(2), Article 2. https://doi.org/10.3390/s19020430

Biemans, H., Siderius, C., Lutz, A. F., Nepal, S., Ahmad, B., Hassan, T., von Bloh, W., Wijngaard, R. R., Wester, P., Shrestha, A. B., & Immerzeel, W. W. (2019). Importance of snow and glacier meltwater for agriculture on the Indo-Gangetic Plain. *Nature Sustainability*, *2*(7), Article 7. https://doi.org/10.1038/s41893-019-0305-3

Dahal, N. M., Xiong, D., Neupane, N., Yigez, B., Zhang, B., Yuan, Y., Koirala, S., Liu, L., & Fang, Y. (2021). Spatiotemporal analysis of drought variability based on the standardized precipitation evapotranspiration index in the Koshi River Basin, Nepal. *Journal of Arid Land*, *13*(5), 433–454. https://doi.org/10.1007/s40333-021-0065-6

Dahal, P., Shrestha, N. S., Shrestha, M. L., Krakauer, N. Y., Panthi, J., Pradhanang, S. M., Jha, A., & Lakhankar, T. (2016). Drought risk assessment in central Nepal: Temporal and spatial analysis. *Natural Hazards*, *80*(3), 1913–1932. https://doi.org/10.1007/s11069-015-2055-5

Dai, A. (2013). Increasing drought under global warming in observations and models. *Nature Climate Change*, *3*(1), 52–58. https://doi.org/10.1038/nclimate1633

Dawadi, B. (2013). Paleoclimatic studies from the tree-ring of Himalayan birch from Langtang National park, central Nepal. *Journal of Nepal Geological Society*, *46*, 191–198. https://doi.org/10.3126/jngs.v46i0.31603

DHM, N. (2015). Study of climate and climatic variation over Nepal. *Ministry of Science, Technology and Environment, Government of Nepal*.

Dong, J., Xiao, X., Wagle, P., Zhang, G., Zhou, Y., Jin, C., Torn, M. S., Meyers, T. P., Suyker, A. E., Wang, J., Yan, H., Biradar, C., & Moore, B. (2015). Comparison of four EVI-based models for estimating gross primary production of maize and soybean croplands and tall grass prairie under severe drought. *Remote Sensing of Environment*, *162*, 154–168. https://doi.org/10.1016/j.rse.2015.02.022

Dutta, D., Kundu, A., Patel, N. R., Saha, S. K., & Siddiqui, A. R. (2015). Assessment of agricultural drought in Rajasthan (India) using remote sensing derived Vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI). *The Egyptian Journal of Remote Sensing and Space Science*, *18*(1), 53–63. https://doi.org/10.1016/j.ejrs.2015.03.006

Eckstein, D., Hutfils, M.-L., & Winges, M. (2021). Who Suffers Most From Extreme Weather Events? Weather-related Loss Events in 2017 and 1998 to 2017. *Germanwatch e.V.*

Eckstein, D., Künzel, V., & Schäfer, L. (2021). The Global Climate Risk Index 2021. Bonn: *Germanwatch*. https://bvearmb.do/handle/123456789/1306

Edwards, D. C., & McKee, T. B. (1997). Characteristics of 20th Century Drought in the United States at Multiple Time Scales. *Colorado State University. Libraries*, 152-155

Guttman, N. B. (1998). Comparing the Palmer Drought Index and the Standardized Precipitation Index. *Journal of the American Water Resources Association*, *34*(1), 113–121. https://doi.org/10.1111/j.1752-1688.1998.tb05964.x

Hayes, M., Svoboda, M., Wall, N., & Widhalm, M. (2011). The Lincoln Declaration on Drought Indices: Universal Meteorological Drought Index Recommended. *Bulletin of the American Meteorological Society*, *92*(4), 485–488. https://doi.org/10.1175/2010BAMS3103.1

Hu, T., van Dijk, A. I. J. M., Renzullo, L. J., Xu, Z., He, J., Tian, S., Zhou, J., & Li, H. (2020). On agricultural drought monitoring in Australia using Himawari-8 geostationary thermal infrared observations. *International Journal of Applied Earth Observation and Geoinformation*, *91*, 102153. https://doi.org/10.1016/j.jag.2020.102153

Hughes, J., Potter, N., Zhang, L., & Bridgart, R. (2021). Conceptual Model Modification and the Millennium Drought of Southeastern Australia. *Water*, *13*(5), Article 5. https://doi.org/10.3390/w13050669

IPCC. (2021). AR6 Climate Change 2021: The Physical Science Basis. *IPCC*

Ji, Y., Li, Y., Yao, N., Biswas, A., Zou, Y., Meng, Q., & Liu, F. (2021). The lagged effect and impact of soil moisture drought on terrestrial ecosystem water use efficiency. *Ecological Indicators*, *133*, 108349. https://doi.org/10.1016/j.ecolind.2021.108349

Kafle, H. K. (2015). Spatial and Temporal Variation of Drought in Far and Mid Western Regions of Nepal: Time Series Analysis (1982-2012). *Nepal Journal of Science and Technology*, *15*(2), 65–76. https://doi.org/10.3126/njst.v15i2.12118

Kansakar, S. R., Hannah, D. M., Gerrard, J., & Rees, G. (2004). Spatial pattern in the precipitation regime of Nepal. *International Journal of Climatology*, *24*(13), 1645–1659. https://doi.org/10.1002/joc.1098

Karki, M., Mool, P., & Shrestha, A. (1970). Climate Change and its Increasing Impacts in Nepal. *The Initiation*, *3*, 30–37. https://doi.org/10.3126/init.v3i0.2425

Karki, R., Hasson, S. ul, Schickhoff, U., Scholten, T., & Böhner, J. (2017). Rising Precipitation Extremes across Nepal. *Climate*, *5*(1), Article 1. https://doi.org/10.3390/cli5010004

Khatiwada, K. R., & Pandey, V. P. (2019). Characterization of hydro-meteorological drought in Nepal Himalaya: A case of Karnali River Basin. *Weather and Climate Extremes*, *26*, 100239. https://doi.org/10.1016/j.wace.2019.100239

Khatiwada, K. R., Panthi, J., Shrestha, M. L., & Nepal, S. (2016). Hydro-Climatic Variability in the Karnali River Basin of Nepal Himalaya. *Climate*, *4*(2), 17. https://doi.org/10.3390/cli4020017

Kogan, F.N, Adamenko, T., & Guo, W. (2013). Global and regional drought dynamics in the climate warming era. *Remote Sensing Letters*, *4*(4), 364–372. https://doi.org/10.1080/2150704X.2012.736033

Kogan, F. N. (1995). Droughts of the Late 1980s in the United States as Derived from NOAA Polar-Orbiting Satellite Data. *Bulletin of the American Meteorological Society*, *76*(5), 655–668. https://doi.org/10.1175/1520-0477(1995)076<0655:DOTLIT>2.0.CO;2

Kogan, F. N. (1997). Global Drought Watch from Space. *Bulletin of the American Meteorological Society*, *78*(4), 621–636. https://doi.org/10.1175/1520 0477(1997)078<0621:GDWFS>2.0.CO;2

Krakauer, N., Lakhankar, T., & Anadón, J. (2017). Mapping and Attributing Normalized Difference Vegetation Index Trends for Nepal. *Remote Sensing*, *9*(10), 986. https://doi.org/10.3390/rs9100986

Lamichhane, D., Dawadi, B., Acharya, R., Pudasainee, S., & Shrestha, I. (2020). Observed Trends and Spatial Distribution in Daily Precipitation Indices of Extremes over the Narayani River Basin, Central Nepal. *Applied Ecology and Environmental Sciences*, *8*(3), 106–118. https://doi.org/10.12691/aees-8-3-6

Lui, W. T., & Kogan, F. N. (1996). Monitoring regional drought using the Vegetation Condition Index. *International Journal of Remote Sensing*, *17*(14), 2761–2782. https://doi.org/10.1080/01431169608949106

Mann, H. B. (1945). Nonparametric Tests Against Trend. *Econometrica*, *13*(3), 245–259. https://doi.org/10.2307/1907187

McKee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. *Applied Climatology*, 17–22.

Mirza, M. M. Q., Ahmed, A. U., & Ahmad, Q. K. (2008). Interlinking of Rivers in India: Issues and Concerns. CRC Press.

Mishra, A. K., & Singh, V. P. (2010). A review of drought concepts. *Journal of Hydrology*, *391*(1), 202–216. https://doi.org/10.1016/j.jhydrol.2010.07.012

Naumann, G., Alfieri, L., Wyser, K., Mentaschi, L., Betts, R. A., Carrao, H., Spinoni, J., Vogt, J., & Feyen, L. (2018). Global Changes in Drought Conditions Under Different Levels of Warming. *Geophysical Research Letters*, *45*(7), 3285–3296. https://doi.org/10.1002/2017GL076521

Nayava, J. (1980). *Rainfall in Nepal*.

Obasi, G. O. P. (1994). WMO's Role in the International Decade for Natural Disaster Reduction. *Bulletin of the American Meteorological Society*, *75*(9), 1655–1661. https://www.jstor.org/stable/26231968

Pandey, A., Mishra, S., & Gautam, A. K. (2015). Soil Erosion Modeling Using Satellite Rainfall Estimates. *Journal of Water Resource and Hydraulic Engineering*, *4*, 318–325. https://doi.org/10.5963/JWRHE0404002

Panthi, J., Aryal, S., Dahal, P., Bhandari, P., Krakauer, N. Y., & Pandey, V. P. (2016). Livelihood vulnerability approach to assessing climate change impacts on mixed agro-livestock smallholders around the Gandaki River Basin in Nepal. *Regional Environmental Change*, *16*(4), 1121–1132. https://doi.org/10.1007/s10113-015-0833-y

Panthi, J., Khatiwada, K. R., Shrestha, M. L., & Dahal, P. (2019). Water poverty in the context of climate change: A case study from Karnali river basin in Nepal Himalaya. *International Journal of River Basin Management*, *17*(2), 243–250. https://doi.org/10.1080/15715124.2018.1531421

Rousta, I., Olafsson, H., Moniruzzaman, M., Zhang, H., Liou, Y.-A., Mushore, T. D., & Gupta, A. (2020). Impacts of Drought on Vegetation Assessed by Vegetation Indices and Meteorological Factors in Afghanistan. *Remote Sensing*, *12*(15), Article 15. https://doi.org/10.3390/rs12152433

Sharma, S., Hamal, K., Khadka, N., Shrestha, D., Aryal, D., & Thakuri, S. (2021). Drought characteristics over Nepal Himalaya and their relationship with climatic indices. *Meteorological Applications*, *28*(2), e1988. https://doi.org/10.1002/met.1988

Sharma, S., Khadka, N., Hamal, K., Shrestha, D., Talchabhadel, R., & Chen, Y. (2020). How Accurately Can Satellite Products (TMPA and IMERG) Detect Precipitation Patterns, Extremities, and Drought Across the Nepalese Himalaya? *Earth and Space Science*, *7*(8), e2020EA001315. https://doi.org/10.1029/2020EA001315

Shrestha, B., Ye, Q., & Khadka, N. (2019). Assessment of Ecosystem Services Value Based on Land Use and Land Cover Changes in the Transboundary Karnali River Basin, Central Himalayas. *Sustainability*, *11*(11), Article 11. https://doi.org/10.3390/su11113183

Shrestha, B., Zhang, L., Sharma, S., Shrestha, S., & Khadka, N. (2022). Effects on ecosystem services value due to land use and land cover change (1990–2020) in the transboundary Karnali River Basin, Central Himalayas. *SN Applied Sciences*, *4*(5), 137. https://doi.org/10.1007/s42452-022-05022-y

Sigdel, M., & Devkota, L. P. (2013). Connection of Winter Time Precipitation System in and around Nepal with Pacific and Indian Ocean Indices. *Pakistan Journal of Meteorology*, *10*(19).

Sigdel, M., & Ikeda, M. (2010). Spatial and Temporal Analysis of Drought in Nepal using Standardized Precipitation Index and its Relationship with Climate Indices. *Journal of Hydrology and Meteorology 1818-2518*, *7*, 59–74. https://doi.org/10.3126/jhm.v7i1.5617

Sigdel, M., & Ikeda, M. (2012). Seasonal Contrast in Precipitation Mechanisms over Nepal Deduced from Relationship with the Large-Scale Climate Patterns. *Nepal Journal of Science and Technology*, *13*(1), Article 1. https://doi.org/10.3126/njst.v13i1.7450

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An Overview of CMIP5 and the Experiment Design. *Bulletin of the American Meteorological Society*, *93*(4), 485–498. https://doi.org/10.1175/BAMS-D-11-00094.1

Thenkabail, P. S., Gamage, M. S. D. N., & Smakhtin, V. U. (2004). The use of remote sensing data for drought assessment and monitoring in Southwest Asia. *International Water Management Institute.*

Trenberth, K. E., Dai, A., van der Schrier, G., Jones, P. D., Barichivich, J., Briffa, K. R., & Sheffield, J. (2014). Global warming and changes in drought. *Nature Climate Change*, *4*(1), Article 1. https://doi.org/10.1038/nclimate2067

Van Loon, A. F. (2015). Hydrological drought explained. *WIREs Water*, *2*(4), 359–392. https://doi.org/10.1002/wat2.1085

Viovy, N., Arino, O., & Belward, A. S. (1992). The Best Index Slope Extraction (BISE): A method for reducing noise in NDVI time-series. *International Journal of Remote Sensing*, *13*(8), 1585–1590. https://doi.org/10.1080/01431169208904212

Wan, Z., Wang, P., & Li, X. (2004). Using MODIS Land Surface Temperature and Normalized Difference Vegetation Index products for monitoring drought in the southern Great Plains, USA. *International Journal of Remote Sensing*, *25*(1), 61–72. https://doi.org/10.1080/0143116031000115328

Wang, A., Lettenmaier, D. P., & Sheffield, J. (2011). Soil Moisture Drought in China, 1950–2006. *Journal of Climate*, *24*(13), 3257–3271. https://doi.org/10.1175/2011JCLI3733.1

Wang, S.-Y., Yoon, J.-H., Gillies, R. R., & Cho, C. (2013). What Caused the Winter Drought in Western Nepal during Recent Years? *Journal of Climate*, *26*(21), 8241–8256. https://doi.org/10.1175/JCLI-D-12-00800.1

Williams, A. P., Funk, C., Michaelsen, J., Rauscher, S. A., Robertson, I., Wils, T. H. G., Koprowski, M., Eshetu, Z., & Loader, N. J. (2012). Recent summer precipitation trends in the Greater Horn of Africa and the emerging role of Indian Ocean sea surface temperature. *Climate Dynamics*, *39*(9), 2307–2328. https://doi.org/10.1007/s00382-011-1222-y

WMO. (2019). Concludes a decade of exceptional global heat and high-impact weather (2019). *WMO*

Yao, N., Li, Y., Lei, T., & Peng, L. (2018). Drought evolution, severity and trends in mainland China over 1961–2013. *Science of The Total Environment*, *616–617*, 73–89. https://doi.org/10.1016/j.scitotenv.2017.10.327

Zhan, C., Liang, C., Zhao, L., Jiang, S., Niu, K., & Zhang, Y. (2022). Drought-related cumulative and time-lag effects on vegetation dynamics across the Yellow River Basin, China. *Ecological Indicators*, *143*, 109409. https://doi.org/10.1016/j.ecolind.2022.109409

Zhang, L., & Zhou, T. (2015). Drought over East Asia: A Review. *Journal of Climate*, *28*(8), 3375–3399. https://doi.org/10.1175/JCLI-D-14-00259.1

Zhang, M., He, J., Wang, B., Wang, S., Li, S., Liu, W., & Ma, X. (2013). Extreme drought changes in Southwest China from 1960 to 2009. *Journal of Geographical Sciences*, *23*(1), 3–16.

Zhang, X., Alexander, L., Hegerl, G. C., Jones, P., Tank, A. K., Peterson, T. C., Trewin, B., & Zwiers, F. W. (2011). Indices for monitoring changes in extremes based on daily temperature and precipitation data. *WIREs Climate Change*, *2*(6), 851–870. https://doi.org/10.1002/wcc.147